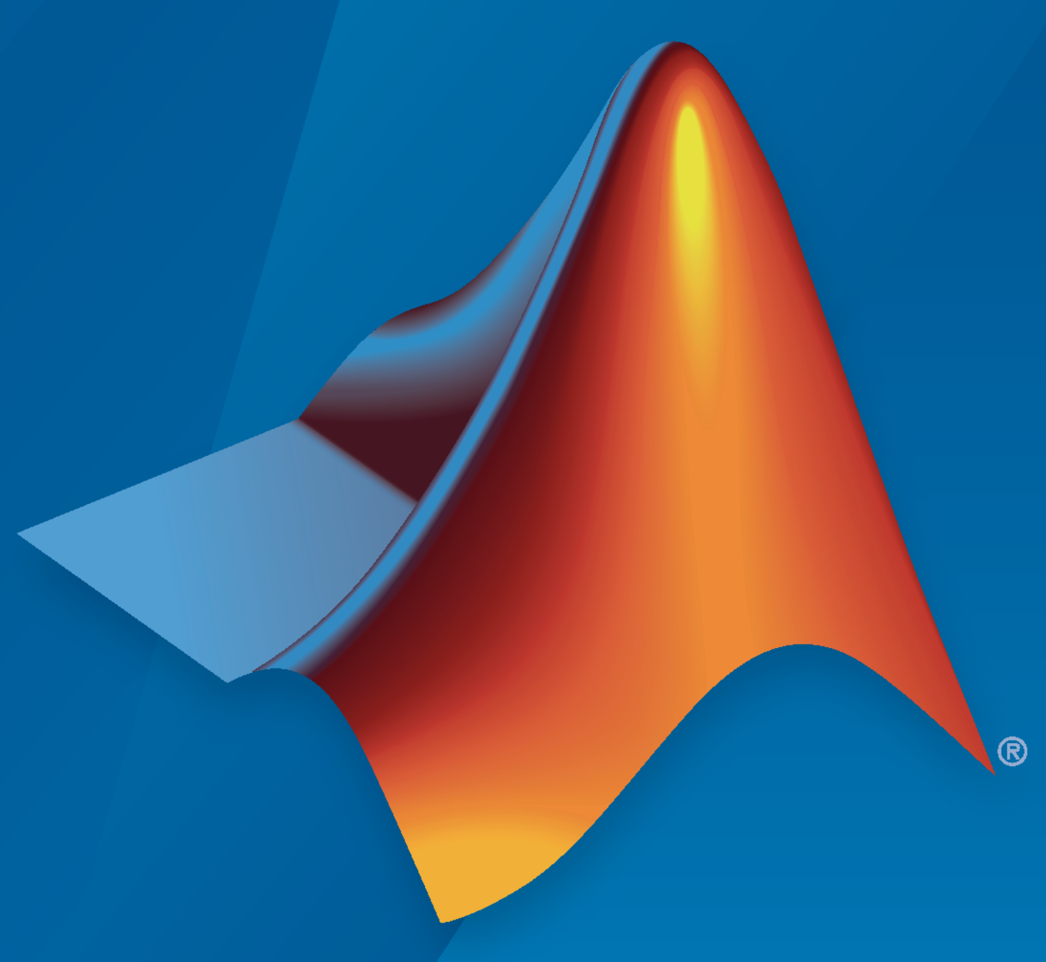
Simulink® Design Optimization™

User's Guide



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Simulink® Design Optimization™ User's Guide

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Data Analysis and Processing

- "Model Requirements for Importing Data" on page 1-2
- "Import Data for Parameter Estimation" on page 1-5
- "Plot and Analyze Data" on page 1-11
- "Preprocess Data" on page 1-13

Model Requirements for Importing Data

Before you can analyze and preprocess the estimation data, you must assign the data to the model ports or signals. In order to assign the data, the Simulink model must contain one of the following elements:

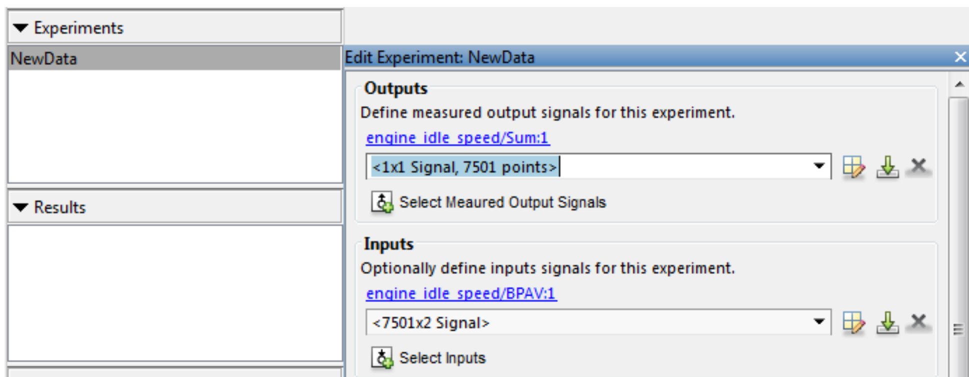
- Root-level model Inport block

  Note You do not need an Inport block if your model already contains a fixed input block, such as a Step block.

- Root-level model Outport block
- Logged signal, which can be a root-level signal in the model or a signal in a model subsystem

  To enable signal logging for a signal, in the Simulink Editor, select the signal, click the **Simulation Data Inspector** button arrow ▾ and click **Log Selected Signals**. For more information, see “Export Signal Data Using Signal Logging”.

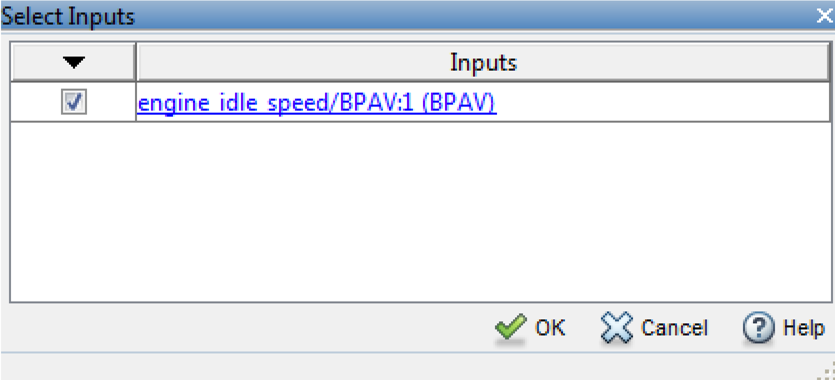
When you create an experiment, as described in “Create Experiment” on page 2-4, the top level input and output ports as well as logged signals are selected by default. You can add or remove the input and output signals using the experiment editor on page 2-5. In the experiment editor, the rows in the **Inputs** panel correspond to the model's root-level Inport blocks.



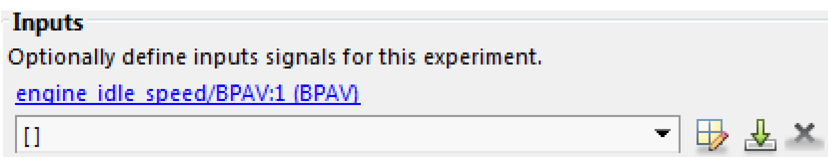
Similarly, the rows in the **Outputs** panel correspond to either the root-level Outport blocks or logged signals in the model.

Select Input Signals

You can add the Inport block in the experiment editor by clicking the **Select Inputs** button in the **Inputs** panel to launch the **Select Inputs** dialog box. You can select the Inport block you want by selecting the check box corresponding to it and clicking **OK**. There is only one Inport block for the `engine_idle_speed` model.

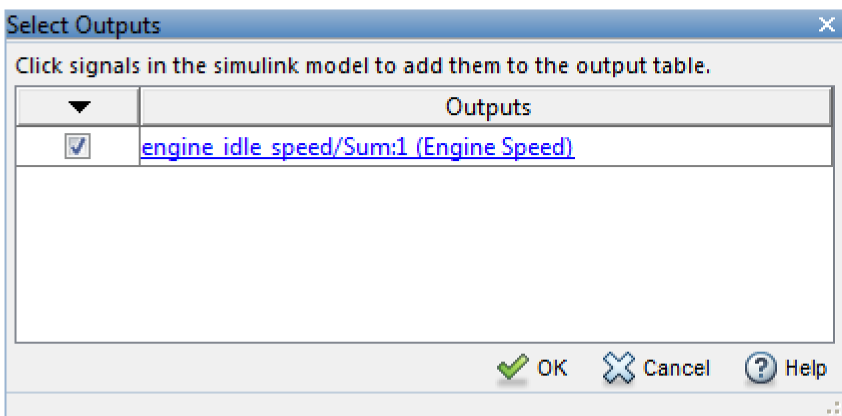


Using the dialog box, you can import the input data by typing, for example, `[time,iodata(:,1)]` in the **Inputs** panel. To learn more about importing data, see Import Data on page 1-5.

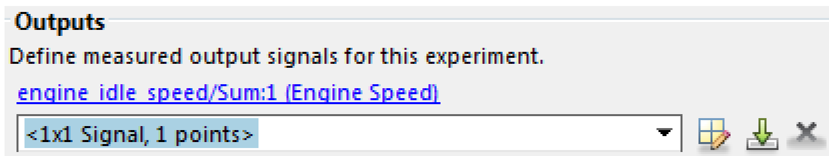


Select Output Signals

You can add the Output block in the experiment editor by clicking **Select Measured Output Signals** in the **Outputs** panel to launch the **Select Outputs** dialog box. You can select the Outport block you want by clicking the check box corresponding to it, and clicking **OK**. There is only one Outport block for the `engine_idle_speed` model.



Using the dialog box, you can import the output data by typing, for example, `[time,iodata(:,2)]` in the **Inputs** panel. To learn more about importing data, see Import Data on page 1-5.



See Also

Related Examples

- "Import Data for Parameter Estimation" on page 1-5

More About

- "What Is an Experiment?" on page 2-3

Import Data for Parameter Estimation

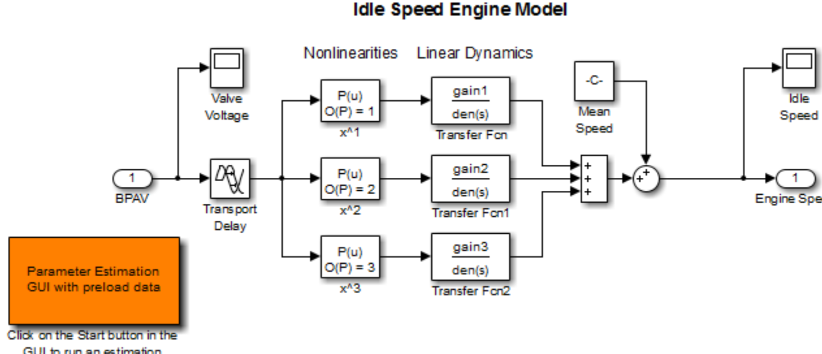
Create Experiment

Before you begin data import, create an experiment. Simulink Design Optimization software provides an app for setting up the estimation session.

To create an estimation session:

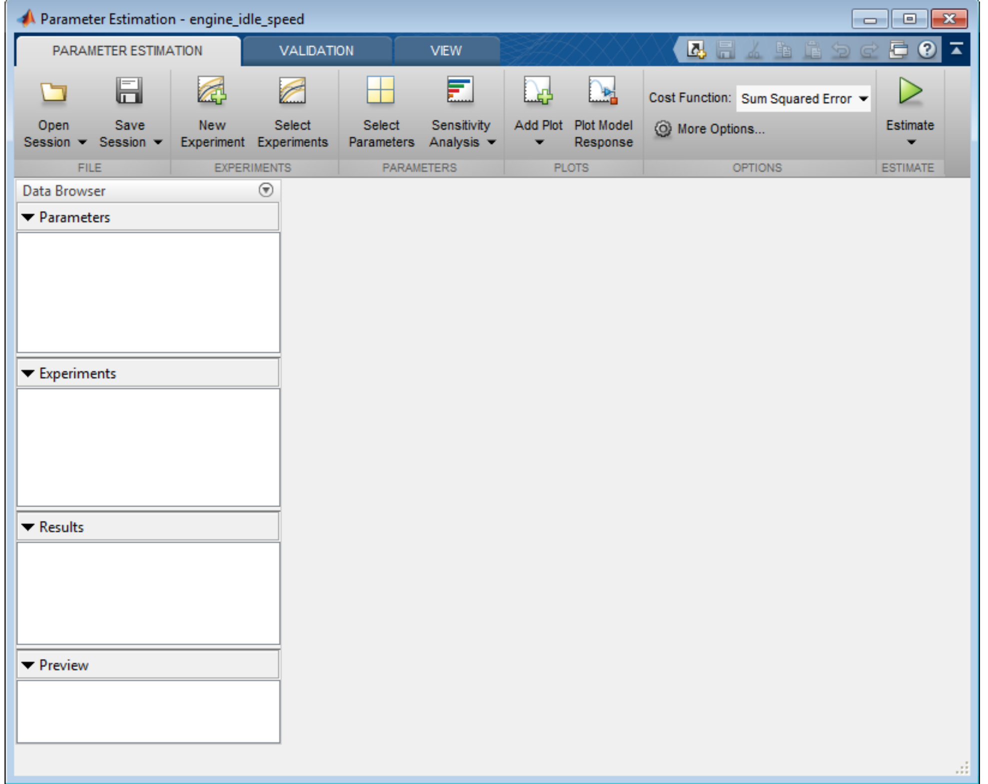
1. At the MATLAB® prompt, open the nonlinear idle speed model of an automotive engine by typing :

   ```
   engine_idle_speed
   ```

   The model contains the Inport block `BPAV` and Outport block `Engine Speed` for importing input and output data, respectively. To learn more, see “Model Requirements for Importing Data” on page 1-2.

2. In the Simulink model window, open the **Parameter Estimator** by selecting **Analysis > Parameter Estimation**.



Parameter Estimator

You can organize the estimation and validation tasks inside **Experiments** under **Data Browser** panel on the left. You can assign each experiment to an estimation task or validation task.

To create an experiment, click the **New Experiment** button.

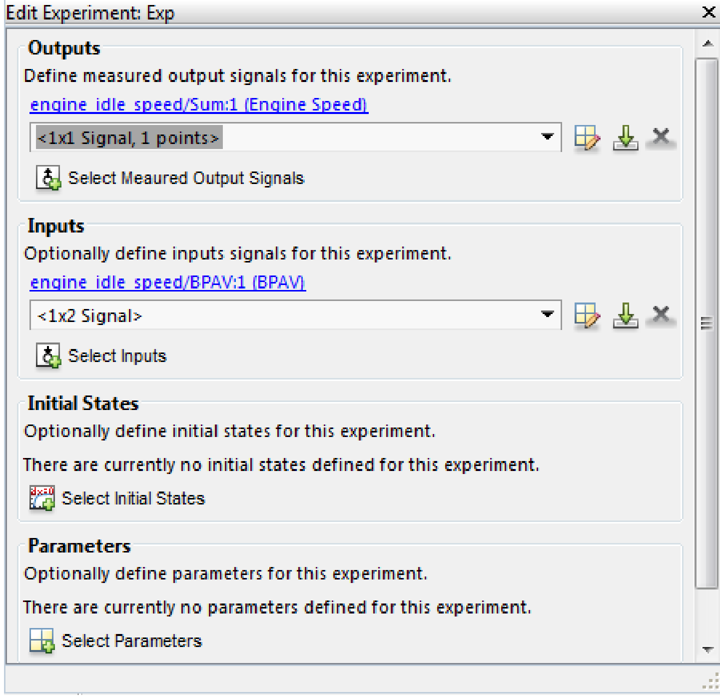
This creates an experiment called `Exp` under **Experiments**. To change the name of the experiment, right-click and select **Rename**. Call it `NewData`.

Note The Simulink model must remain open to perform parameter estimation tasks.

Time-Domain Data

Experiments are collections of signal data, specifically input and output signal data. After you create an experiment, as described in “Create Experiment” on page 1-5, you can import data into your experiment from various sources including MATLAB® variables, MAT-files, Excel® files, or comma-separated-value files.

To import data into your experiment right-click and select **Edit...**. This will launch the experiment editor. In the experiment editor, you can define the signals contained in the experiment.

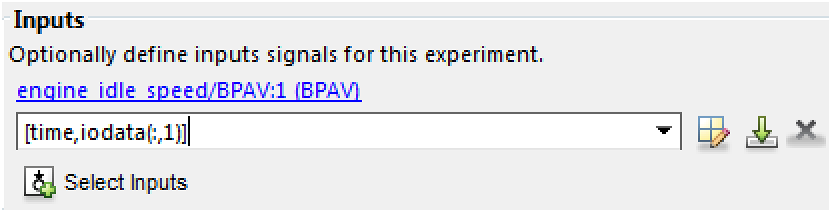


For example, the rows in the **Inputs** panel of the editor correspond to Inport block `BPAV` in the `engine_idle_speed` model.

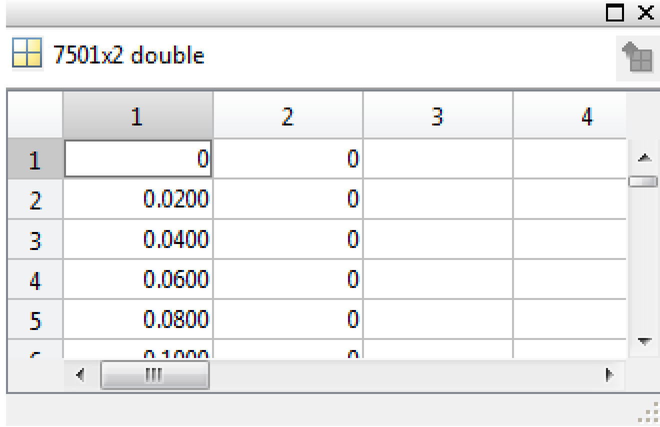
The rows in the **Outputs** panel correspond to Outport block `Engine Speed`. You can import signal data from files or MATLAB workspace.

Note The Simulink model must contain an Inport or Outport block or logged signals to enable importing data. For more information, see "Model Requirements for Importing Data" on page 1-2. To select more output signals to specify data for, click **Select Measured Output Signals** in the **Outputs** panel.

The idle-speed model of an automotive engine contains the measured data stored in the `iodata` array in the workspace. The array contains two columns: the first for input data, and the second for output data. The time data is in the `time` array in the workspace. You can import the input data by typing `[time,iodata(:,1)]` in the **Inputs** panel.



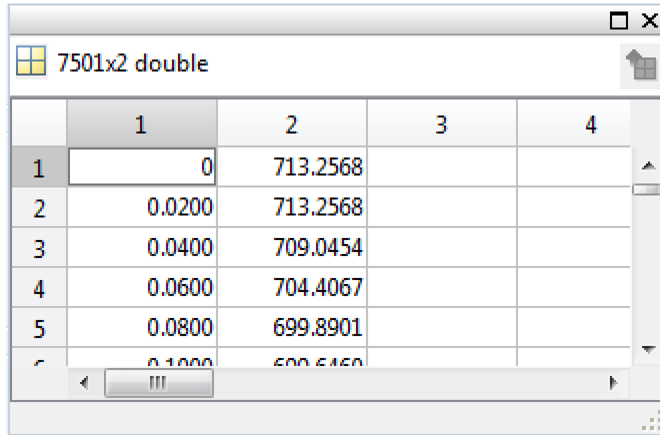
You can import the output data by typing `[time,iodata(:,2)]` in the **Outputs** panel. You can view the data by clicking . The input data should look like this:



7501x2 double

	1	2	3	4
1	0	0		
2	0.0200	0		
3	0.0400	0		
4	0.0600	0		
5	0.0800	0		

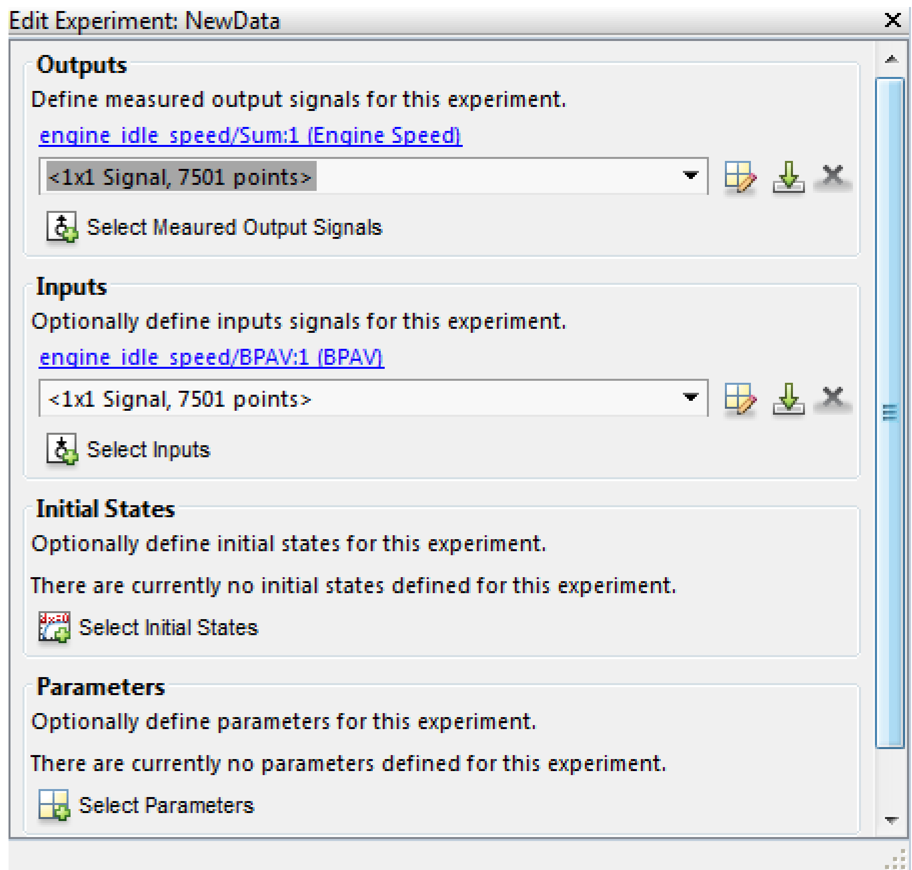
Output data should look like this:



7501x2 double

	1	2	3	4
1	0	713.2568		
2	0.0200	713.2568		
3	0.0400	709.0454		
4	0.0600	704.4067		
5	0.0800	699.8901		

After importing the data for `NewData` experiment, the experiment editor looks like this:



To import data from a file, click the button.

To learn more about the **Edit Experiment:** dialog box, see “Edit Experiment Data” on page 2-5.

Time-Series Data

Time-series data is stored in time-series objects. For more information, see “Time Series Objects and Collections”.

When you import input data from a time-series object, `t`, for parameter estimation, you must specify the time vector and data as `[t.time,t.inputdata]` in the Inport signal dialog box. Similarly, to import output data, you must specify the time vector and data as `[t.time,t.outputdata]` in the Outport signal dialog box. For more information on how to import data into the experiment, see “Time-Domain Data” on page 1-6.

Complex Data

Complex-valued data is data whose value is a complex number. For example, a signal with the value `1+2j` is complex. You can use complex data to estimate parameters of electrical systems, such as the magnitude and phase.

Note You must sample the real and imaginary parts of the data as a function of the same time vector.

To use complex data for parameter estimation:

1. Split the data into two data sets that contain the real and imaginary parts. To split the data, use the MATLAB functions `real`, and `imag`.
2. Create two signals, one for the real part and one for the imaginary part for the Inport or Outport block.
3. Select both signals in the experiment editor.
4. Import the data to the corresponding signal as described in "Time-Domain Data" on page 1-6.

See Also

Related Examples

- "Plot and Analyze Data" on page 1-11
- "Preprocess Data" on page 1-13

More About

- "Model Requirements for Importing Data" on page 1-2

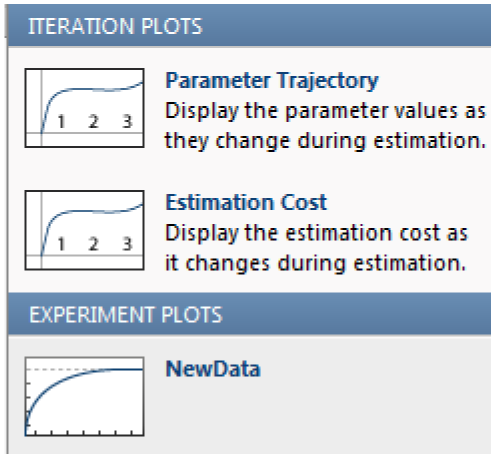
Plot and Analyze Data

Why Plot the Data Before Parameter Estimation

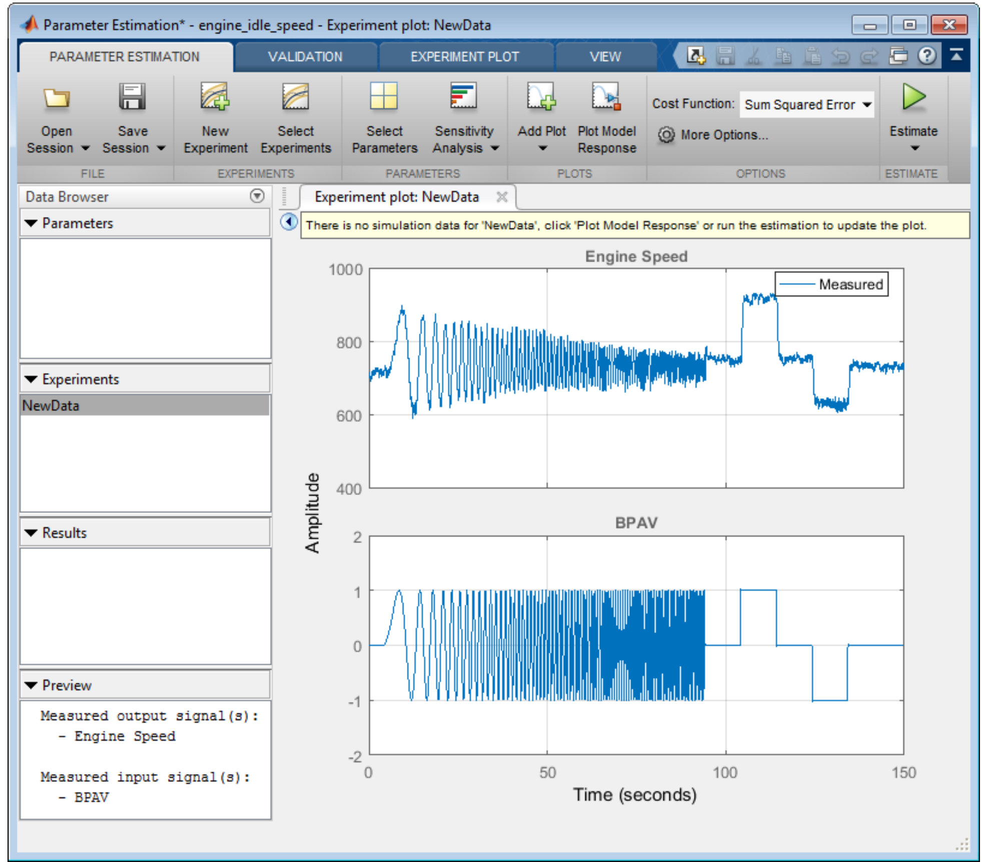
After you import the estimation data as described in “Import Data for Parameter Estimation” on page 1-5, you can remove outliers, smooth, detrend, or otherwise treat the data to prepare for analysis and estimation. To view and analyze data characteristics, plot the data on a time plot.

Plot Data

Use an experiment plot to visualize experiment data. First, create an experiment and import data as described in “Import Data for Parameter Estimation” on page 1-5. To create an experiment plot, in the **Parameter Estimator**, on the **Parameter Estimation** tab, click **Add Plot**, and select NewData under **Experiment Plots**.



This creates plots of the input signal for the Inport block `BPAV` and output signal for the Outport block `Engine Speed` for the `engine_idle_speed` model (see “Create Experiment” on page 1-5).



You can also plot the experiment data by right-clicking `NewData` and selecting **Plot measured experiment data** from the list.

Using the time plot, you can examine the data characteristics such as noise, outliers and portions of the data to use for estimating parameters. After you analyze the data, you can preprocess it as described in “Preprocess Data” on page 1-13.

See Also

Related Examples

- “Import Data for Parameter Estimation” on page 1-5
- “Preprocess Data” on page 1-13

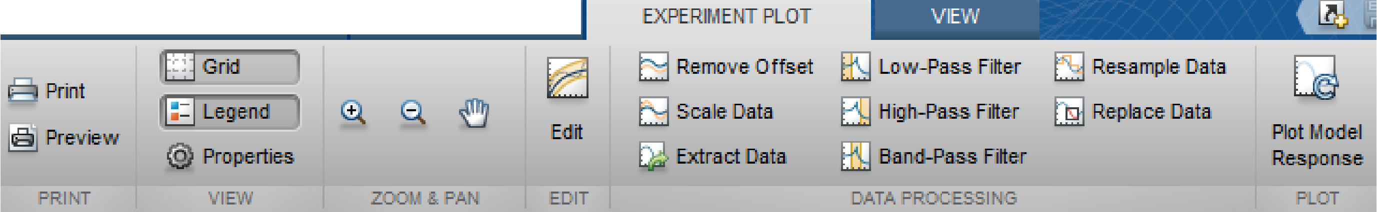
More About

- “Model Requirements for Importing Data” on page 1-2

Preprocess Data

Ways to Preprocess Data

In the **Parameter Estimator** and **Sensitivity Analyzer**, you can preprocess imported data before you use it for estimation or evaluation. After plotting the measured data, you have access to the **Experiment Plot** tab where you can preprocess the data.



For information about how to plot the imported data in the **Parameter Estimator**, see "Plot and Analyze Data" on page 1-11. For information about how to import and plot the data in the **Sensitivity Analyzer**, see "Match Model Outputs to Measured Signals" on page 4-21.

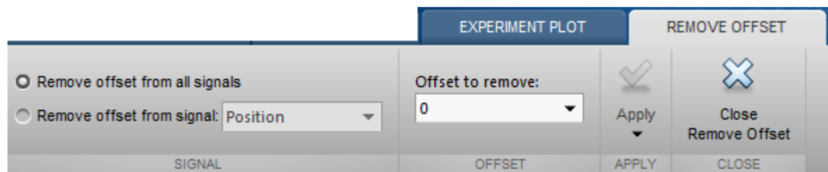
You can perform the following preprocessing operations:

- "Remove Offset" on page 1-13 — Remove mean values, a constant value, or an initial value from the data.
- "Scale Data" on page 1-14 — Scale data by a constant value, signal maximum value, or signal initial value.
- "Extract Data" on page 1-14 — Select a subset of the data to use in the estimation or evaluation. You can graphically select the data to extract, or enter start and end times in the text boxes.
- "Filter Data" on page 1-15 — Process data using a low-pass, high-pass, or band-pass filter.
- "Resample Data" on page 1-15 –– Resample data using zero-order hold or linear interpolation.
- "Replace Data" on page 1-16 –– Replace data with a constant value, region initial value, region final value, or a line. You can use this functionality to replace outliers.

You can perform as many preprocessing operations on your data as are required for your application. For instance, you can both filter the data and remove an offset.

Remove Offset

On the **Experiment Plot** tab, click **Remove Offset**.



It is important for good estimation results to remove data offsets. In the **Remove Offset** tab, you can remove offset from all signals at once or select a particular signal using the **Remove offset from**

signal drop down list. Specify the value to remove using the **Offset to remove** drop down list. The options are:

- A constant value. Enter the value in the box. (Default: 0)
- Mean of the data, to create zero-mean data.
- Signal initial value.

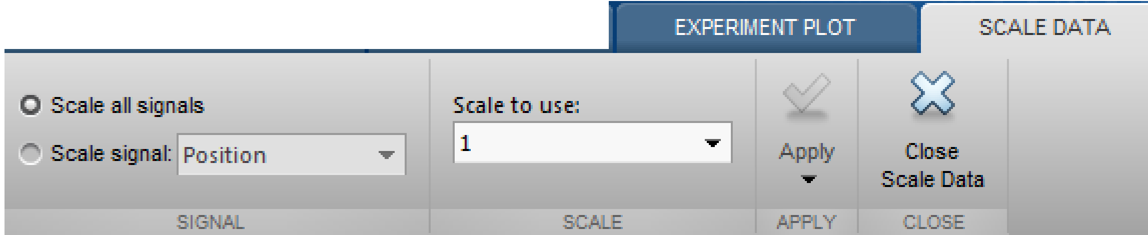
As you change the offset value, the modified data is shown in preview in the plot.

After making choices, update the existing data with the preprocessed data by clicking .

Or, to save the modified data values in a new experiment (in the **Parameter Estimator**) or requirement (in the **Sensitivity Analyzer**), click Apply and select **Save As: Create a new experiment from the modified data**.

Scale Data

On the **Experiment Plot** tab, click **Scale Data**.



In the **Scale Data** tab, you can choose to scale all signals or specify a signal to scale. Select the scaling value from the **Scale to use** drop-down list. The options are:

- A constant value. Enter the value in the box. (Default: 1)
- Signal maximum value.
- Signal initial value.

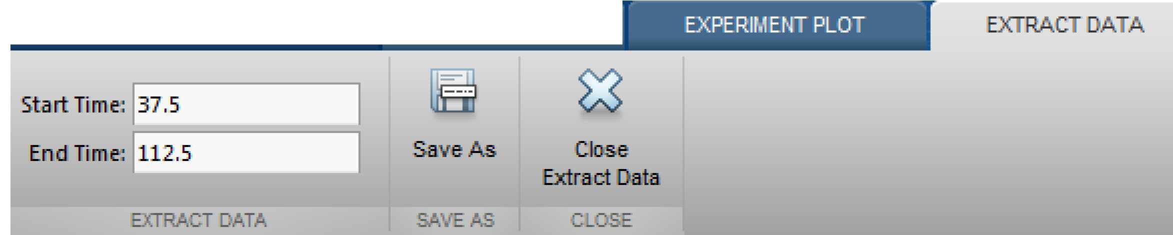
As you change the scaling, the modified data is shown in preview in the plot.

After making choices, update the existing data with the preprocessed data by clicking .

Or, to save the modified data values in a new experiment (in the **Parameter Estimator**) or requirement (in the **Sensitivity Analyzer**), click Apply and select **Save As: Create a new experiment from the modified data**.

Extract Data

To extract a portion of your data to use in the estimation or evaluation process, on the **Experiment Plot** tab, click **Extract Data**.

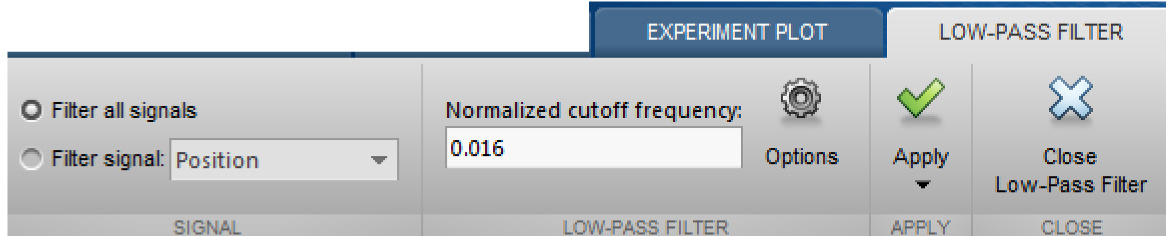


Select a subset of data to use in **Extract Data** tab. You can extract data graphically or by specifying start time and end time. To extract data graphically, click and drag the vertical bars to select a region of the data to use.

After you choose the data to extract, you can save it in a new experiment (in the **Parameter Estimator**) or requirement (in the **Sensitivity Analyzer**) by clicking **Save As**.

Filter Data

You can filter your data using a low-pass, high-pass, or band-pass filter. A low-pass filter blocks high frequency signals, a high-pass filter blocks low frequency signals, and a band-pass filter combines the properties of both low- and high-pass filters. On the **Experiment Plot** tab click one of the **Low-Pass Filter**, **High-Pass Filter**, or **Band-Pass Filter** to open a new tab. For example, the low-pass filter tab appears as shown:



On the **Low-Pass Filter**, **High-Pass Filter**, or **Band-Pass Filter** tab, you can choose to filter all signals or specify a particular signal. For the low-pass and high-pass filtering, you can specify the normalized cutoff frequency of the signal. Where, a normalized frequency of 1 corresponds to half the sampling rate. For the band-pass filter, you can specify the normalized start and end frequencies. Specify the frequencies by either entering the value in the associated field on the tab. Alternatively, you can specify filter frequencies graphically, by dragging the vertical bars in the frequency-domain plot of your data.

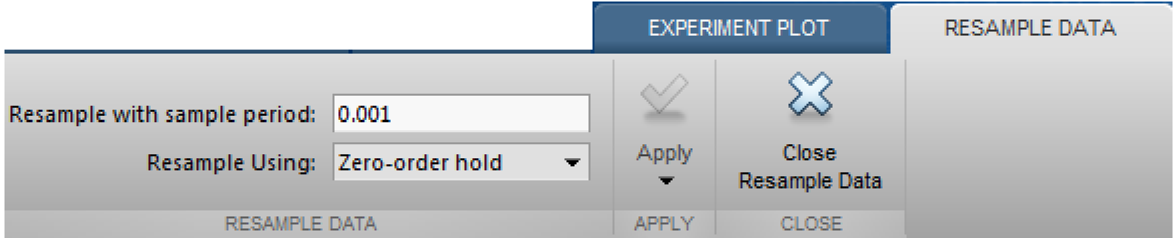
Click **Options** to specify the filter order, and select zero-phase shift filter.

After making choices, update the existing data with the preprocessed data by clicking .

Or, to save the modified data values in a new experiment (in the **Parameter Estimator**) or requirement (in the **Sensitivity Analyzer**), click Apply and select **Save As: Create a new experiment from the modified data**.

Resample Data

On the **Experiment Plot** tab, click the **Resample Data** button.



In the **Resample Data** tab, specify the sampling period using the **Resample with sample period:** field. You can resample your data using one of the following interpolation methods:

- `Zero-order hold` — Fill the missing data sample with the data value immediately preceding it.
- `Linear interpolation` — Fill the missing data using a line that connects the two data points.

By default, the resampling method is set to `zero-order hold`. You can select the `linear interpolation` method from the **Resample Using** drop-down list.

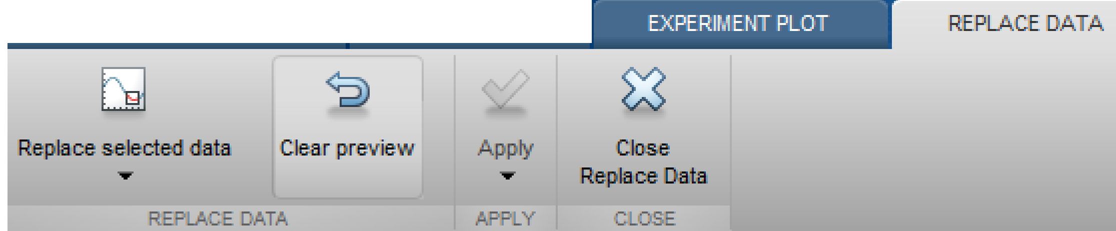
The modified data is shown in preview in the plot.

After making choices, update the existing data with the preprocessed data by clicking .

Or, to save the modified data values in a new experiment (in the **Parameter Estimator**) or requirement (in the **Sensitivity Analyzer**), click Apply and select **Save As: Create a new experiment from the modified data**.

Replace Data

On the **Experiment Plot** tab click the **Replace Data** button.



In the **Replace Data** tab, select data to replace by dragging across a region in the plot. Once you select data, choose how to replace it using the **Replace selected data** drop-down list. You can replace the data you select with one of these options:

- A constant value
- Region initial value
- Region final value
- A line

The replaced preview data changes color and the replacement data appears on the plot. At any time before updating, click **Clear preview** to clear the data you replaced and start over.

After making choices, update the existing data with the preprocessed data by clicking .

Or, to save the modified data values in a new experiment (in the **Parameter Estimator**) or requirement (in the **Sensitivity Analyzer**), click Apply and select **Save As: Create a new experiment from the modified data**.

Replace Data can be useful, for example, to replace outliers. Outliers can be defined as data values that deviate from the mean by more than three standard deviations. When estimating parameters from data containing outliers, the results may not be accurate. Hence, you might choose to replace the outliers in the data before you estimate the parameters.

See Also

More About

- “Import Data for Parameter Estimation” on page 1-5
- “Match Model Outputs to Measured Signals” on page 4-21

Parameter Estimation

- “What Is an Experiment?” on page 2-3
- “Specify Estimation Data” on page 2-4
- “Specify Parameters for Estimation” on page 2-7
- “Specify Known Initial States” on page 2-14
- “Specify Estimation Options” on page 2-17
- “Estimate Parameters and States” on page 2-19
- “Validate Estimation Results” on page 2-25
- “Speed Up Parameter Estimation Using Parallel Computing” on page 2-30
- “Use Parallel Computing for Parameter Estimation” on page 2-33
- “Estimating Initial Conditions for Blocks with External Initial Conditions” on page 2-38
- “Save and Load Estimation Sessions” on page 2-39
- “How the Software Formulates Parameter Estimation as an Optimization Problem” on page 2-41
- “Specify Steady-State Operating Point for Parameter Estimation” on page 2-47
- “Write a Cost Function” on page 2-49
- “Gradient Computations” on page 2-57
- “Estimate Model Parameter Values (Code)” on page 2-58
- “Estimate Model Parameters and Initial States (Code)” on page 2-67
- “Estimate Model Parameters Using Multiple Experiments (Code)” on page 2-76
- “Estimate Model Parameters Per Experiment (Code)” on page 2-86
- “Set Model to Steady-State When Estimating Parameters (Code)” on page 2-97
- “Parameter Estimation for Power Plant Excitation System Starting at Steady-State (GUI)” on page 2-107
- “Set Model to Steady-State When Estimating Parameters (GUI)” on page 2-118
- “Estimate Model Parameters with Parameter Constraints (Code)” on page 2-125
- “Importing and Preprocessing Experiment Data (GUI)” on page 2-133
- “Estimate Model Parameter Values (GUI)” on page 2-144
- “Estimate Model Parameters Per Experiment (GUI)” on page 2-155
- “Estimate Model Parameters and Initial States (GUI)” on page 2-169
- “Generate MATLAB Code for Parameter Estimation Problems (GUI)” on page 2-179
- “Improving Optimization Performance Using Fast Restart (GUI)” on page 2-182
- “Improving Optimization Performance Using Fast Restart (Code)” on page 2-188
- “Parameter Tuning for Digital Twins” on page 2-192
- “Muscle Reflex Parameter Estimation” on page 2-199
- “DC Servo Motor Parameter Estimation” on page 2-206
- “Engine Speed Model Parameter Estimation” on page 2-213

- “Clutch Friction Coefficient Estimation” on page 2-215
- “Inverted Pendulum Parameter Estimation” on page 2-222
- “Simplified Alternator Parameter Estimation” on page 2-231
- “Generate MATLAB Code for Deployed Parameter Estimation Problems (GUI)” on page 2-237

What Is an Experiment?

To estimate unknown parameter values of a Simulink model, first create an experiment. An experiment specifies measured input and output data. During estimation, the experiment input data is used to simulate the model and the model output is compared with the measured experiment output data. For more information about creating experiments and importing data, see “Specify Estimation Data” on page 2-4.

In an experiment, you can specify initial-state values. To do so, specify the model initial states for each experiment. You can optionally specify an initial guess for the initial state values for any experiment. For more information, see “Specify Known Initial States” on page 2-14.

To estimate a model parameter on a per-experiment basis, specify the model parameter for each experiment. You can specify the initial values and limits for the parameter value for any of the experiments. Alternatively, you can specify a parameter value as a known quantity, not to be estimated. For more information, see “Specify Parameters for Estimation” on page 2-7. You can choose to update experiments with estimated model initial states and parameter values, or save the results in a new experiment. For more information, see “Specify Estimation Options” on page 2-17.

To use experiments for validating the estimated parameter values, see “Validate Estimation Results” on page 2-25.

See Also

Related Examples

- “Specify Estimation Data” on page 2-4
- “Specify Parameters for Estimation” on page 2-7
- “Specify Known Initial States” on page 2-14
- “Estimate Parameters and States” on page 2-19

More About

- “Edit Experiment Data” on page 2-5

Specify Estimation Data

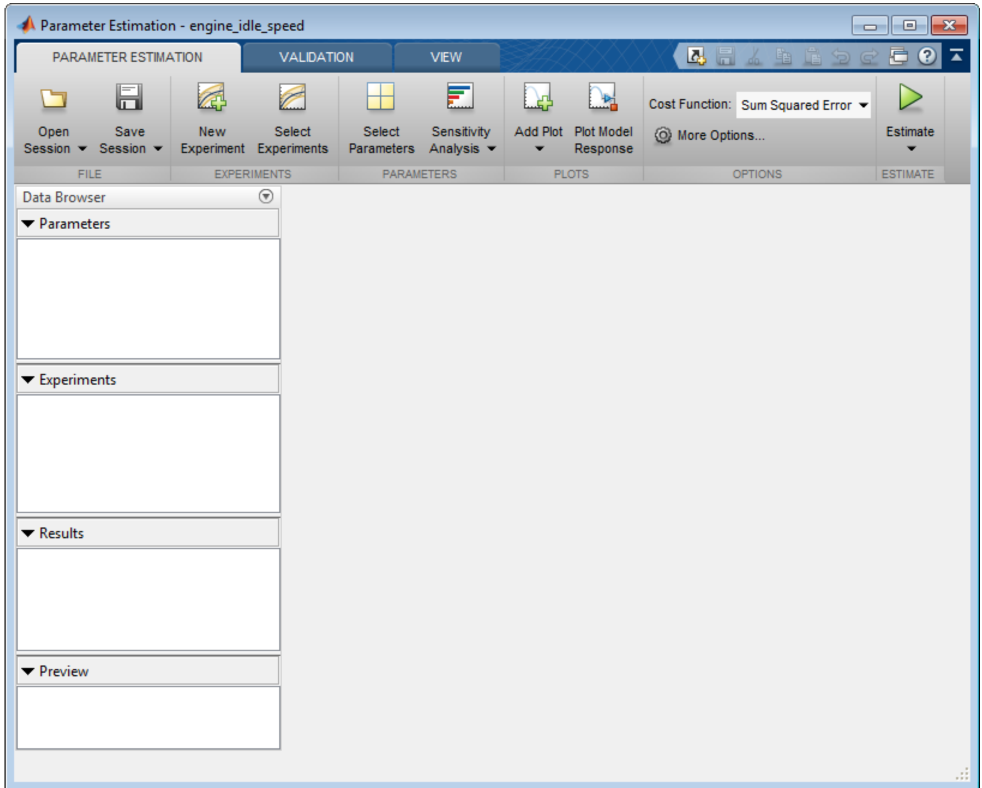
This topic shows how to specify estimation data for parameter estimation.

Create Experiment

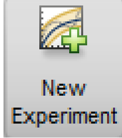
Before you specify estimation data, create an experiment. At the MATLAB prompt, open the nonlinear idle speed model of an automotive engine by typing

```
engine_idle_speed
```

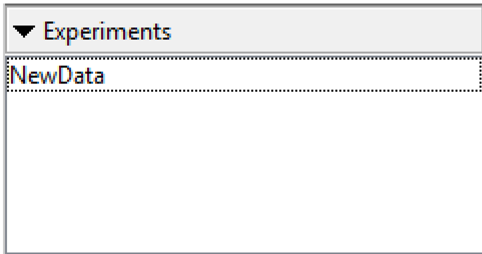
In the Simulink model window, open the **Parameter Estimator** by selecting **Analysis** > **Parameter Estimation**.



In the **Parameter Estimator**, on the **Parameter Estimation** tab, click **New Experiment**.

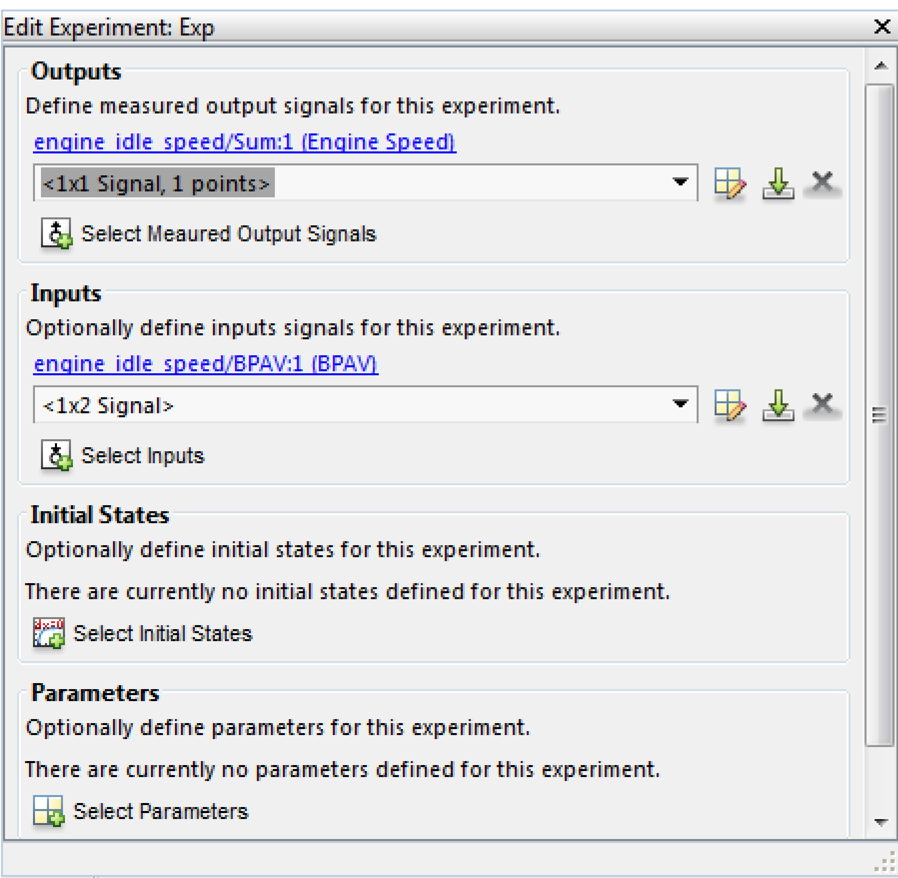


This action creates an experiment called `Exp` in the **Experiments** list in the **Data Browser** panel and opens the experiment editor. To change the name of the experiment, right-click `Exp` and select **Rename**. If you rename it `NewData`, the **Experiments** list now looks like this:



Edit Experiment Data

After creating an experiment, launch the experiment editor by right-clicking on the experiment name and selecting **Edit...** from the list. The experiment editor resembles the following figure.

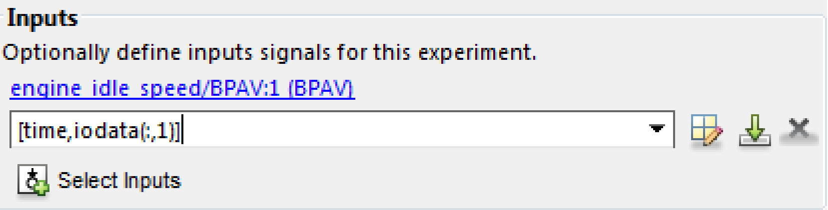


The experiment editor has four panels. You select output signals on page 1-3 and import output data on page 1-5 in the **Outputs** panel. You select input signals on page 1-2 and import input data on page 1-5 in the **Inputs** panel. You can specify model initial states on page 2-14 in the **Initial States** panel. You can specify parameters to estimate on page 2-11 in the **Parameters** panel.

The rows in the **Inputs** panel of the editor correspond to Inport block `BPAV` in the `engine_idle_speed` model. See "Import Data for Parameter Estimation" on page 1-5.

The rows in the **Outputs** panel correspond to Outport block `Engine Speed`. You can import signal data from files or MATLAB workspace.

The idle-speed model of an automotive engine contains the measured data stored in the `iodata` array in the workspace. The array contains two columns: the first for input data, and the second for output data. The time data is in the `time` array in the workspace. Import the input data by typing `[time,iodata(:,1)]` in the dialog box in the **Inputs** panel.



Import the output data by typing `[time,iodata(:,2)]` in the dialog box in the **Outputs** panel.

Note You can have more than one input or output signal, but you can have only one data set for a signal. If you have multiple data sets, create multiple experiments.

See Also

Related Examples

- “Model Requirements for Importing Data” on page 1-2
- “Specify Parameters for Estimation” on page 2-7
- “Specify Known Initial States” on page 2-14
- “Estimate Parameters and States” on page 2-19

More About

- “What Is an Experiment?” on page 2-3

Specify Parameters for Estimation

Choosing Which Parameters to Estimate First

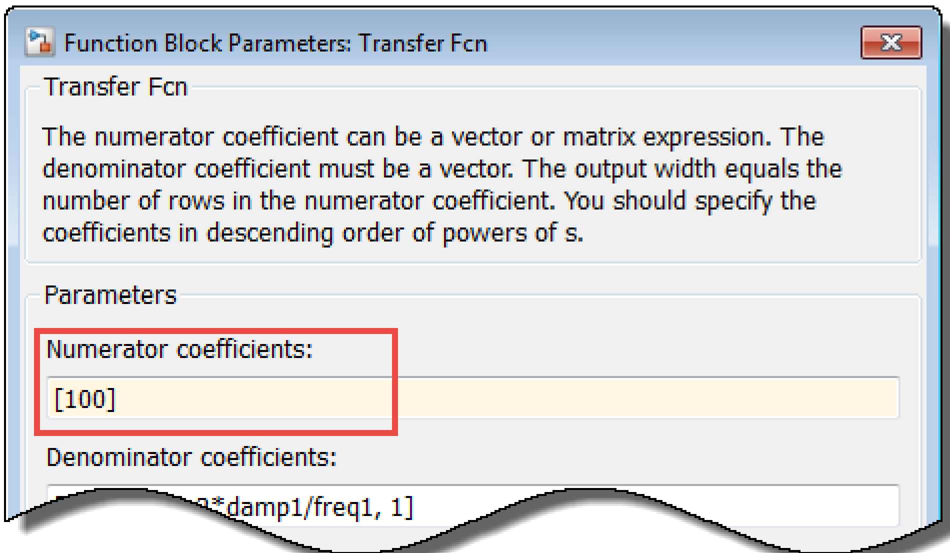
Simulink Design Optimization software lets you estimate scalar, vector, and matrix parameters. You can take an iterative approach to estimating model parameters. For example, if you have a large number of parameters to estimate, start by estimating those that most influence the output. After you estimate a subset of parameters and validate the estimated parameters, you can select the remaining parameters for estimation.

You can also first use sensitivity analysis to identify the parameters that most influence the estimation, and then specify these parameters for estimation. To open the **Sensitivity Analyzer**, in the **Parameter Estimation** tab, click **Sensitivity Analysis**. In the **Sensitivity Analyzer**, you can identify the model parameters that most influence the estimation problem and compute initial values for the estimation parameters.

Add Model Parameters as Variables for Estimation

The software can only estimate variables that are in use by the model. Create variables for estimation in the MATLAB or model workspace, and specify your Simulink model or block parameters using these variables.

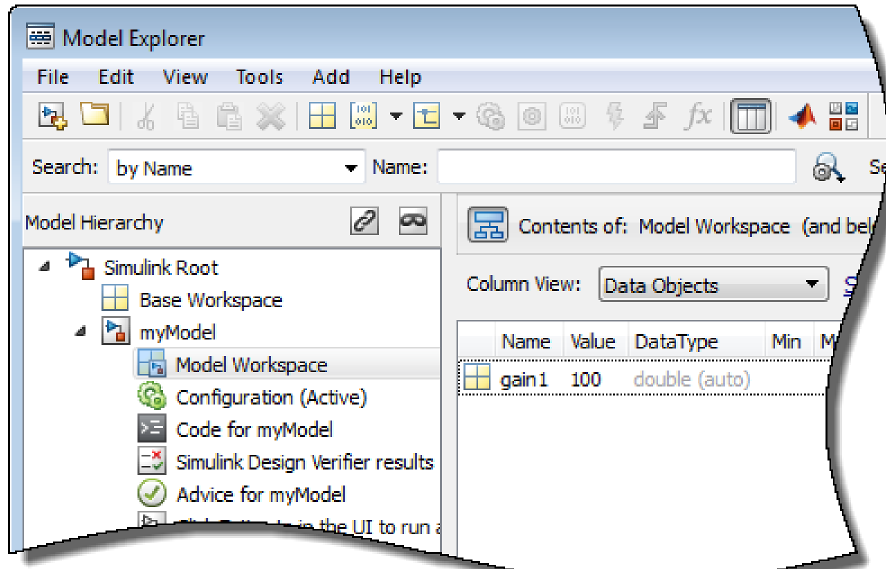
In this figure, the **Numerator coefficients** parameter of a Transfer Fcn block is specified as a numerical value.



To estimate the **Numerator coefficients** parameter, specify it as variable `gain1`:

1 Create the variable `gain1` in one of the following ways:

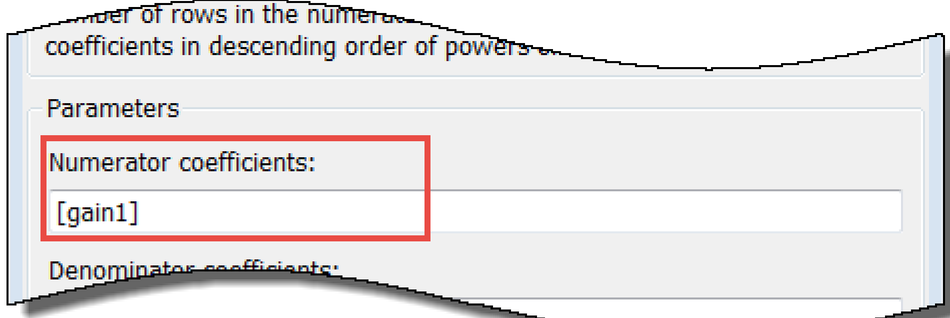
   - Add the variables to the model workspace, and specify initial values.



- Write initialization code in the **PreloadFcn** callback of the model. For more information, see “Model Callbacks”.

  ```
  gain1 = 100
  ```

2 Specify the block parameter as variable `gain1` in the Transfer Fcn block dialog box.



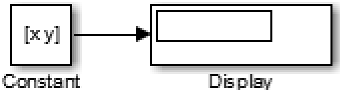
You can now select `gain1` for estimation. See, “Specify Parameters for Estimation” on page 2-9.

Specify Independent Parameters for Estimation

You can also specify independent parameters that do not appear explicitly in the model as variables for estimation. However, you cannot use this workflow with Simulink fast restart.

Suppose that a model parameter `Kint` is related to independent parameters `x` and `y` such that `Kint = x+y`. To estimate `x` and `y` instead of `Kint`:

- Create the independent variables `x` and `y` by adding them to the model workspace and specifying initial values.
- The software only allows tuning of variables that are used by model blocks. To ensure that the software detects `x` and `y` for tuning, add a Constant block to your model, and specify the **Constant value** of the block as `[x y]`. Connect the block to a Display block.



- Write code in the **InitFcn** callback of the model that defines the relationship between `Kint`, `x`, and `y`. You must first use the `get_param` function to get the variables `x` and `y` from the model workspace before you can use them to define `Kint`.

```
wks = get_param(gcs,'ModelWorkspace')
x = evalin(wks,'x')
y = evalin(wks,'y')
Kint = x+y;
```

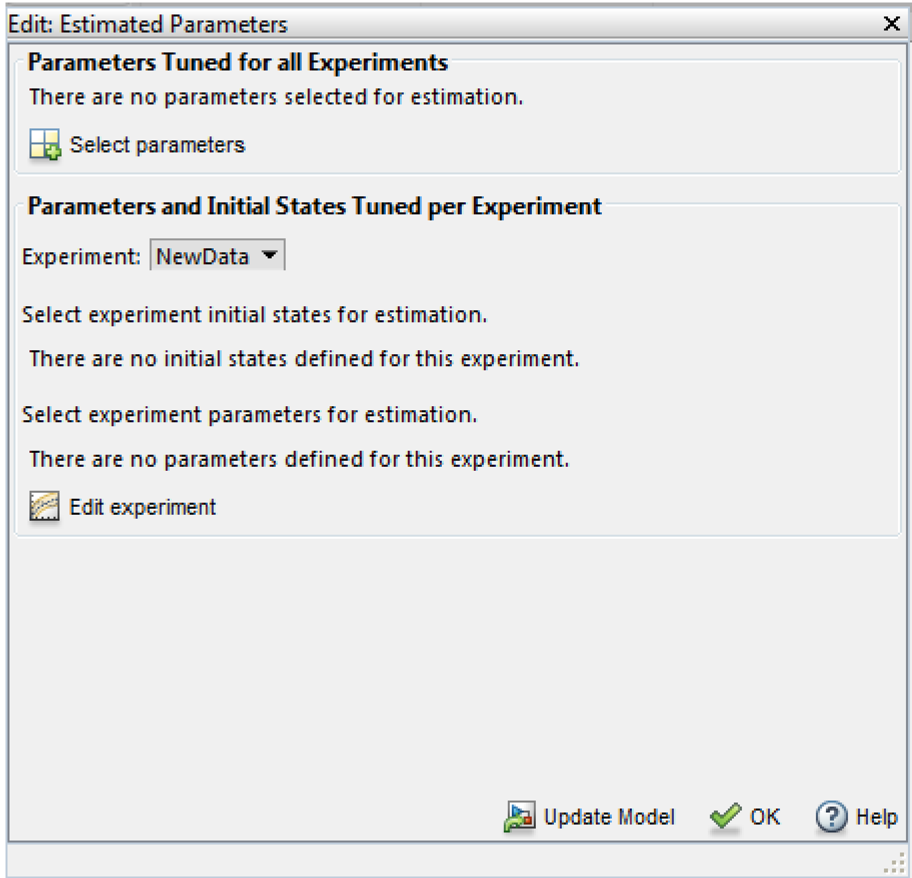
You can now select `x` and `y` for estimation. Do not estimate the independent and dependent parameters simultaneously. Doing so can lead to incorrect results. For example, do not estimate `Kint`, `x` and `y` together.

Specify Parameters for Estimation

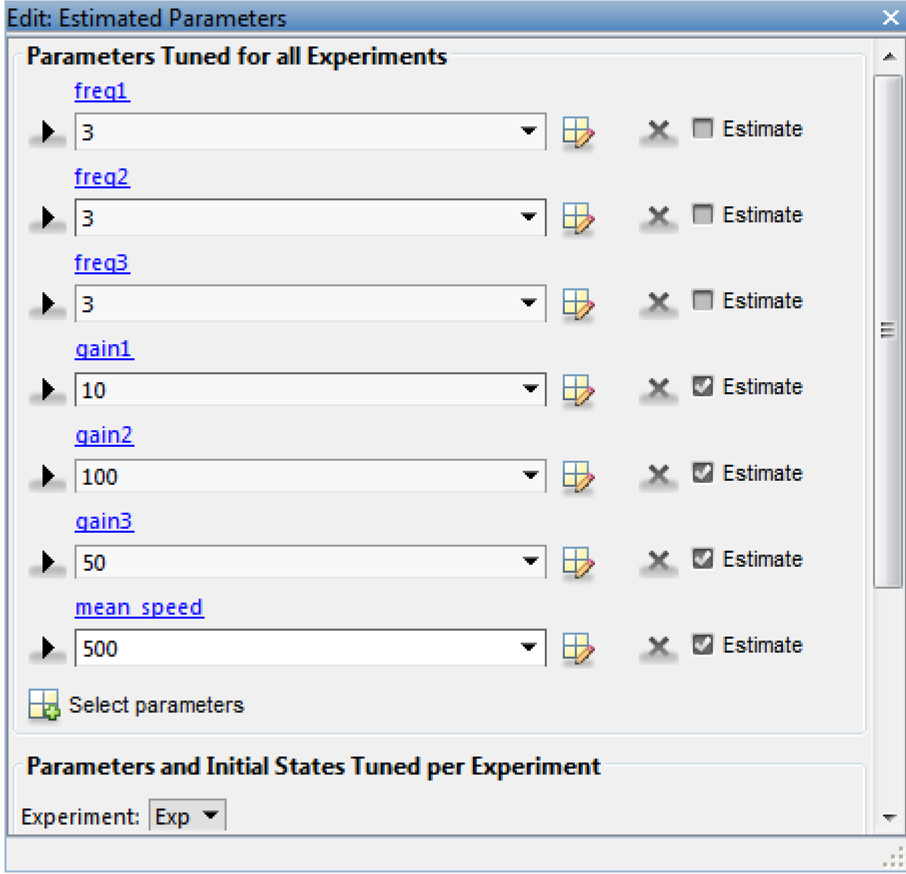
You can specify the parameters for estimation experiments using the **Estimated Parameters** editor. In the **Parameter Estimator**, on the **Parameter Estimation** tab, click **Select Parameters**.

To select parameters for all experiments, click **Select Parameters** in the **Parameters Tuned for all Experiments** panel. This opens the **Select model variables** dialog. Here you can select the parameters you want to estimate by clicking the check box next to it or specifying an expression. For more information see “Select Parameters Using Select Model Variables Dialog Box” on page 2-11.

The editor looks like



For example, in the `engine_idle_speed` model, select `freq1`, `freq2`, `freq3`, `gain1`, `gain2`, `gain3` and `mean_speed` for estimation. You do not need to estimate the parameters all at once. You can first select all the parameters you are interested in, and then later select a subset to estimate. By default, all the parameters are selected for estimation. To deselect the ones you do not want to estimate, clear the **Estimate** check box for a parameter. For this example, only estimate `gain1`, `gain2`, `gain3` and `mean_speed`. Set their initial values 10, 100, 50, and 500, respectively, and then click **OK**. The **Edit: Estimated Parameters** dialog box looks like



To learn how to specify initial values and upper and lower bounds of the parameters, see "Specifying Initial Guesses and Upper/Lower Bounds" on page 2-13.

Select Parameters to Estimate for a Specific Experiment

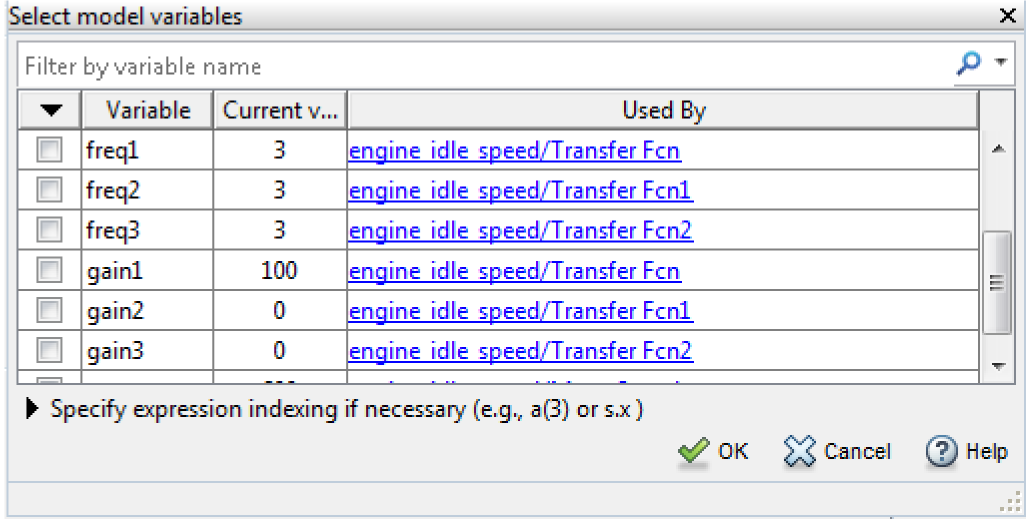
To select the parameters to estimate in a specific experiment, first, select the experiment for estimation as described in "Estimate Parameters and States" on page 2-19. Then, you can use the **Edit:Estimated Parameters** dialog to select parameters to estimate for that experiment. Select the experiment name from the **Experiment:** combo box in the **Parameters and Initial States Tuned per Experiment** panel. Then click **Edit experiment** to launch the experiment editor for the experiment you select.

Alternatively, you can right click the experiment name in the **Experiments** list and select **Edit...**. In the experiment editor, click the **Select parameters** button in the **Parameters** panel. In the Select model variables dialog box, you can select the parameters you want to estimate in this experiment by checking the box next to it or specifying an expression. For more information see "Select Parameters Using Select Model Variables Dialog Box" on page 2-11.

Select Parameters Using Select Model Variables Dialog Box

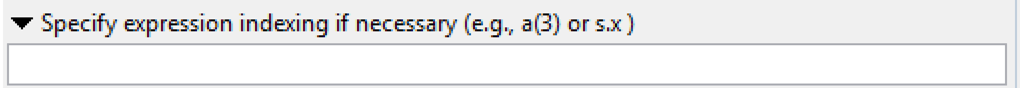
Use this dialog box to specify parameters to estimate. The table lists the variables that the model uses to set block parameter values. The variables can reside in the model workspace, the base workspace, or a data dictionary.

Select variables by clicking the check box next to each variable. If your model contains many variables, filter the list by typing in the **Filter by variable name** field. The **Used By** column lists all blocks in the model that use the variable. When a variable is used in more than one block, all blocks are listed. To highlight blocks in the model that use the variable, click the block name.



The variables that you select must have a numeric value that uses the data type `double`. If the value of a variable is not a `double` number, use these techniques:

- To select a single element or a subset of a matrix or array variable, click **Specify expression indexing if necessary**.

  Enter an expression such as `myArray(2)`, which selects the second element of an array variable `myArray`.

  After you type the expression, press the **Enter** key to add the variable to the list of model variables.
- To use a variable of a numeric data type other than `double`, convert the variable to a `Simulink.Parameter` object, which separates a parameter value from its data type. Set the `Value` property to a default `double` number, and use the `DataType` property to control the data type.
- To use the value of a `Simulink.Parameter` object, specify the `Value` property. Enter the expression `myParamObj.Value`.
- To use a numeric field of a structure, enter `myStruct.PID.P1`. If you store the structure in a `Simulink.Parameter` object, enter `myStruct.Value.PID.P1`.
- To use one cell of a cell array, enter `myCells{3}`.

You cannot use mathematical expressions such as $a + b$. Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters, see “Add Model Parameters as Variables for Estimation” on page 2-7.

Specifying Initial Guesses and Upper/Lower Bounds

After you select parameters, you can specify

- **Initial guess** — The value the estimation uses to start the process.
- **Minimum** — The smallest allowable parameter value. The default is `-Inf`.
- **Maximum** — The largest allowable parameter value. The default is `+Inf`.

  You can enter the initial value in the dialog box below the parameter name. You can specify the minimum and maximum value fields by clicking the arrow . The default minimum and maximum values are `-Inf` and `+Inf`, respectively, but you can select any range you want.

  If you believe a parameter lies within a finite range, it is best not to use the default minimum and maximum values. Often, there are computational advantages in specifying finite bounds. It can be very important to specify lower and upper bounds. For example, if a parameter specifies the weight of a part, be sure to specify `0` as the absolute lower bound if better information is unavailable.

  Note When you specify the minimum and maximum values for the parameters, it does not affect your settings in the **Parameters** list under **Data Browser** pane. You make these choices for each experiment.

- **Scale** — The scale value to use for normalization. The parameters are scaled, or normalized, by dividing their current value by the scale value. **Scale** is useful, in situations, for example, when parameters have different orders of magnitude.

  The default scale value is the next power of 2 greater than the current value of the parameter. For example, if the current parameter value is `15`, **Scale** is `16` ($=2^4$). You can edit this field to provide an alternate scaling factor.

See Also

Related Examples

- "Specify Known Initial States" on page 2-14

More About

- "What Is an Experiment?" on page 2-3

Specify Known Initial States

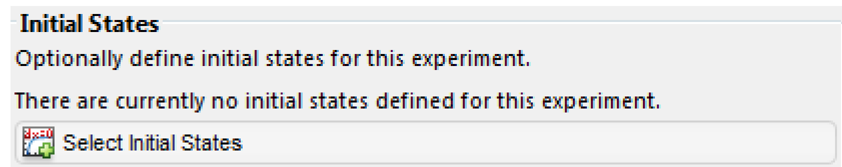
When to Specify Initial States Versus Estimate Initial States

Sets of measured data are often collected at various times and under different initial conditions. When you estimate model parameters using one data set and subsequently run another estimation with a second data set, your parameter values may not match.

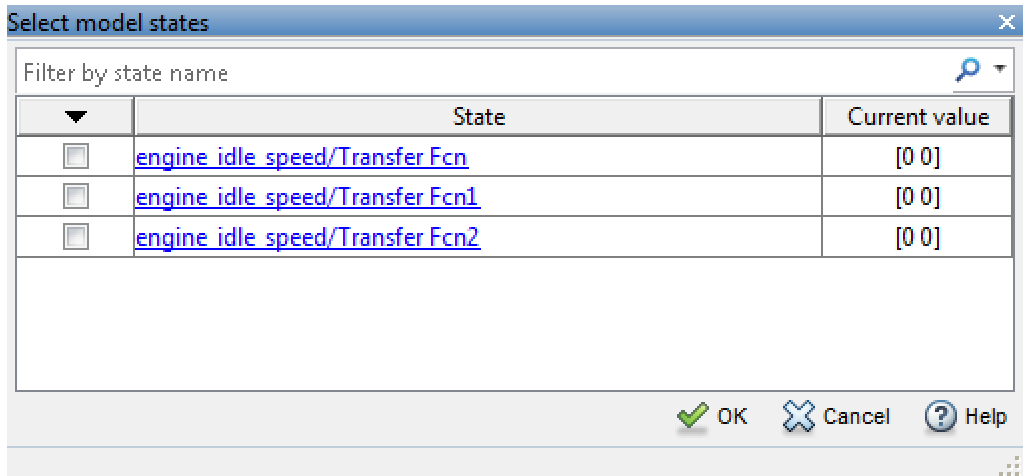
You can use the **Parameter Estimator** to estimate the initial conditions using procedures that are similar to those you use to estimate parameters. You can then use these initial condition estimates as a basis for estimating parameters for your Simulink model.

Specify Model Initial States

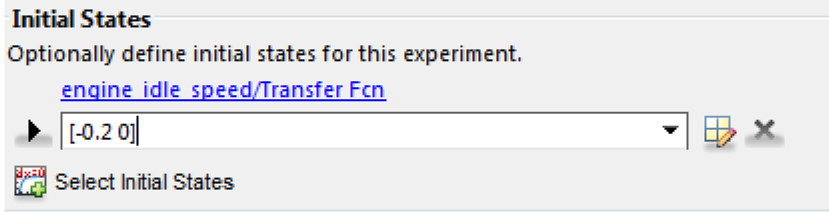
After you select parameters for estimation, as described in "Specify Parameters for Estimation" on page 2-7, you can specify initial conditions of states in your model. By default, the estimation uses initial conditions specified in the Simulink model. If you want to specify initial conditions other than the defaults, use the **Initial States** panel in the experiment editor dialog. For this example, right click `NewData` and select **Edit...** from the list to open the experiment editor on page 2-5. Then, click **Select Initial States** button.



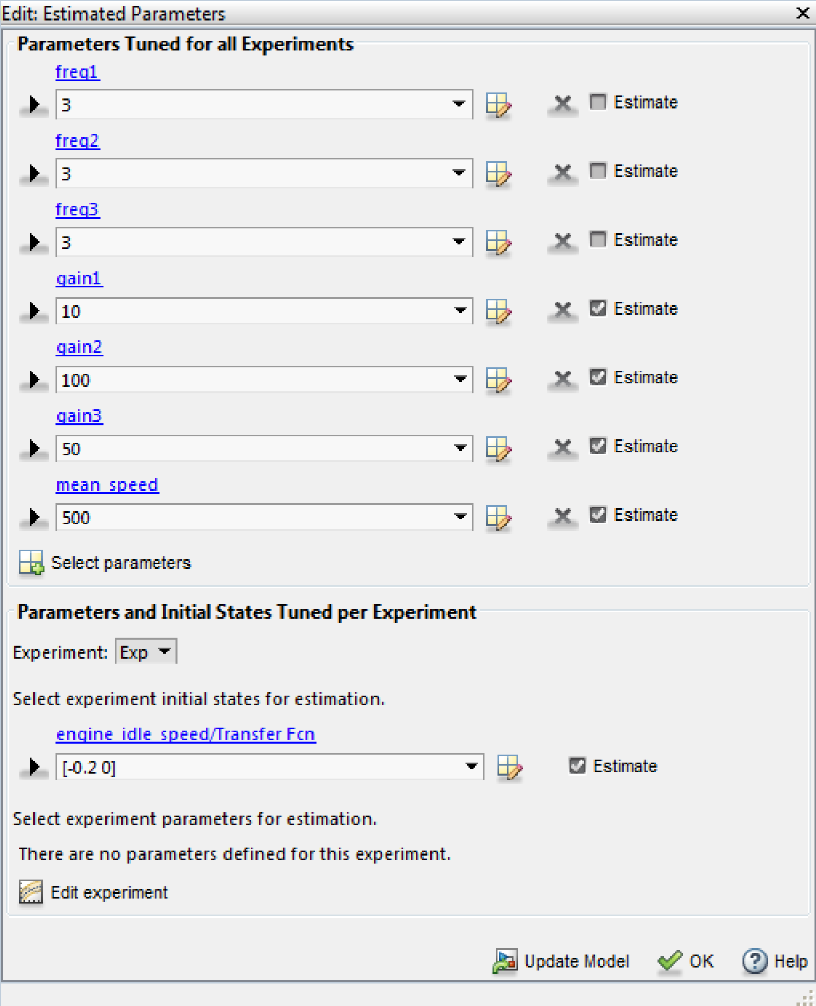
The Select Model States dialog for the `engine_idle_speed` model looks like



Click the check box next to the state you would like to modify. For example, if you select **engine_idle_speed/Transfer Fcn** and enter the initial values `-0.2` and `0`, the **Initial States** panel now looks like



Click **Select Parameters** in the **Parameter Estimation** tab. After you also select the parameters as described in "Specify Parameters for Estimation" on page 2-7, the Edit: Estimated Parameters dialog looks like the following figure.



See Also

Related Examples

- "Specify Estimation Data" on page 2-4
- "Specify Parameters for Estimation" on page 2-7

More About

- "Edit Experiment Data" on page 2-5

Specify Estimation Options

This topic shows how to specify estimation options in the **Parameter Estimator**.

After you have specified estimation data and parameters, specify the following estimation options:

1. Goodness of fit criteria (cost function)

   Cost Function: Sum Squared Error

   The cost function is a function that estimation methods minimize. To specify the method for calculating the cost function, in the **Parameter Estimation** tab of the app, select one of the following from the **Cost Function** drop-down list:

   - `Sum Squared Error` — Uses a least-squares approach (default).
   - `Sum-Absolute Error` — Uses the sum of absolute errors.

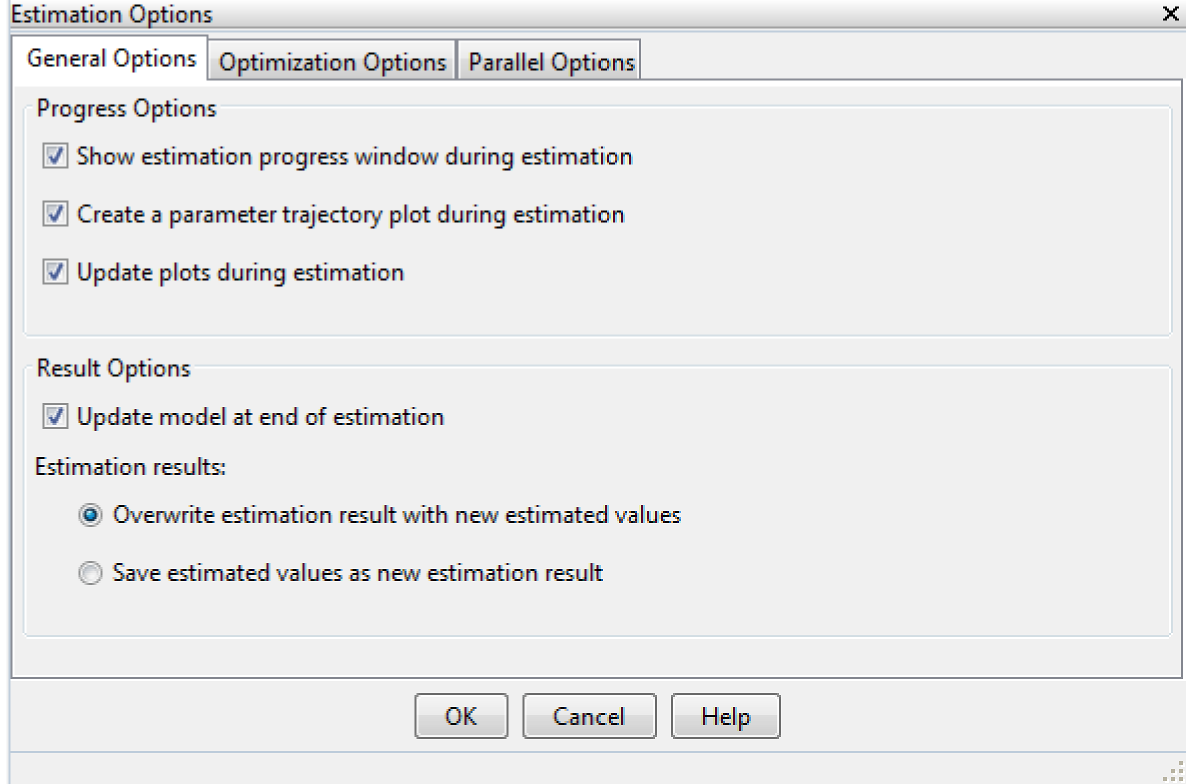
   If the experimental data has many outliers, you can select the robust cost option. The software uses a Huber loss function to handle the outliers in the cost function and improves the fit quality. This option reduces the influence of outliers on the estimation without you having to manually modify your data. To select this option, in the **Parameter Estimation** tab, click **More Options** to open the Estimation Options dialog box. In the **Optimization Options** tab of the dialog box, select **Use robust cost**.

   The software uses the error statistics to identify the outliers. The error, *e*, is calculated as the difference between measured and simulated output. The cost function used, $F(x)$, depends on the method used.

Method Name	Cost Function for Nonoutliers	Cost Function for Outliers
`Sum Squared Error`	$F(x) = \sum_{t \in NOL} e(t) \times e(t)$ *NOL* is the set of nonoutlier samples.	$F(x) = \sum_{t \in OL} w \times \lvert e(t) \rvert$ *w* is a linear weight. *OL* is the set of outlier samples.
`Sum-Absolute Error`	$F(x) = \sum_{t \in NOL} \lvert e(t) \rvert$ *NOL* is the set of nonoutlier samples.	$F(x) = \sum_{t \in OL} w$ *w* is a constant value. *OL* is the set of outlier samples.

2. Estimation progress and result options for estimation task

   To specify these options, in the **Parameter Estimation** tab, click **More Options** to open the Estimation Options dialog box. In the **General Options** tab, specify the estimation progress and result options. For details about the options, click the **Help** button.



3 Optimization options, such as optimization method and optimization termination options.

   Specify these options in the **Optimization Options** tab of the Estimation Options dialog box. For details about the options, click the **Help** button.

4 Parallel computing options

   Specify these options in the **Parallel Options** tab of the Estimation Options dialog box. For details about the options, see "Estimate Parameters Using Parallel Computing in the Parameter Estimator App" on page 2-34.

See Also

Related Examples

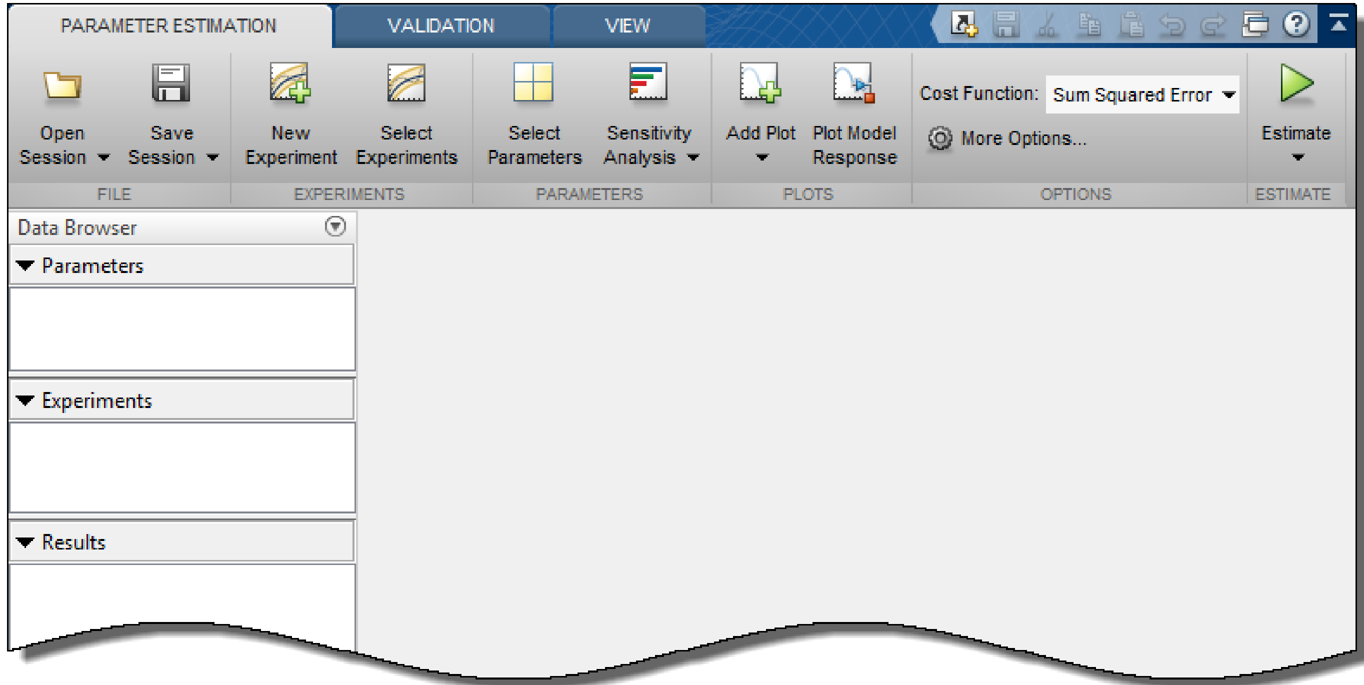
- "Specify Estimation Data" on page 2-4
- "Specify Parameters for Estimation" on page 2-7

More About

- "How the Software Formulates Parameter Estimation as an Optimization Problem" on page 2-41

Estimate Parameters and States

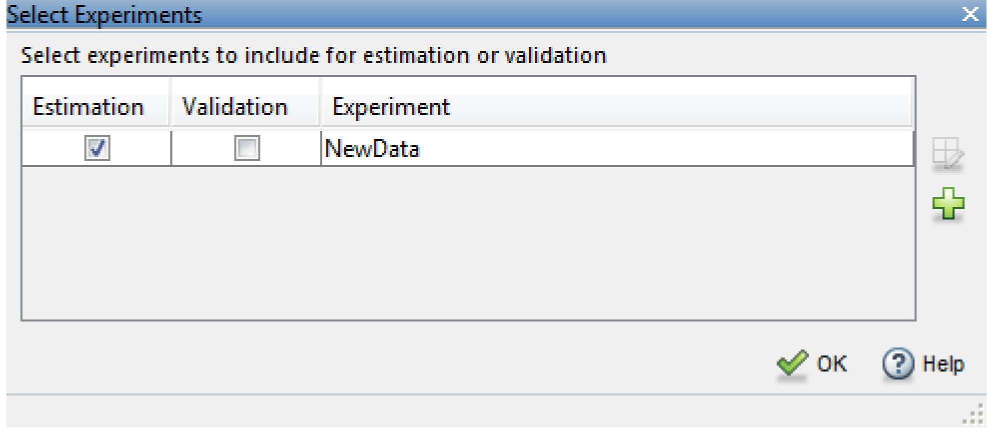
This topic shows how to estimate parameters and states in the **Parameter Estimator**.



To estimate parameters and states after you have specified estimation data on page 2-4, parameters on page 2-7, and estimation options on page 2-17:

1 Specify experiments for estimation.

In the **Parameter Estimator**, in the **Parameter Estimation** tab, click **Select Experiments**. In the Select Experiments dialog box, in the **Estimation** column, select the experiment to use.



For information about the **Validation** column, see “Validate Estimation Results” on page 2-25.

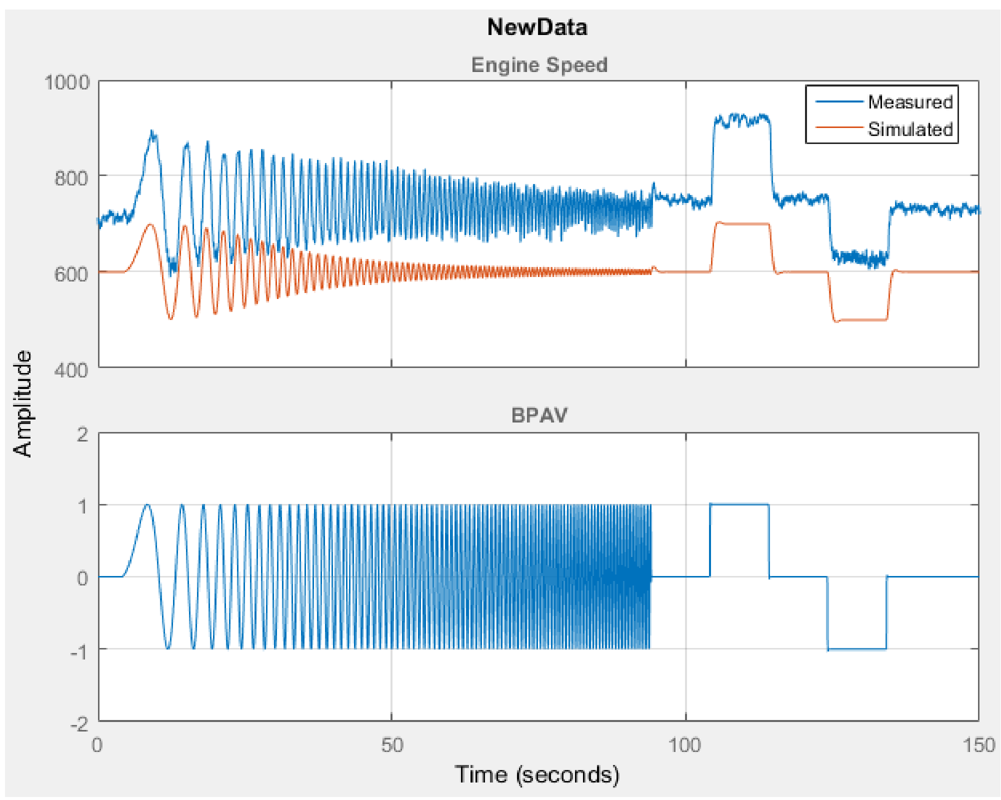
2 (Optional) Create progress plots to view estimation progress.

When you start the estimation, the app automatically displays a parameter trajectory plot that shows the change in the parameter values during estimation. You can create other plots for viewing the progress of the estimation before you begin estimating the parameters. During estimation, all these plots update with each iteration.

- To plot the measured data, on the **Parameter Estimation** tab, click **Add Plot**. Select the experiment to use for estimation under **Experiment Plots** of the drop-down list.

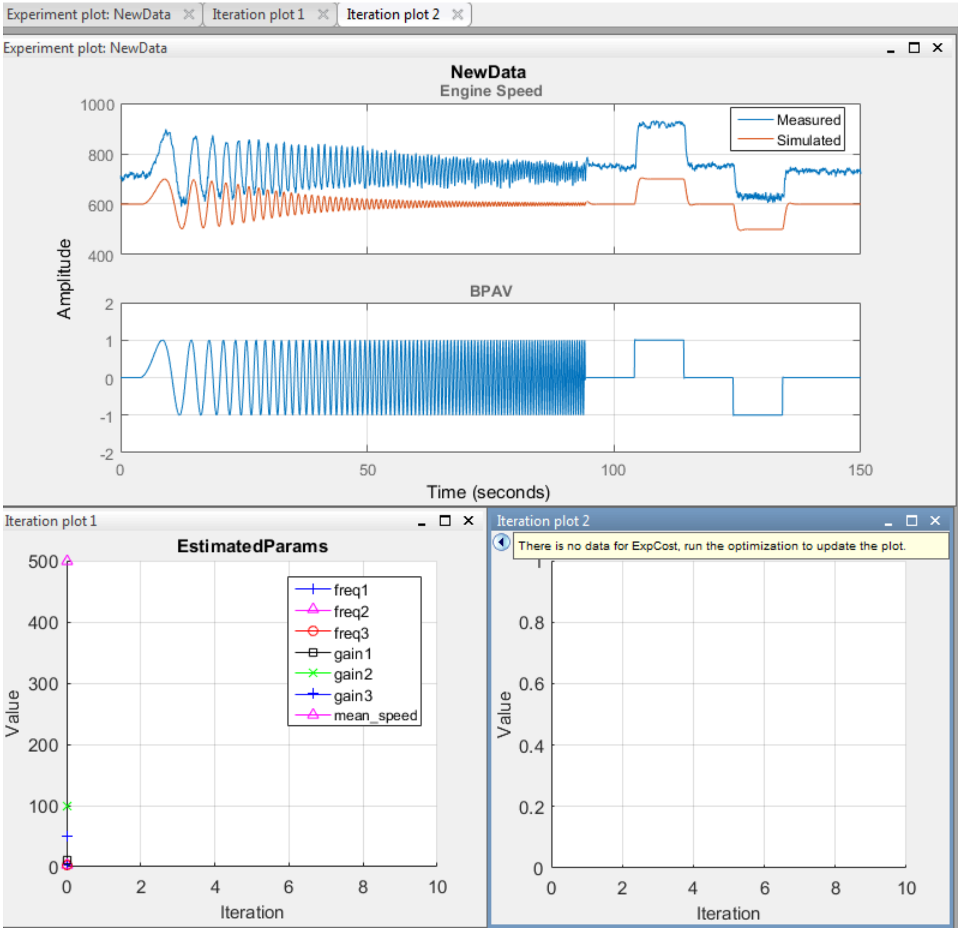
  To add the simulated response to the measured data plot, on the **Parameter Estimation** tab, click **Plot Model Response**.

  Alternatively, right-click the experiment name in the **Experiments** area of the app, and select **Plot measured & simulated data** from the menu.

  You can edit the labels, adjust the limits, change the units, and the font style of the plot in the **Property Editor**. To open the editor, right-click the experiment plot and select **Properties** from the list.
- To plot the parameter values as they change, click **Add Plot**, and select **Parameter Trajectory**. To add the scaled values or save iteration data, right-click the plot.
- To add a plot for the estimation cost, click **Add Plot**, and select **Estimation Cost**. To add the scaled values or save iteration data, right-click the plot.

Use the **View** tab of the app to arrange the layout of the plots, so that all the progress plots you created are visible.



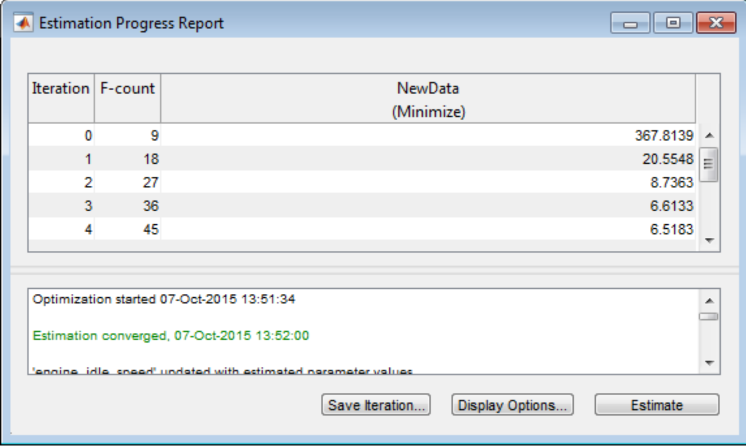
3 Estimate the parameters and states.

In the **Parameter Estimation** tab, click **Estimate**.

An Estimation Progress Report window opens at the start of estimation. The report and progress plots update with each iteration.

4 View the Estimation Progress Report after the estimation completes.

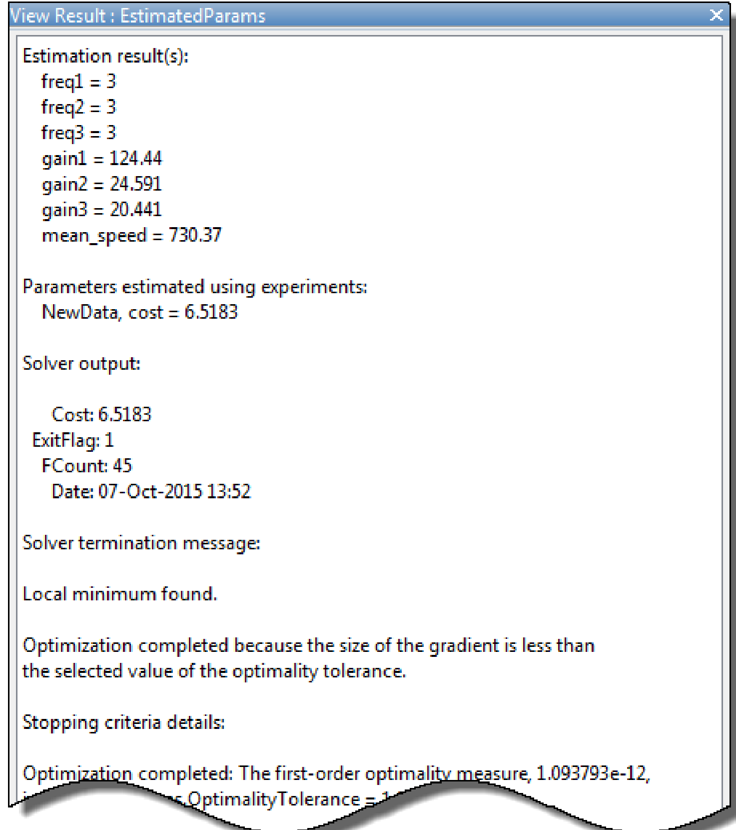
By default, the report displays the iteration number (**Iteration**), the number of times the objective function is calculated (**F-count**), and cost function value (**f(x)**, for example, **NewData(Minimize)**). You can change the display table by clicking **Display Options**. To learn more about the display table, see “Iterative Display”.



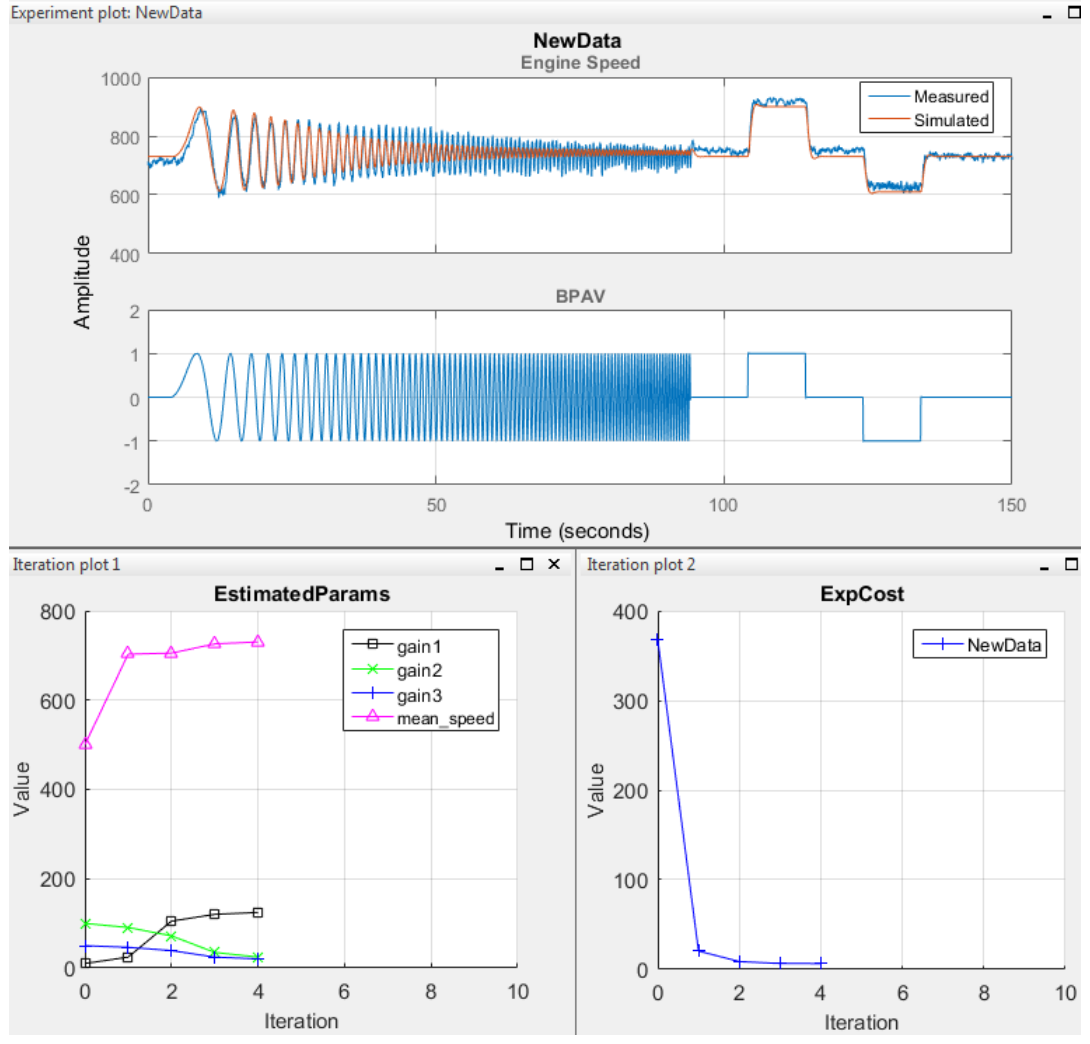
5 View the estimated results.

The estimation results are saved in a new variable, `EstimatedParams`, in the **Results** area of the app.

To view the contents of the variable, right-click `EstimatedParams` and select **Open...** from the menu. `EstimatedParams` includes the values of the parameters, the cost function value, and information about the stopping criteria for the estimation.



6 View the progress plots.



The measured versus simulated data plot shows how closely the simulated data matches the measured estimation data. The estimated parameters plot and cost function plots show the changes in the estimated value of the parameters and estimated cost function for each iteration.

Typically, a lower cost function value indicates the model simulation with the estimated parameters closely matches experimental data. If the optimization went well, you should see your cost function converge to a minimum value. The lower the cost, the more successful the estimation.

For information on types of problems you may encounter using optimization solvers, see "When the Solver Fails", "When the Solver Might Have Succeeded", and "When the Solver Succeeds".

See Also

Related Examples

- "Specify Estimation Data" on page 2-4
- "Specify Parameters for Estimation" on page 2-7

- “Specify Known Initial States” on page 2-14
- “Specify Estimation Options” on page 2-17
- “Validate Estimation Results” on page 2-25
- “Save and Load Estimation Sessions” on page 2-39

More About

- “What Is an Experiment?” on page 2-3

Validate Estimation Results

This topic shows how to validate estimation results in the Parameter Estimator. After you estimate parameters as described in “Estimate Parameters and States” on page 2-19, validate the estimation results using another data set.

Configure and Perform Validation

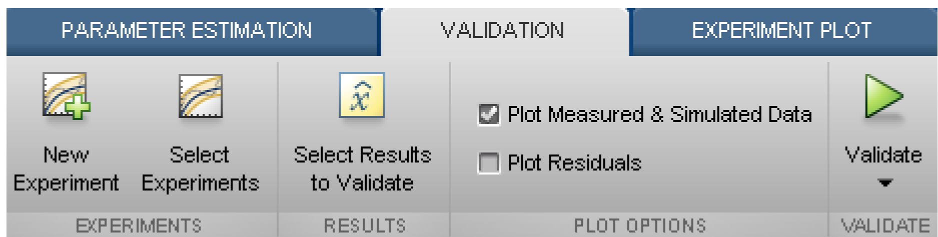
To validate a model using the **Parameter Estimator**:

1. Load the validation data set.

   At the MATLAB prompt, load the validation data into the MATLAB workspace.

   ```
   load iodataval;
   ```
2. Add a new experiment for validation.

   In the **Parameter Estimator**, in the **Validation** tab, click **New Experiment**. A new experiment with default name appears in the **Experiments** area of the app. To rename the experiment `ValidationData`, right-click the experiment and select **Rename** from the drop-down menu.

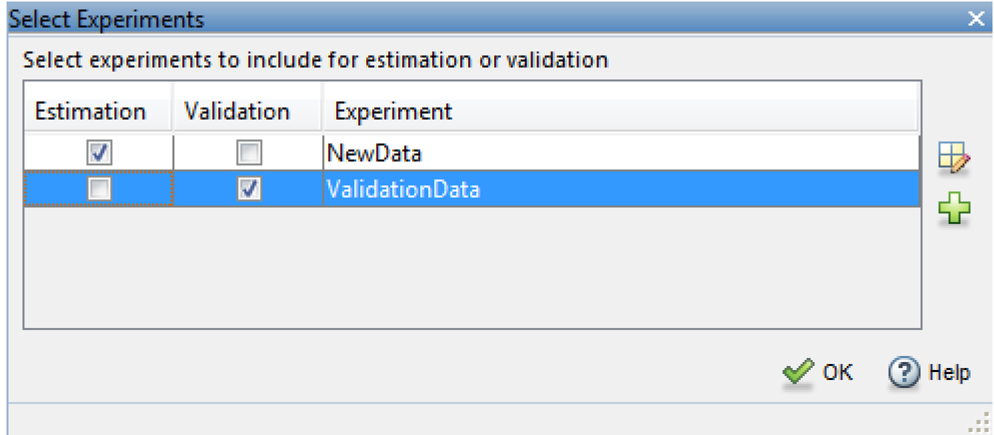
   

3. Import the validation data set into the validation experiment.

   Right click the experiment name, and select **Edit**. Specify `[time,iodataval(:,1)]` in **Inputs** , and `[time,iodataval(:,2)]` in **Outputs**.
4. Specify the experiment for validation.

   When you create an experiment, it is by default selected for estimation. To select another experiment for validation, in the **Validation** tab, click **Select Experiments**.

   In the Select Experiments dialog box, clear **Estimation** and select **Validation** for the validation experiment.

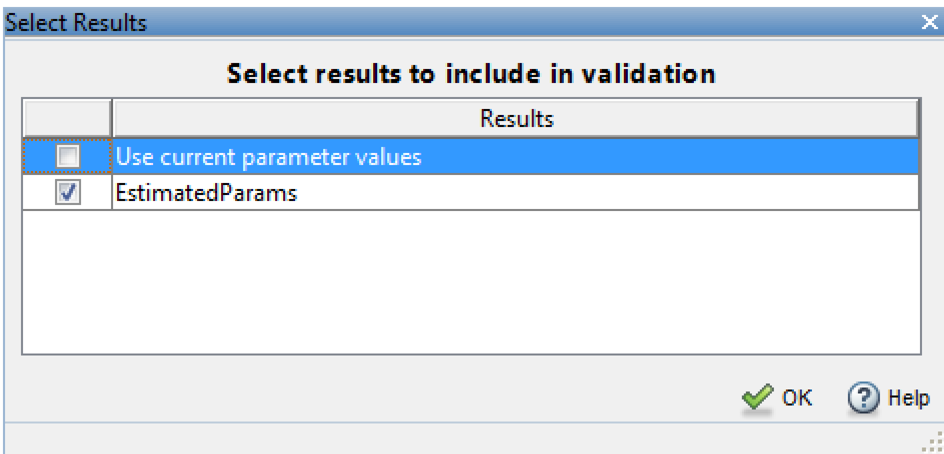


5 Specify the estimation results to use in the validation.

After you import validation data, select the estimated parameter values to validate.

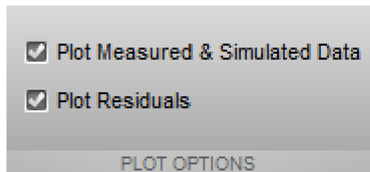
The estimation results are saved in the `EstimatedParams` variable in the **Results** area of the app. In the **Validation** tab, click **Select Results to Validate**.

To validate the estimated parameters, in the Select Results dialog box, select `EstimatedParams` and clear `Use current parameter values`.



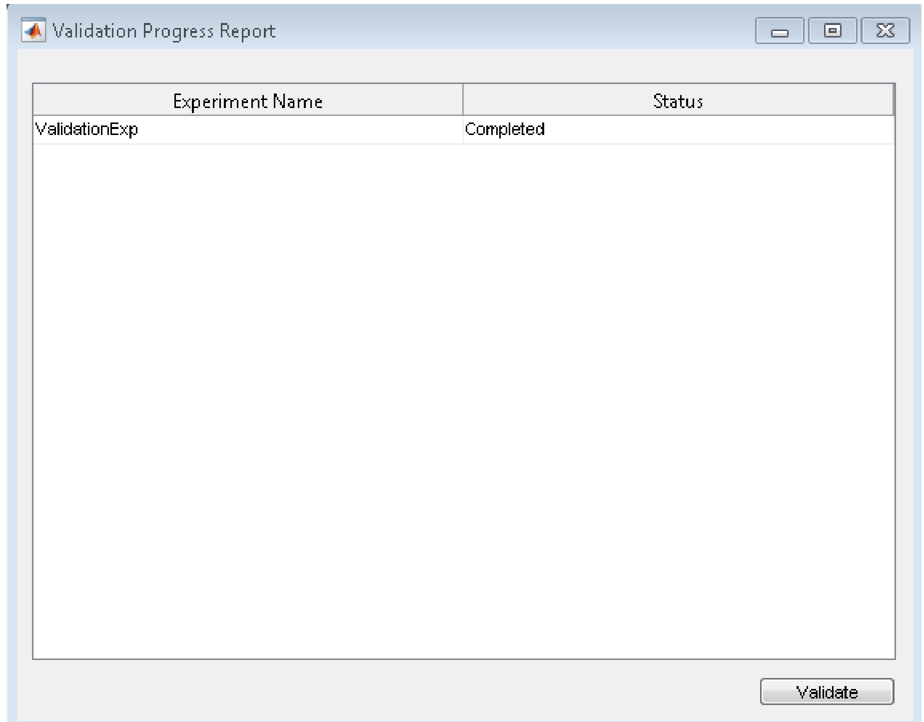
6 Select the plots to display at the end of validation.

Parameter Estimator can display the measured and simulated responses and the residuals plot at the end of validation. Select the plots to display by checking the corresponding box on the **Validation Tab**.



7 Validate the estimation results.

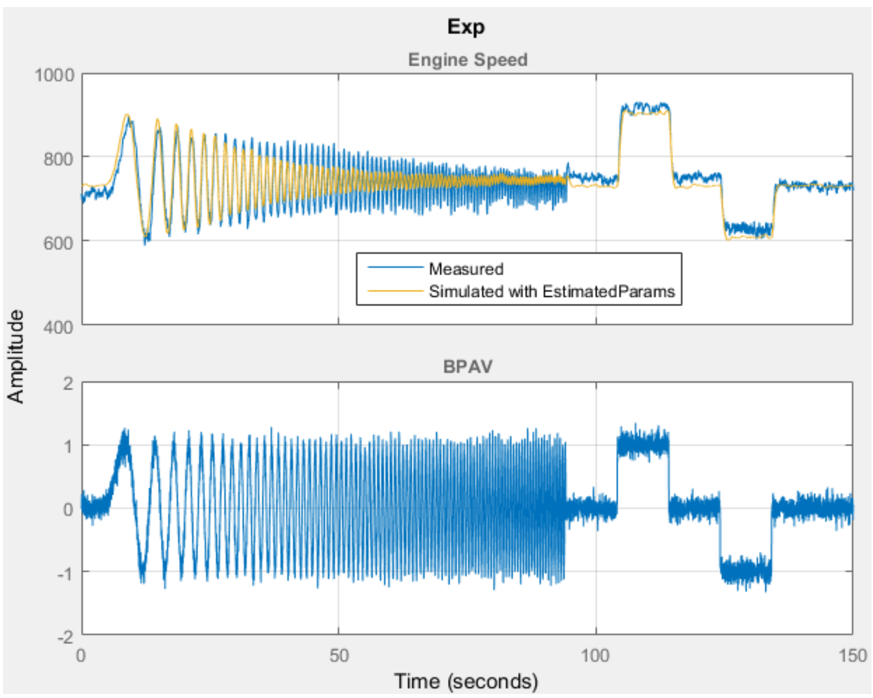
On the **Validation** tab, click **Validate**. The Validation Progress Report shows the status of the validation.



Compare Measured and Simulated Responses

1 Compare measured validation data against the model output simulated with the estimated parameters.

The app displays the experiment plot for each experiment selected for validation. Each experiment plot shows the measured data, and data from simulation using each set of results selected. For example, the following figure shows the experiment plot for the `ValidationExp` data.

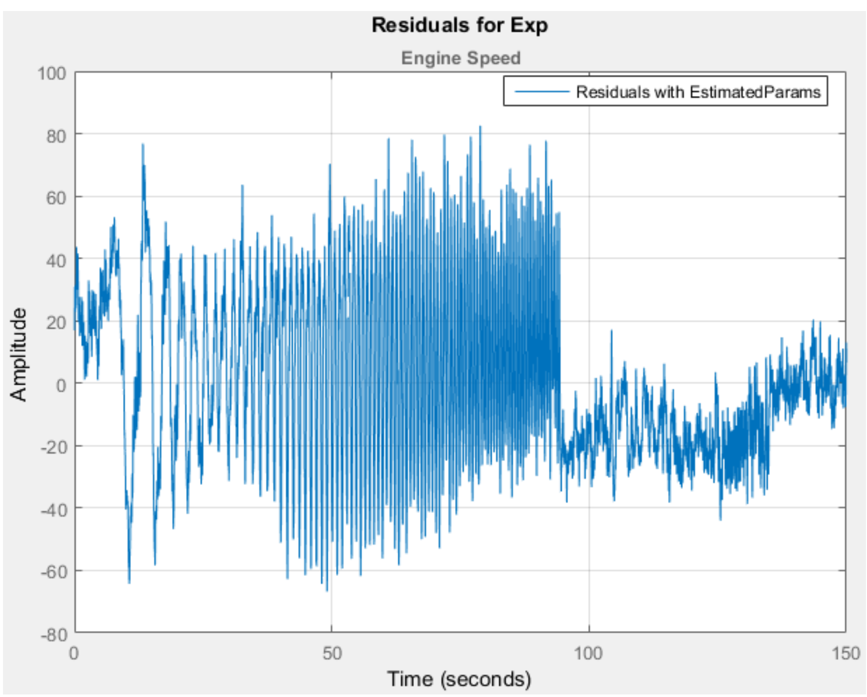


2 Examine the Residuals Plot.

The residuals plot shows the difference between simulated response and measured data. When there is a good fit between the simulated output and measured data, the residuals show the following behavior:

- Lie within a small percent of the maximum output variation.
- Do not display any systematic patterns.

For example, you can see from the following figure that the residuals for `ValidationExp` data satisfy both criteria.



See Also

Related Examples

- "Estimate Parameters and States" on page 2-19

More About

- "What Is an Experiment?" on page 2-3

Speed Up Parameter Estimation Using Parallel Computing

When to Use Parallel Computing for Parameter Estimation

You can use Simulink Design Optimization software with Parallel Computing Toolbox™ software to speed up parameter estimation of Simulink models. Using parallel computing may reduce the estimation time in the following cases:

- The model contains a large number parameters to estimate, and the estimation method is specified as either `Nonlinear least squares` or `Gradient descent`.
- The `Pattern search` method is selected as the estimation method.
- The model is complex and takes a long time to simulate.

When you use parallel computing, the software distributes independent simulations to run them in parallel on multiple MATLAB sessions, also known as *workers*. The time required to simulate the model dominates the total estimation time. Therefore, distributing the simulations significantly reduces the estimation time.

For information on how the software distributes the simulations and the expected speedup, see "How Parallel Computing Speeds Up Estimation" on page 2-30.

For information on configuring your system and using parallel computing, see "Use Parallel Computing for Parameter Estimation" on page 2-33.

How Parallel Computing Speeds Up Estimation

You can enable parallel computing with the `Nonlinear least squares`, `Gradient descent` and `Pattern search` estimation methods.

Parallel Computing with Nonlinear least squares and Gradient descent Methods

When you select `Gradient descent` as the estimation method, the model is simulated during the following computations:

- Objective value computation — One simulation per iteration
- Objective gradient computations — Two simulations for every tuned parameter per iteration
- Line search computations — Multiple simulations per iteration

The total time, *Ttotal*, taken per iteration to perform these simulations is given by the following equation:

$$Ttotal = T + (Np \times 2 \times T) + (Nls \times T) = T \times (1 + (2 \times Np) + Nls)$$

where T is the time taken to simulate the model and is assumed to be equal for all simulations, Np is the number of parameters to estimate, and Nls is the number of line searches. Nls is difficult to estimate and you generally assume it to be equal to one, two, or three.

When you use parallel computing, the software distributes the simulations required for objective gradient computations. The simulation time taken per iteration when the gradient computations are performed in parallel, *TtotalP*, is approximately given by the following equation:

$$TtotalP = T + \left(ceil\left(\frac{Np}{Nw}\right) \times 2 \times T\right) + (Nls \times T) = T \times \left(1 + 2 \times ceil\left(\frac{Np}{Nw}\right) + Nls\right)$$

where Nw is the number of MATLAB workers.

Note The equation does not include the time overheads associated with configuring the system for parallel computing and loading Simulink software on the remote MATLAB workers.

The expected reduction of the total estimation time is given by the following equation:

$$\frac{TtotalP}{Ttotal} = \frac{1 + 2 \times ceil\left(\frac{Np}{Nw}\right) + Nls}{1 + (2 \times Np) + Nls}$$

For example, for a model with N_p=3, N_w=4, and N_{ls}=3, the expected reduction of the total estimation time equals $\frac{1 + 2 \times ceil\left(\frac{3}{4}\right) + 3}{1 + (2 \times 3) + 3} = 0.6$.

Parallel Computing with the Pattern search Method

The `Pattern search` method uses search and poll sets to create and compute a set of candidate solutions at each estimation iteration.

The total time, *Ttotal*, taken per iteration to perform these simulations, is given by the following equation:

$$Ttotal = (T \times Np \times Nss) + (T \times Np \times Nps) = T \times Np \times (Nss + Nps)$$

where T is the time taken to simulate the model and is assumed to be equal for all simulations, Np is the number of parameters to estimate, Nss is a factor for the search set size, and Nps is a factor for the poll set size. Nss and Nps are typically proportional to Np.

When you use parallel computing, Simulink Design Optimization software distributes the simulations required for the search and poll set computations, which are evaluated in separate `parfor` loops. The simulation time taken per iteration when the search and poll sets are computed in parallel, *TtotalP*, is given by the following equation:

$$\begin{aligned} TtotalP &= (T \times ceil(Np \times \frac{Nss}{Nw})) + (T \times ceil(Np \times \frac{Nps}{Nw})) \\ &= T \times (ceil(Np \times \frac{Nss}{Nw}) + ceil(Np \times \frac{Nps}{Nw})) \end{aligned}$$

where Nw is the number of MATLAB workers.

Note The equation does not include the time overheads associated with configuring the system for parallel computing and loading Simulink software on the remote MATLAB workers.

The expected speed up for the total estimation time is given by the following equation:

$$\frac{TtotalP}{Ttotal} = \frac{ceil(Np \times \frac{Nss}{Nw}) + ceil(Np \times \frac{Nps}{Nw})}{Np \times (Nss + Nps)}$$

For example, for a model with N_p=3, N_w=4, N_{ss}=15, and N_{ps}=2, the expected speedup equals

$$\frac{ceil(3 \times \frac{15}{4}) + ceil(3 \times \frac{2}{4})}{3 \times (15 + 2)} = 0.27.$$

Using the `Pattern search` method with parallel computing may not speed up the estimation time. When you do not use parallel computing, the method stops searching for a candidate solution at each iteration as soon as it finds a solution better than the current solution. When you use parallel computing, the candidate solution search is more comprehensive. Although the number of iterations may be larger, the estimation without using parallel computing may be faster.

See Also

Related Examples

- "Use Parallel Computing for Parameter Estimation" on page 2-33

Use Parallel Computing for Parameter Estimation

Configure Your System for Parallel Computing

You can speed up parameter estimation using parallel computing on multicore processors or multiprocessor networks. Use parallel computing with the **Parameter Estimator** and `sdo.optimize` to estimate parameters using the `fmincon`, `lsqnonlin`, and `patternsearch` methods. Parallel computing is not supported for the `fminsearch` (**Simplex search**) method.

When you estimate model parameters using parallel computing, the software uses the available parallel pool. If none is available, and you select **Automatically create a parallel pool** in your Parallel Computing Toolbox preferences, the software starts a parallel pool using the settings in those preferences. To open a parallel pool that uses a specific cluster profile, use:

```
parpool(MyProfile);
```

`MyProfile` is the name of a cluster profile.

For information regarding creating a cluster profile, see “Add and Modify Cluster Profiles” (Parallel Computing Toolbox).

Model Dependencies

Model dependencies are any referenced models, data such as model variables, S-functions, and additional files necessary to run the model. Before starting the optimization, verify that the model dependencies are complete. Otherwise, you may get unexpected results.

Making Model Dependencies Accessible to Remote Workers

When you use parallel computing, the Simulink Design Optimization software helps you identify model dependencies. To do so, the software uses the Dependency Analyzer. The dependency analysis may not find all the files required by your model. To learn more, see “Dependency Analyzer Scope and Limitations”. If your model has dependencies that are undetected or inaccessible by the parallel pool workers, then add them to the list of model dependencies.

The dependencies are made accessible to the parallel pool workers by specifying one of the following:

- File dependencies: the model dependency files are copied to the parallel pool workers.
- Path dependencies: the paths to the model dependencies are added to the paths of the parallel pool workers. If you are working in a multi-platform scenario, ensure that the paths are compatible across platforms.

Using file dependencies is recommended, however, in some cases it can be better to choose path dependencies. For example, if parallel computing is set up on a local multi-core computer, using path dependencies is preferred as using file dependencies creates multiple copies of the dependent files on the local computer.

For more information, see:

- “Estimate Parameters Using Parallel Computing in the Parameter Estimator App” on page 2-34 (Not supported in Simulink Online™.)
- “Estimate Parameters Using Parallel Computing (Code)” on page 2-35

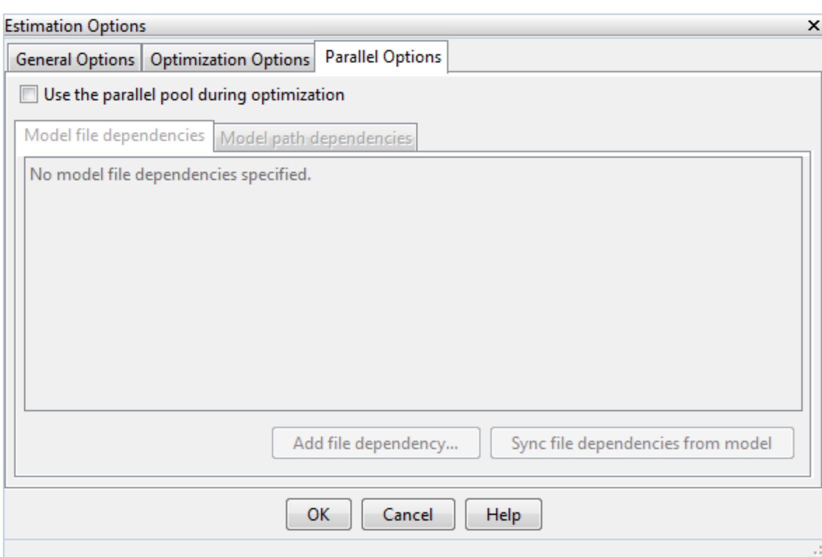
Estimate Parameters Using Parallel Computing in the Parameter Estimator App

To estimate model parameters using parallel computing in the **Parameter Estimator**:

1. Ensure that the software can access parallel pool workers that use the appropriate cluster profile.

   For more information, see “Configure Your System for Parallel Computing” on page 2-33.
2. Open the **Parameter Estimator** for the Simulink model.
3. Configure the estimation data, estimation parameters and states, and, optionally, estimation settings.

   For more information, see “Specify Estimation Data” on page 2-4, “Specify Parameters for Estimation” on page 2-7, and “Specify Estimation Options” on page 2-17.
4. On the **Parameter Estimation** tab, click **More Options** to open the **Estimation Options** dialog box.
5. Select the **Parallel Options** tab.



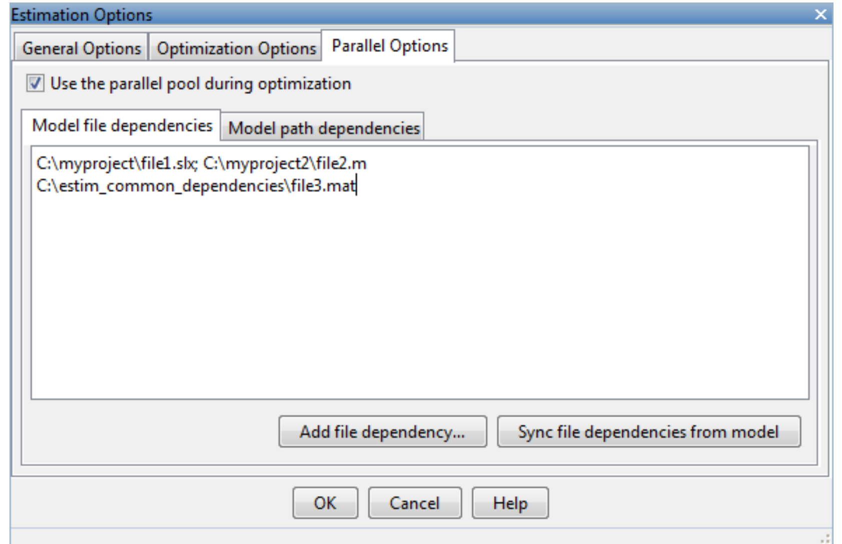
6. Select the **Use the parallel pool during optimization** check box.

   This option checks for dependencies in your Simulink model. The file dependencies are displayed in the **Model file dependencies** list box, and corresponding path to the files in **Model path dependencies**. The files listed in **Model file dependencies** are copied to the remote workers.

   Note The automatic dependencies check may not detect all the dependencies in your model.

   For more information, see “Model Dependencies” on page 2-33. In this case, add the undetected dependencies manually.
7. Add any file dependencies that the automatic check does not detect.

Specify the files in the **Model file dependencies** list box separated by semicolons or on separate lines.



Alternatively, click **Add file dependency** to open a dialog box, and select the file to add.

Note If you do not want to copy the files to the remote workers, delete all entries in the **Model file dependencies** list box. Populate the **Model path dependencies** list box by clicking the **Sync path dependencies from model**, and add any undetected path dependencies. In addition, in the list box, update the paths on local drives to make them accessible to remote workers. For example, change `C:\` to `\\\\hostname\\C$\\`.

---

8 If you modify the Simulink model, resync the dependencies to ensure that any new dependencies are detected. Click **Sync file dependencies from model** in the **Parallel Options** tab to rerun the automatic dependency check for your model.

   This action updates the **Model file dependencies** list box with any new file dependency found in the model.
9 Click **OK**.
10 In the **Parameter Estimation** tab, click **Estimate** to estimate the model parameters using parallel computing.

For information on troubleshooting problems related to estimation using parallel computing, see “Troubleshooting” on page 2-36.

Estimate Parameters Using Parallel Computing (Code)

To use parallel computing for parameter estimation at the command line:

1 Ensure that the software can access parallel pool workers that use the appropriate cluster profile.

   For more information, see “Configure Your System for Parallel Computing” on page 2-33.
2 Open the model.

3. Configure an estimation experiment. For example, see "Estimate Model Parameter Values (Code)" on page 2-58.
4. Enable parallel computing using an optimization option set, `opt`.

```
opt = sdo.OptimizeOptions;
opt.UseParallel = true;
```

5. Find the model dependencies.

```
[dirs,files] = sdo.getModelDependencies(modelname)
```

Note `sdo.getModelDependencies` may not detect all the dependencies in your model. For more information, see "Model Dependencies" on page 2-33. In this case, add the undetected dependencies manually.

---

6. Modify `files` to include any file dependencies that `sdo.getModelDependencies` does not detect.

```
files = vertcat(files,'C:\matlab\work\filename.m')
```

Note If you do not want to copy the files to the remote workers, use the path dependencies. Add any undetected path dependencies to `dirs` and update the paths on local drives to make them accessible to remote workers. See `sdo.getModelDependencies` for more details.

---

7. Add the file dependencies for optimization.

```
opt.ParallelFileDependencies = files;
```

8. Run the optimization.

```
[pOpt,opt_info] = sdo.optimize(opt_fcn,param,opt);
```

For information on troubleshooting problems related to estimation using parallel computing, see "Troubleshooting" on page 2-36.

Troubleshooting

Why Are the Estimation Results With and Without Parallel Computing Different?

- Different numerical precision on the client and worker machines can produce marginally different simulation results. Thus, the optimization method can take a different solution path and produce a different result.
- When you use parallel computing with the `Pattern search` method, the search is more comprehensive and can result in a different solution. To learn more, see "Parallel Computing with the Pattern search Method" on page 2-31.

Why Didn't the Estimation Speed up Using Parallel Computing?

- When you estimate a few parameters or when the model does not take long to simulate, you do not see a speedup in the estimation time. In such cases, the overhead associated with creating and distributing the parallel tasks outweighs the benefits of running the estimation in parallel.
- Using the `Pattern search` method with parallel computing might not speed up the optimization time. Without parallel computing, the method stops the search at each iteration as soon as it finds a solution better than the current solution. The candidate solution search is more comprehensive

when you use parallel computing. Although the number of iterations might be larger, the optimization without using parallel computing might be faster.

To learn more about the expected speedup, see “Parallel Computing with the Pattern search Method” on page 2-31.

Why Doesn’t the Estimation Using Parallel Computing Make Any Progress?

To troubleshoot the problem:

1. Run the optimization for a few iterations without parallel computing to see if the optimization progresses.
2. Check whether the remote workers have access to all model dependencies. Model dependencies include data variables and files required by the model to run.

   To learn more, see “Model Dependencies” on page 2-33.

Why Does the Estimation Using Parallel Computing Continue When I Click Stop?

When you use parallel computing with the `Pattern search` method, the software must wait until the current optimization iteration completes before it notifies the workers to stop. The optimization does not terminate immediately when you click **Stop**, and, instead, appears to continue running.

See Also

`sdo.optimize` | `sdo.OptimizeOptions` | `sdo.getModelDependencies` | `parpool`

More About

- “Speed Up Parameter Estimation Using Parallel Computing” on page 2-30
- “Ways to Speed Up Design Optimization Tasks”

Estimating Initial Conditions for Blocks with External Initial Conditions

When an integrator block uses an initial-condition port, which you specify by an `IC` block, you cannot estimate the initial conditions of the integrator using Simulink Design Optimization software. Estimation is not possible because external initial conditions have priority over the initial conditions of a specific block to maintain the integrity of the model.

To tune the initial conditions of an integrator block with external initial conditions, you must modify the model to make the external signal into a tunable parameter. For example, you can set the IC block that feeds into the integrator to be a tunable variable and estimate it.

See Also

Save and Load Estimation Sessions

This topic shows how to save and load estimation sessions in the **Parameter Estimator**.

Structure of an Estimation Session

The **Parameter Estimator** stores and organizes data from a given Simulink model inside a *session*. An estimation session includes the following information:

- One or more estimation or validation experiments along with their configurations
- Parameter information
- Estimation results
- Estimation settings
- Plots — Changes to plots layout and plot characteristics, such as axis limits, line colors, are not included.

The default session name is the same as the Simulink model name. The session name is shown on the title pane of the **Parameter Estimator**.

Save Parameter Estimator App Sessions

Saving a session lets you reuse your estimation settings and results later. You can save the session as a MAT-file or workspace variable:

- To save the session as a MAT-file, in the **Parameter Estimation** tab, in the **Save Session** drop-down list, click **Save to file**. A window opens where you specify the MAT-file name.
- To save the session as a model or MATLAB workspace variable, select **Save to model workspace** or **Save to MATLAB workspace** in the **Save Session** drop-down list.

Load Parameter Estimator App Sessions

To load a previously saved MAT-file or workspace sessions:

1. Open a **Parameter Estimator** for the model.
2. To load a MAT-file, in the **Parameter Estimation** tab click the **Open Session** drop-down list, and select **Open from file**. A window opens where you select the MAT-file to load.

   To load a workspace variable, select **Open from model workspace** or **Open from MATLAB workspace** in the **Open Session** drop-down list.

Load Legacy Projects

Open legacy projects that are in MAT-files by selecting `Open from file` from the **Open Session** drop-down list. The **Parameter Estimator** recognizes and converts them into the new session format.

See Also

More About

- "What Is an Experiment?" on page 2-3

How the Software Formulates Parameter Estimation as an Optimization Problem

Overview of Parameter Estimation as an Optimization Problem

When you perform parameter estimation, the software formulates an optimization problem. The optimization problem solution is the estimated parameter values set. This optimization problem consists of:

- x — Design variables. The model parameters and initial states to be estimated.
- $F(x)$ — Objective function. A function that calculates a measure of the difference between the simulated and measured responses. Also called cost function or estimation error.
- (Optional) $\underline{x} \leq x \leq \bar{x}$ — Bounds. Limits on the estimated parameter values.
- (Optional) $C(x)$ — Constraint function. A function that specifies restrictions on the design variables.

The optimization solver tunes the values of the design variables to satisfy the specified objectives and constraints. The exact formulation of the optimization depends on the optimization method that you use.

Cost Function

The software tunes the model parameters to obtain a simulated response (y_{sim}) that tracks the measured response or reference signal (y_{ref}). To do so, the solver minimizes the *cost function* or *estimation error*, a measure of the difference between the simulated and measured responses. The cost function, $F(x)$, is the objective function of the optimization problem.

Types

The raw estimation error, $e(t)$, is defined as:

$$e(t) = y_{ref}(t) - y_{sim}(t)$$

$e(t)$ is also referred to as the error residuals or, simply, residuals.

Simulink Design Optimization software provides you the following cost functions to process $e(t)$:

Cost Function	Formulation	Option Name in GUI or Command Line
Sum squared error (default)	$F(x) = \sum_{t=0}^{t_N} e(t) \times e(t)$ N is the number of samples.	`'SSE'`
Sum absolute error	$F(x) = \sum_{t=0}^{t_N} \left\| e(t) \right\|$ N is the number of samples.	`'SAE'`

Cost Function	Formulation	Option Name in GUI or Command Line
Raw error	$F(x) = \begin{bmatrix} e(0) \\ \vdots \\ e(N) \end{bmatrix}$ N is the number of samples.	`'Residuals'` This option is available only at the command line.
Custom function	N/A	This option is available only at the command line.

Time Base

The software evaluates the cost function for a specific time interval. This interval is dependent on the measured signal time base and the simulated signal time base.

- The measured signal time base consists of all the time points for which the measured signal is specified. In case of multiple measured signals, this time base is the union of the time points of all the measured signals.
- The simulated signal time base consists of all the time points for which the model is simulated.

If the model uses a variable-step solver, then the simulated signal time base can change from one optimization iteration to another. The simulated and measured signal time bases can be different. The software evaluates the cost function for only the time interval that is common to both. By default, the software uses only the time points specified by the measured signal in the common time interval.

- In the GUI, you can specify the simulation start and stop times in the **Simulation time** area of the **Simulation Options** dialog box.
- At the command line, the software specifies the simulation stop time as the last point of the measured signal time base. For example, the following code simulates the model until the end time of the longest running output signal of `exp`, an `sdo.Experiment` object:

  ```
  sim_obj = createSimulator(exp);
  sim_obj = sim(sim_obj);
  ```

  `sim_obj` contains the simulated response for the model associated with `exp`.

Bounds and Constraints

You can specify bounds for the design variables (estimated model parameters), based on your knowledge of the system. Bounds are expressed as:

$$\underline{x} \leq x \leq \bar{x}$$

$\underline{x}$ and $\bar{x}$ are the lower and upper bounds for the design variables.

For example, in a battery discharging experiment, the estimated battery initial charge must be greater than zero and less than `Inf`. These bounds are expressed as:

$$0 < x < \infty$$

For an example of how to specify these types of bounds, see “Estimate Model Parameters and Initial States (Code)” on page 2-67.

You can also specify other constraints, $C(x)$, on the design variables at the command line. $C(x)$ can be linear or nonlinear and can describe equalities or inequalities. $C(x)$ can also specify multiparameter constraints. For example, for a simple friction model, $C(x)$ can specify that the static friction coefficient must be greater than or equal to the dynamic friction coefficient. One way of expressing this constraint is:

$$C(x): x_1 - x_2$$
$$C(x) \leq 0$$

x_1 and x_2 are the dynamic and static friction coefficients, respectively.

For an example of how to specify a constraint, see “Estimate Model Parameters with Parameter Constraints (Code)” on page 2-125.

Optimization Methods and Problem Formulations

An optimization problem can be one of the following types:

- Minimization problem — Minimizes an objective function, $F(x)$. You specify the measured signal that you want the model output to track. You can optionally specify bounds for the estimated parameters.
- Mixed minimization and feasibility problem — Minimizes an objective function, $F(x)$, subject to specified bounds and constraints, $C(x)$. You specify the measured signal that you want the model to track and bounds and constraints for the estimated parameters.
- Feasibility problem — Finds a solution that satisfies the specified constraints, $C(x)$. You specify only bounds and constraints for the estimated parameters. This type of problem is not common in parameter estimation.

The optimization method that you specify determines the formulation of the estimation problem. The software provides the following optimization methods:

Optimization Method Name	Description	Optimization Problem Formulation
• User interface: **Nonlinear Least Squares** • Command line: `'lsqnonlin'`	Minimizes the squares of the residuals, recommended method for parameter estimation. This method requires a vector of error residuals, computed using a fixed time base. Do not use this approach if you have a scalar cost function or if the number of error residuals can change from one iteration to another. This method uses the Optimization Toolbox™ function, `lsqnonlin`.	**Minimization Problem** $\min_x \lVert F(x) \rVert_2^2 = \min_x \left(f_1(x)^2 + f_2(x)^2 + \ldots + f_n(x)^2 \right)$ $s.t. \;\; \underline{x} \leq x \leq \overline{x}$ $f_1(x), f_2(x),\ldots,f_n(x)$ represent residuals. n is the number of samples. **Mixed Minimization and Feasibility Problem** Not supported. **Feasibility Problem** Not supported.

<table>
<tr><th>Optimization Method Name</th><th>Description</th><th>Optimization Problem Formulation</th></tr>
<tr><td>
User interface: Gradient Descent
Command line: <code>'fmincon'</code>
</td><td>
General nonlinear solver, uses the cost function gradient.

Use this approach if you want to specify one or any combination of the following:
Custom cost functions
Parameter-based constraints
Signal-based constraints
This method uses the Optimization Toolbox function, <code>fmincon</code>.

For information on how the gradient is computed, see “Gradient Computations” on page 2-57.
</td><td>
Minimization Problem
$$\min_x F(x) \quad s.t.\ \underline{x} \le x \le \bar{x}$$
Mixed Minimization and Feasibility Problem
$$\min_x F(x) \quad s.t.\ C(x) \le 0,\ \underline{x} \le x \le \bar{x}$$
Note When tracking a reference signal, the software ignores the maximally feasible solution option.

Feasibility Problem
If you select the maximally feasible solution option (i.e., the optimization continues after an initial feasible solution is found), the software uses the following problem formulation:
$$\min_{[x,\gamma]} \gamma \quad s.t.\ C(x) \le \gamma,\ \underline{x} \le x \le \bar{x},\ \gamma \le 0$$
γ is a slack variable that permits a feasible solution with $C(x) \le \gamma$ rather than $C(x) \le 0$.
If you do not select the maximally feasible solution option (i.e., the optimization terminates as soon as a feasible solution is found), the software uses the following problem formulation:
$$\min_x 0 \quad s.t.\ C(x) \le 0,\ \underline{x} \le x \le \bar{x}$$
</td></tr>
</table>

Optimization Method Name	Description	Optimization Problem Formulation
• User interface: **Simplex Search** • Command line: `'fminsearch'`	Based on the Nelder-Mead algorithm, this approach does not use the cost function gradient. Use this approach if your cost function or constraints are not continuous or differentiable. This method uses the Optimization Toolbox functions, `fminsearch` and `fminbnd`. `fminbnd` is used if one scalar parameter is being optimized. Otherwise, `fminsearch` is used. You cannot specify parameter bounds, $\underline{x} \le x \le \bar{x}$, with `fminsearch`.	**Minimization Problem** $\min_x F(x)$ **Mixed Minimization and Feasibility Problem** The software formulates the problem in two steps: **1** Finds a feasible solution. $\min_x \max(C(x))$ **2** Minimizes the objective. The software uses the results from step 1 as initial guesses. It maintains feasibility by introducing a discontinuous barrier in the optimization objective. $\min_x \Gamma(x)$ where $\Gamma(x) = \begin{cases} \infty & \text{if} \max(C(x)) > 0 \\ F(x) & \text{otherwise.} \end{cases}$ **Feasibility Problem** $\min_x \max(C(x))$

Optimization Method Name	Description	Optimization Problem Formulation
• User interface: **Pattern Search** • Command line: `'patternsearch'`	Direct search method, based on the generalized pattern search algorithm, this method does not use the cost function gradient. Use this approach if your cost function or constraints are not continuous or differentiable. This method uses the Global Optimization Toolbox function, `patternsearch`.	**Minimization Problem** $\min_x \; F(x)$ $s.t. \quad \underline{x} \le x \le \bar{x}$ **Mixed Minimization and Feasibility Problem** The software formulates the problem in two steps: **1** Finds a feasible solution. $\min_x \max(C(x))$ $s.t. \quad \underline{x} \le x \le \bar{x}$ **2** Minimizes the objective. The software uses the results from step 1 as initial guesses. It maintains feasibility by introducing a discontinuous barrier in the optimization objective. $\min_x \Gamma(x)$ $s.t. \; \underline{x} \le x \le \bar{x}$ where $\Gamma(x) = \begin{cases} \infty & \text{if} \max(C(x)) > 0 \\ F(x) & \text{otherwise.} \end{cases}$ **Feasibility Problem** $\min_x \max(C(x))$ $s.t. \quad \underline{x} \le x \le \bar{x}$

See Also

`sdo.SimulationTest` | `sdo.Experiment` | `sdo.requirements.SignalTracking` | `evalRequirement` | `lsqnonlin` | `fmincon` | `fminsearch` | `fminbnd` | `patternsearch`

Related Examples

- “Estimate Model Parameter Values (Code)” on page 2-58
- “Estimate Model Parameters with Parameter Constraints (Code)” on page 2-125
- “Estimate Parameters from Measured Data”

More About

- “Write a Cost Function” on page 2-49

Specify Steady-State Operating Point for Parameter Estimation

What is a Steady-State Operating Point?

An *operating point* of a dynamic system defines the states and root-level input signals of the model at a specific time. For example, in a car engine model, variables such as engine speed, throttle angle, engine temperature, and surrounding atmospheric conditions typically describe the operating point.

A *steady-state operating point* of a model, also called an equilibrium or *trim* condition, includes state variables that do not change with time.

A model can have several steady-state operating points. For example, a hanging damped pendulum has two steady-state operating points at which the pendulum position does not change with time. A *stable steady-state operating point* occurs when a pendulum hangs straight down. When the pendulum position deviates slightly, the pendulum always returns to equilibrium. In other words, small changes in the operating point do not cause the system to leave the region of good approximation around the equilibrium value.

When using optimization search to compute operating points for nonlinear systems, your initial guesses for the states and input levels must be near the desired operating point to ensure convergence.

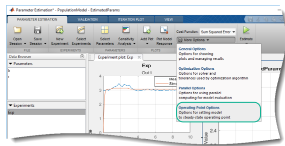
When linearizing a model with multiple steady-state operating points, it is important to have the right operating point. For example, linearizing a pendulum model around the stable steady-state operating point produces a stable linear model, whereas linearizing around the unstable steady-state operating point produces an unstable linear model.

For more information on operating points, see “What Is an Operating Point?” (Simulink Control Design) and “What Is a Steady-State Operating Point?” (Simulink Control Design).

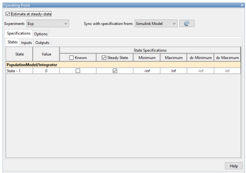
Setting up a Steady-State Operating Point

This topic shows how to setup a steady-state operating point in **Parameter Estimator**. To improve the fit between the model and measured data, the model must be set to steady-state when parameters are estimated.

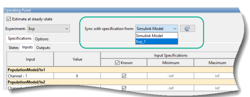
1. Open the **Parameter Estimator** and setup your experiment using the steps outlined in “Estimate Model Parameter Values (GUI)” on page 2-144.
2. In the toolstrip, click **More Options** and select `Operating Point Options` from the drop down menu.



3. The following **Operating Point** dialog box opens.

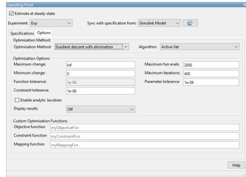


The **Estimate at steady-state** option is checked by default when you open the operating point dialog. Select the appropriate experiment to change the parameters for from the `Experiment:` drop down menu. Use the **States**, **Inputs** and **Outputs** tabs to specify the known parameters, bounds and deviations. For instance, there is one state in the above figure. Use the operating point dialog to specify that this state should be treated as an unknown, and it should be set to steady state. During parameter estimation, the operating point computation will vary this state to set it at steady-state.



You can also sync operating point specifications from your Simulink model or another experiment using the `Sync with specification from:` drop-down list. After you make your selection, click on the button to copy the parameters.

4. The Simulink Design Optimization software uses optimization methods to search for operating points in a model. Use the **Options** tab of the dialog to specify these optimization methods. These options specify the optimization algorithm, tolerances, and stopping conditions. For instance, the option `Gradient descent with projection` is often used to find the operating point for systems that use physical modeling. For more information, click on the button.



5. Having specified the operating point parameters, continue with the estimation workflow as described in “Estimate Model Parameter Values (GUI)” on page 2-144.

See Also

More About

- “What Is an Operating Point?” (Simulink Control Design)
- “What Is a Steady-State Operating Point?” (Simulink Control Design)
- “Set Model to Steady-State When Estimating Parameters (GUI)” on page 2-118
- “Set Model to Steady-State When Estimating Parameters (Code)” on page 2-97

Write a Cost Function

A cost function is a MATLAB function that evaluates your design requirements using design variable values. After writing and saving the cost function, you can use it for estimation, optimization, or sensitivity analysis at the command line.

When you optimize or estimate model parameters, you provide the saved cost function as an input to `sdo.optimize`. At every optimization iteration, `sdo.optimize` calls this function and uses the function output to decide the optimization direction. When you perform sensitivity analysis using `sdo.evaluate`, you generate sample values of the design variables and evaluate the cost function for each sample value using `sdo.evaluate`.

Anatomy of a Cost Function

To understand the parts of a cost function, consider the following sample function `myCostFunc`. For a design variable x, `myCostFunc` evaluates the objective x^2 and the nonlinearity constraint x^2-4x+1 <= 0.

```
function [vals,derivs] = myCostFunc(params)
% Extract the current design variable values from the parameter object, params.
x = params.Value;
% Compute the requirements (objective and constraint violations) and
% assign them to vals, the output of the cost function.
vals.F = x.^2;
vals.Cleq = x.^2-4*x+1;
% Compute the cost and constraint derivatives.
derivs.F = 2*x;
derivs.Cleq = 2*x-4;
end
```

This cost function performs the following tasks:

1. Specifies the inputs of the cost function.

   A cost function must have as input, `params`, a vector of the design variables to be estimated, optimized, or used for sensitivity analysis. Design variables are model parameter objects (`param.Continuous` objects) or model initial states (`param.State` objects).

   Since the cost function is called repeatedly during estimation, optimization, or evaluation, you can specify additional inputs to the cost function to help reduce code redundancy and computation cost. For more information, see “Specify Inputs of the Cost Function” on page 2-50.
2. Computes the requirements.

   Requirements can be objectives and constraints based on model parameters, model signals, or linearized models. In this sample cost function, the requirements are based on the design variable x, a model parameter. The cost function first extracts the current values of the design variables and then computes the requirements.

   For information about computing requirements based on model parameters, model signals, or linearized models, see “Compute Requirements” on page 2-51.
3. Specifies the requirement values as outputs, `vals` and `derivs`, of the cost function.

   A cost function must return `vals`, a structure with one or more fields that specify the values of the objective and constraint violations.

The output can optionally include `derivs`, a structure with one or more fields that specify the values of the gradients of the objective and constraint violations. For more information, see “Specify Outputs of the Cost Function” on page 2-52.

After saving the cost function as a MATLAB file `myCostFunc.m`, to perform the optimization, use the cost function as an input to `sdo.optimize`.

```
[param_opt,opt_info] = sdo.optimize(@myCostFunc,params)
```

When performing sensitivity analysis, to compute the requirements in the cost function for a range of design variable sample values `paramsamples`, use the cost function as an input to `sdo.evaluate`.

```
[y,info] = sdo.evaluate(@myCostFunc,paramsamples)
```

Specify Inputs of the Cost Function

The sample cost function `myCostFunc` takes one input, `params`.

```
function [vals,derivs] = myCostFunc(params)
```

A cost function must have as input, `params`, a vector of the design variables to be estimated, optimized, or used for sensitivity analysis. Design variables are model parameter objects (`param.Continuous` objects) or model initial states (`param.State` objects). You obtain `params` by using the `sdo.getParameterFromModel` and `sdo.getStateFromModel` commands.

Specify Multiple Inputs

Because the cost function is called repeatedly during estimation, optimization, or evaluation, you can specify additional inputs to the cost function to help reduce code redundancy and computation cost. However, `sdo.optimize` and `sdo.evaluate` accept a cost function with only one input argument. To use a cost function that accepts more than one input argument, you use an anonymous function. Suppose that the `myCostFunc_multi_inputs.m` file specifies a cost function that takes `params` and `arg1` as inputs. For example, you can make the model name an input argument, `arg1`, and configure the cost function to be used for multiple models. Then, assuming that all input arguments are variables in the workspace, specify an anonymous function `myCostFunc2`, and use it as an input to `sdo.optimize` or `sdo.evaluate`.

```
myCostFunc2 = @(params) myCostFunc_multi_inputs(params,arg1);
[param_opt,opt_info] = sdo.optimize(@myCostFunc2,params);
```

You can also specify additional inputs using convenience objects provided by Simulink Design Optimization software. You create convenience objects once and pass them as an input to the cost function to reduce code redundancy and computation cost.

For example, you can create a simulator (`sdo.SimulationTest` object) to simulate your model using alternative model parameters without modifying the model, and pass the simulator to your cost function.

```
simulator = sdo.SimulationTest(model)
myCostFunc2 = @(params) myCostFunc_multi_inputs(params,arg1,arg2,simulator);
[param_opt,opt_info] = sdo.optimize(@myCostFunc2,params);
```

For more information about the available convenience objects, see “Convenience Objects as Additional Inputs” on page 2-54. For an example, see “Design Optimization to Meet a Custom Objective (Code)” on page 3-125.

Compute Requirements

The sample cost function `myCostFunc` computes the requirements based on a model parameter `x`. In general, requirements can be objectives or constraints based on model parameters, model signals, or linearized models. As seen in `myCostFunc`, you can use MATLAB functions to compute the requirements. You can also use the requirements objects that Simulink Design Optimization software provides. These objects enable you to specify requirements such as step-response characteristics, gain and phase margin bounds, and Bode magnitude bounds. You can use the `evalRequirement` method of these objects to evaluate the objective and constraint violations. For a list of available requirement objects, see "Convenience Objects as Additional Inputs" on page 2-54.

Parameter-Based Requirements

If you have requirements on model parameters, in the cost function you first extract the current parameter values, and then compute the requirements.

1. Extract the current parameter value from `params`.

   ```
   x = params.Value;
   ```
2. Compute the requirement, and specify it as `vals`, the output of the cost function.

   Suppose that the objective to be computed is x^2 and the constraint is the nonlinearity constraint x^2-4x+1.

   ```
   vals.F = x.^2;
   vals.Cleq = x.^2-4*x+1;
   ```

   In the context of optimization, x^2 is minimized subject to satisfying the constraints. For sensitivity analysis, the cost and constraints are evaluated for all values of the parameter `params`.

   For more information about the output of a cost function, see "Specify Outputs of the Cost Function" on page 2-52.

For an example of a cost function with a parameter-based requirement, see "Design Optimization to Meet a Custom Objective (Code)" on page 3-125. In this example, you minimize the cylinder cross-sectional area, a design variable in a hydraulic cylinder.

Model Signal Requirements

If you have requirements on model signals, in the cost function you simulate the model using current design variable values, extract the signal of interest, and compute the requirement on the signal.

1. Simulate the model using the current design variable values in `param`. There are multiple ways to simulate your model:

   - **Using `sdo.SimulationTest` object** — If an `sdo.SimulationTest` object, `simulator`, is a cost function input, you update the model parameter values using the `Parameters` property of the simulator. Then use `sim` to simulate the model.

     ```
     simulator.Parameters = params;
     simulator = sim(simulator);
     ```

     For an example, see "Design Optimization to Meet a Custom Objective (Code)" on page 3-125.
   - **Using `sdo.Experiment` object** — If you are performing parameter estimation based on input-output data defined in an `sdo.Experiment` object, `exp`, update the design variable

values associated with the experiment using the `setEstimatedValues` method. Create a simulator using the `createSimulator` method, and simulate the model using the updated model configuration.

```
exp = setEstimatedValues(exp,params);
simulator = createSimulator(exp,simulator);
simulator = sim(simulator);
```

For an example, see "Estimate Model Parameters Per Experiment (Code)" on page 2-86.

- **Using `sim` command** — If you are not using `sdo.SimulationTest` or `sdo.Experiment` objects, use `sdo.setValueInModel` to update the model parameter values, and then call `sim` to simulate the model.

```
sdo.setValueInModel('model_name',param);
LoggedData = sim('model_name');
```

2. Extract the logged signal of interest, `SignalOfInterest`.

   Use the `SignalLoggingName` model parameter to get the simulation log name.

```
logName = get_param(simulator.ModelName,'SignalLoggingName');
simLog = get(simulator.LoggedData,logName);
Sig = get(simLog,'SignalOfInterest')
```

3. Evaluate the requirement, and specify it as the output of the cost function.

   For example, if you specified a step-response bound on a signal using a `sdo.requirements.StepResponseEnvelope` object, `StepResp`, you can use the `evalRequirement` method of the object to evaluate the objective and constraint violations.

```
vals.Cleq = evalRequirement(StepResp,SignalOfInterest.Values);
```

   For an example, see "Design Optimization to Meet Step Response Requirements (Code)". For more information about the output of a cost function, see "Specify Outputs of the Cost Function" on page 2-52.

Linearization-Based Requirements

If you are optimizing or evaluating frequency-domain requirements, in the cost function you linearize the model, and compute the requirement values. Linearizing the model requires Simulink Control Design™ software.

Use the `SystemLoggingInfo` property of `sdo.SimulationTest` to specify linear systems to log when simulating the model. For an example, see "Design Optimization to Meet Frequency-Domain Requirements (Code)" on page 3-224. Alternatively, use `linearize` to linearize the model.

Note For models in Simulink fast restart mode, you cannot use the `linearize` command.

Specify Outputs of the Cost Function

The sample cost function `myCostFunc` outputs `vals`, a structure with fields that specify the values of the objective and constraint violations. The second output is `derivs`, a structure with fields that specify the derivatives of the objective and constraint.

```
function [vals,derivs] = myCostFunc(params)
```

A cost function must output `vals`, a structure with one or more of the following fields that specify the values of the objective and constraint violations:

- `F` — Value of the cost or objective evaluated at `param`.
- `Cleq` — Value of the nonlinear inequality constraint violations evaluated at `param`. For optimization, the solver ensures `Cleq ≤ 0`.
- `Ceq` — Value of the nonlinear equality constraint violations evaluated at `param`. For optimization, the solver ensures `Ceq = 0`.
- `leq` — Value of the linear inequality constraint violations evaluated at `param`. For optimization, the solver ensures `leq ≤ 0`.
- `eq` — Value of the linear equality constraint violations evaluated at `param`. For optimization, the solver ensures `eq = 0`.
- `Log` — Additional optional information from evaluation.

If you have multiple constraints of one type, concatenate the values into a vector, and specify this vector as the corresponding field value. For instance, if you have a hydraulic cylinder, you can specify nonlinear inequality constraints on the piston position (`Cleq1`) and cylinder pressure (`Cleq2`). In this case, specify the `Cleq` field of the output structure `vals` as:

```
vals.Cleq = [Cleq1; Cleq2];
```

For an example, see “Design Optimization to Meet a Custom Objective (Code)” on page 3-125.

By default, the `sdo.optimize` command computes the objective and constraint gradients using numeric perturbation. You can also optionally return the gradients as an additional cost function output, `derivs`. Where `derivs` must contain the derivatives of all applicable objective and constraint violations and is specified as a structure with one or more of the following fields:

- `F` — Derivatives of the cost or objective.
- `Cleq` — Derivatives of the nonlinear inequality constraints.
- `Ceq` — Derivatives of the nonlinear equality constraints.

The derivatives are not required for sensitivity analysis. For estimation or optimization, specify the `GradFcn` property of `sdo.OptimizeOptions` as `'on'`.

Multiple Objectives

Simulink Design Optimization software does not support multi-objective optimization. However, you can return the objective value (`vals.F`) as a vector that represents the multiple objective values. The software sums the elements of the vector and minimizes this sum. The exception to this behavior is in the use of the nonlinear least squares (`lsqnonlin`) optimization method. The nonlinear least squares method, used for parameter estimation, requires that you return the error residuals as a vector. In this case, the software minimizes the sum square of this vector. If you are tracking multiple signals and using `lsqnonlin`, then concatenate the error residuals for the different signals into one vector. Specify this vector as the `F` field value.

For an example of single-objective optimization using the gradient descent method, see “Design Optimization to Meet a Custom Objective (Code)” on page 3-125.

For an example of multiple-objective optimization using the nonlinear least squares method, see “Estimate Model Parameters Per Experiment (Code)” on page 2-86.

Convenience Objects as Additional Inputs

A cost function must have as input, `params`, a vector of the design variables to be estimated, optimized, or used for sensitivity analysis. You can specify additional inputs to the cost function using convenience objects provided by the Simulink Design Optimization software. You create convenience objects once and pass them as an input to the cost function to reduce code redundancy and computation cost. For information about specifying additional inputs to the cost function, see “Specify Multiple Inputs” on page 2-50.

Convenience Object	Class Name	Description
Simulator objects	`sdo.SimulationTest`	Use the simulator object to simulate the model using alternative inputs, model parameters, and initial-state values without modifying the model. Use the `SystemLoggingInfo` property of `sdo.SimulationTest` to specify linear systems to log when you have frequency-domain requirements. In the cost function, use the `sim` method to simulate the model. Then extract the model response from the object, and evaluate the requirements. For an example, see “Design Optimization to Meet a Custom Objective (Code)” on page 3-125. **Note** To perform estimation, optimization, or evaluation using Simulink fast restart, it is necessary to create the simulator before the cost function, and then pass the simulator to the cost function.

<table>
<tr><th>Convenience Object</th><th>Class Name</th><th>Description</th></tr>
<tr><td>Requirements objects</td><td>Available Requirements Objects

Time-domain requirements:
• <code>sdo.requirements.SignalBound</code>
• <code>sdo.requirements.StepResponseEnvelope</code>
• <code>sdo.requirements.SignalTracking</code>
• <code>sdo.requirements.PhasePlaneEllipse</code>
• <code>sdo.requirements.PhasePlaneRegion</code>

Parameter requirements:
• <code>sdo.requirements.FunctionMatching</code>
• <code>sdo.requirements.MonotonicVariable</code>
• <code>sdo.requirements.RelationalConstraint</code>
• <code>sdo.requirements.SmoothnessConstraint</code>

Frequency-domain requirements:
• <code>sdo.requirements.GainPhaseMargin</code>
• <code>sdo.requirements.BodeMagnitude</code>
• <code>sdo.requirements.ClosedLoopPeakGain</code>
• <code>sdo.requirements.PZDampingRatio</code>
• <code>sdo.requirements.PZNaturalFrequency</code>
• <code>sdo.requirements.PZSettlingTime</code>
• <code>sdo.requirements.SignalTracking</code>
• <code>sdo.requirements.StepResponseEnvelope</code>
• <code>sdo.requirements.OpenLoopGainPhase</code></td><td>Use these objects to specify time-domain and frequency-domain costs or constraints that depend on the design variable values.

In the cost function, use the <code>evalRequirement</code> method of the object to evaluate how closely the current design variables satisfy your design requirement.

For an example, see “Design Optimization to Meet Step Response Requirements (Code)”.</td></tr>
</table>

Convenience Object	Class Name	Description
Experiment objects	`sdo.Experiment`	Use an experiment object to specify the input-output data, model parameters, and initial-state values for parameter estimation. In the cost function, update the design variable values associated with the experiment using the `setEstimatedValues` method. Then, to simulate the model using the updated model configuration, create a simulator using the `createSimulator` method. For an example, see “Estimate Model Parameters Per Experiment (Code)” on page 2-86.

See Also

`sdo.optimize` | `sdo.OptimizeOptions` | `sdo.evaluate` | `sdo.setValueInModel` | `param.Continuous` | `sdo.SimulationTest` | `sdo.Experiment`

Related Examples

- “How the Optimization Algorithm Formulates Minimization Problems” on page 3-3
- “Design Optimization to Meet a Custom Objective (Code)” on page 3-125
- “How the Software Formulates Parameter Estimation as an Optimization Problem” on page 2-41
- “Estimate Model Parameter Values (Code)” on page 2-58
- “What is Sensitivity Analysis?” on page 4-2
- “Identify Key Parameters for Estimation (Code)” on page 4-169

Gradient Computations

For the `Gradient descent` (`fmincon`) optimization solver, the gradients are computed using numerical perturbation:

$$dx = \sqrt[3]{eps} \times \max\left(\left|x\right|, \frac{1}{10}x_{typical}\right)$$

$$dL = \max(x - dx, x_{\min})$$

$$dR = \min(x + dx, x_{\max})$$

$$F_L = opt_fcn(dL)$$

$$F_R = opt_fcn(dR)$$

$$\frac{dF}{dx} = \frac{(F_L - F_R)}{(dL - dR)}$$

- x is a scalar design variable.
- x_{min} is the lower bound of x.
- x_{max} is the upper bound of x.
- $x_{typical}$ is the scaled value of x.
- *opt_fcn* is the objective function.

dx is relatively large to accommodate simulation solver tolerances.

If you want to compute the gradients in any other way, you can do so in the cost function you write for performing design optimization programmatically. See `sdo.optimize` and `GradFcn` of `sdo.OptimizeOptions` for more information.

See Also

`fmincon`

More About

- "How the Software Formulates Parameter Estimation as an Optimization Problem" on page 2-41
- "How the Optimization Algorithm Formulates Minimization Problems" on page 3-3

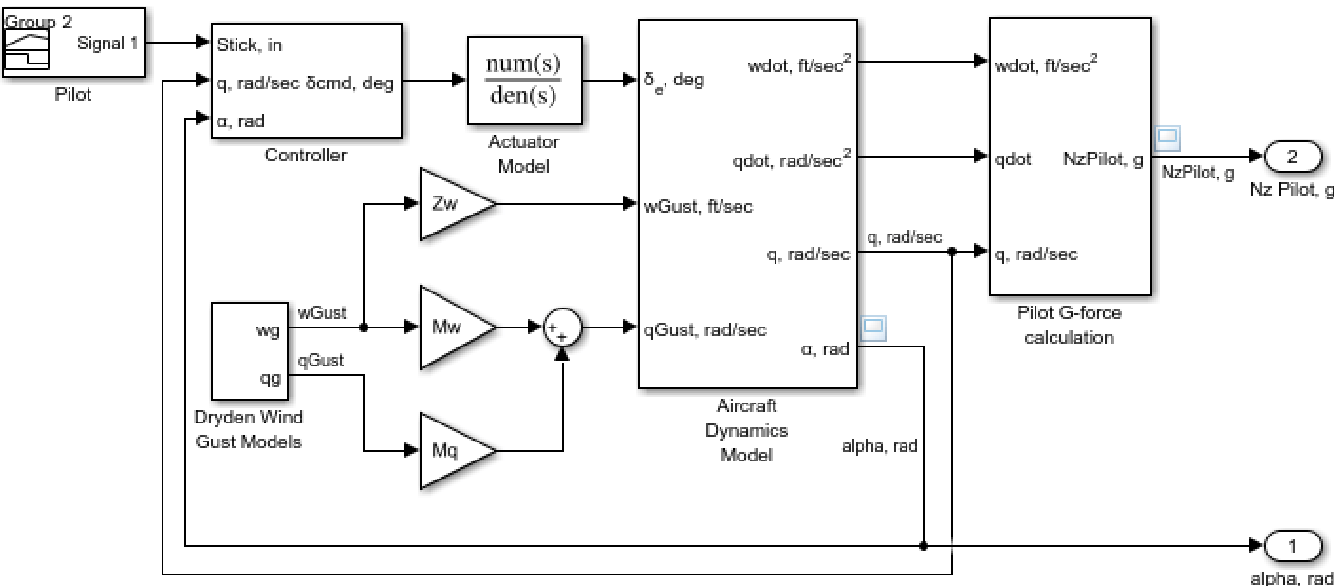
Estimate Model Parameter Values (Code)

This example shows how to use experimental data to estimate model parameter values.

Aircraft Model

The Simulink® model, `sdoAircraftEstimation`, models the longitudinal flight control system of an aircraft.

```
open_system('sdoAircraftEstimation')
```



Estimation Problem

You use measured data to estimate the aircraft model parameters and states.

Measured output data:

- Pilot G force, output of the Pilot G-force calculation block
- Angle of attack, fourth output of the Aircraft Dynamics Model block

Parameters:

- Actuator time constant, `Ta`, used by the Actuator Model block
- Vertical velocity, `Zd`, used by the Aircraft Dynamics Model block
- Pitch rate gains, `Md`, used by the Aircraft Dynamics Model block

State:

- Initial state of the first-order actuator model, sdoAircraftEstimation/Actuator Model

Define the Estimation Experiment

Get the measured data.

```
[time,iodata] = sdoAircraftEstimation_Experiment;
```

The `sdoAircraftEstimation_Experiment` function returns the measured output data, `iodata`, and the corresponding time vector. The first column of `iodata` is the pilot G force and the second column is the angle of attack.

To see the code for this function, type `edit sdoAircraftEstimation_Experiment`.

Create an experiment object to store the measured input/output data.

```
Exp = sdo.Experiment('sdoAircraftEstimation');
```

Create an object to store the measured pilot G-Force output.

```
PilotG = Simulink.SimulationData.Signal;
PilotG.Name      = 'PilotG';
PilotG.BlockPath = 'sdoAircraftEstimation/Pilot G-force calculation';
PilotG.PortType  = 'outport';
PilotG.PortIndex = 1;
PilotG.Values    = timeseries(iodata(:,2),time);
```

Create an object to store the measured angle of attack (alpha) output.

```
AoA = Simulink.SimulationData.Signal;
AoA.Name = 'AngleOfAttack';
AoA.BlockPath = 'sdoAircraftEstimation/Aircraft Dynamics Model';
AoA.PortType  = 'outport';
AoA.PortIndex = 4;
AoA.Values    = timeseries(iodata(:,1),time);
```

Add the measured pilot G-Force and angle of attack data to the experiment as the expected output data.

```
Exp.OutputData = [...
    PilotG; ...
    AoA];
```

Add the initial state for the Actuator Model block to the experiment. Set its `Free` field to `true` so that it is estimated.

```
Exp.InitialStates = sdo.getStateFromModel('sdoAircraftEstimation','Actuator Model');
Exp.InitialStates.Minimum = 0;
Exp.InitialStates.Free    = true;
```

Compare the Measured Output and the Initial Simulated Output

Create a simulation scenario using the experiment and obtain the simulated output.

```
Simulator    = createSimulator(Exp);
Simulator    = sim(Simulator);
```

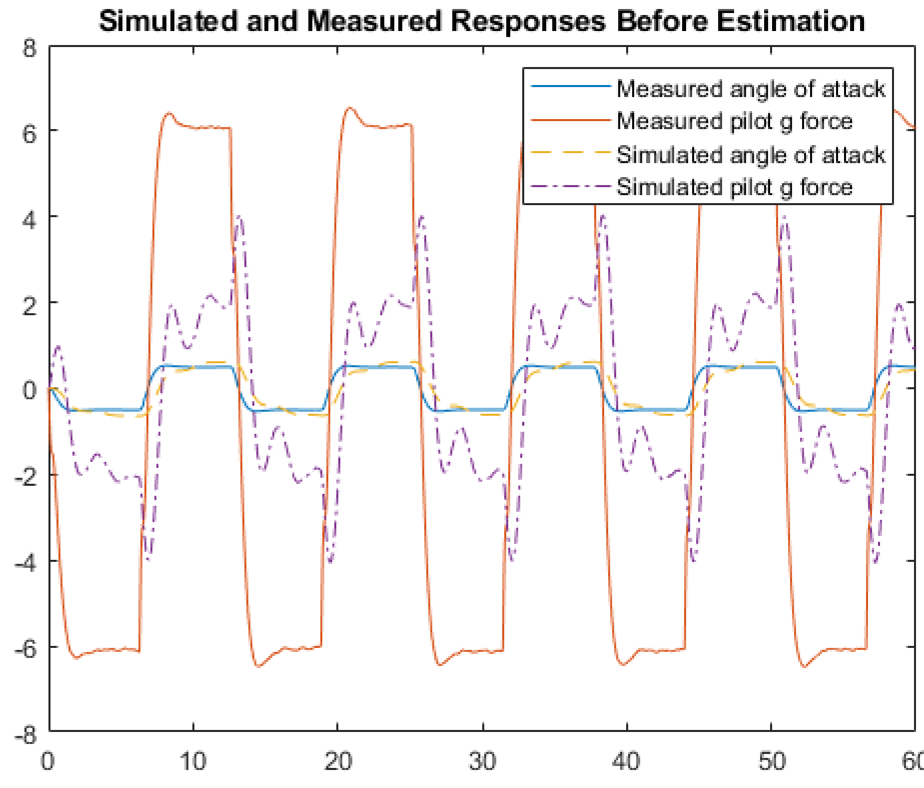
Search for the pilot G-Force and angle of attack signals in the logged simulation data.

```
SimLog       = find(Simulator.LoggedData,get_param('sdoAircraftEstimation','SignalLoggingName'));
PilotGSignal = find(SimLog,'PilotG');
AoASignal    = find(SimLog,'AngleOfAttack');
```

Plot the measured and simulated data.

As expected, the model response does not match the experimental output data.

```
plot(time, iodata, ...
    AoASignal.Values.Time,AoASignal.Values.Data,'--', ...
    PilotGSignal.Values.Time,PilotGSignal.Values.Data,'-.');
title('Simulated and Measured Responses Before Estimation')
legend('Measured angle of attack',  'Measured pilot g force', ...
     'Simulated angle of attack', 'Simulated pilot g force');
```



Specify the Parameters to Estimate

Select the model parameters that describe the flight control actuation system. Specify bounds for the estimated parameter values based on the understanding of the actuation system.

```
p = sdo.getParameterFromModel('sdoAircraftEstimation',{'Ta','Md','Zd'});
p(1).Minimum = 0.01;  %Ta
p(1).Maximum = 1;
p(2).Minimum = -10;   %Md
p(2).Maximum = 0;
p(3).Minimum = -100;  %Zd
p(3).Maximum = 0;
```

Get the actuator initial state value that is to be estimated from the experiment.

```
s = getValuesToEstimate(Exp);
```

Group the model parameters and initial states to be estimated together.

```
v = [p;s]
```

```
v(1,1) =

       Name: 'Ta'
      Value: 0.5000
    Minimum: 0.0100
    Maximum: 1
       Free: 1
      Scale: 0.5000
       Info: [1x1 struct]


v(2,1) =

       Name: 'Md'
      Value: -1
    Minimum: -10
    Maximum: 0
       Free: 1
      Scale: 1
       Info: [1x1 struct]


v(3,1) =

       Name: 'Zd'
      Value: -80
    Minimum: -100
    Maximum: 0
       Free: 1
      Scale: 128
       Info: [1x1 struct]


v(4,1) =

       Name: 'sdoAircraftEstimation/Actuator...'
      Value: 0
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 1
```

```
    dxValue: 0
     dxFree: 1
       Info: [1x1 struct]


4x1 param.Continuous
```

Define the Estimation Objective Function

Create an estimation objective function to evaluate how closely the simulation output, generated using the estimated parameter values, matches the measured data.

Use an anonymous function with one input argument that calls the `sdoAircraftEstimation_Objective` function. Pass the anonymous function to `sdo.optimize`, which evaluates the function at each optimization iteration.

```
estFcn = @(v) sdoAircraftEstimation_Objective(v,Simulator,Exp);
```

The `sdoAircraftEstimation_Objective` function:

- Has one input argument that specifies the actuator parameter values and the actuator initial state.
- Has one input argument that specifies the experiment object containing the measured data.
- Returns a vector of errors between simulated and experimental outputs.

The `sdoAircraftEstimation_Objective` function requires two inputs, but `sdo.optimize` requires a function with one input argument. To work around this, `estFcn` is an anonymous function with one input argument, `v`, but it calls `sdoAircraftEstimation_Objective` using two input arguments, `v` and `Exp`.

For more information regarding anonymous functions, see “Anonymous Functions”.

The `sdo.optimize` command minimizes the return argument of the anonymous function `estFcn`, that is, the residual errors returned by `sdoAircraftEstimation_Objective`. For more details on how to write an objective/constraint function to use with the `sdo.optimize` command, type `help sdoExampleCostFunction` at the MATLAB® command prompt.

To examine the estimation objective function in more detail, type `edit sdoAircraftEstimation_Objective` at the MATLAB command prompt.

```
type sdoAircraftEstimation_Objective
```

```
function vals = sdoAircraftEstimation_Objective(v,Simulator,Exp)
%SDOAIRCRAFTESTIMATION_OBJECTIVE
%
%    The sdoAircraftEstimation_Objective function is used to compare model
%    outputs against experimental data.
%
%    vals = sdoAircraftEstimation_Objective(v,Exp)
%
%    The |v| input argument is a vector of estimated model parameter values
%    and initial states.
%
%    The |Simulator| input argument is a simulation object used
```

```
%    simulate the model with the estimated parameter values.
%
%    The |Exp| input argument contains the estimation experiment data.
%
%    The |vals| return argument contains information about how well the
%    model simulation results match the experimental data and is used by
%    the |sdo.optimize| function to estimate the model parameters.
%
%    See also sdo.optimize, sdoExampleCostFunction,
%    sdoAircraftEstimation_cmddemo
%

% Copyright 2012-2015 The MathWorks, Inc.

%%
% Define a signal tracking requirement to compute how well the model output
% matches the experiment data. Configure the tracking requirement so that
% it returns the tracking error residuals (rather than the
% sum-squared-error) and does not normalize the errors.
%
r = sdo.requirements.SignalTracking;
r.Type      = '==';
r.Method    = 'Residuals';
r.Normalize = 'off';

%%
% Update the experiments with the estimated parameter values.
%
Exp  = setEstimatedValues(Exp,v);

%%
% Simulate the model and compare model outputs with measured experiment
% data.
%
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);

SimLog       = find(Simulator.LoggedData,get_param('sdoAircraftEstimation','SignalLoggingName'))
PilotGSignal = find(SimLog,'PilotG');
AoASignal    = find(SimLog,'AngleOfAttack');

PilotGError = evalRequirement(r,PilotGSignal.Values,Exp.OutputData(1).Values);
AoAError    = evalRequirement(r,AoASignal.Values,Exp.OutputData(2).Values);

%%
% Return the residual errors to the optimization solver.
%
vals.F = [PilotGError(:); AoAError(:)];
end
```

Estimate the Parameters

Use the `sdo.optimize` function to estimate the actuator parameter values and initial state.

Specify the optimization options. The estimation function `sdoAircraftEstimation_Objective` returns the error residuals between simulated and experimental data and does not include any constraints, making this problem ideal for the `lsqnonlin` solver.

```
opt = sdo.OptimizeOptions;
opt.Method = 'lsqnonlin';
```

Estimate the parameters.

```
vOpt = sdo.optimize(estFcn,v,opt)
```

```
 Optimization started 01-Sep-2022 14:14:58

                                                  First-order
 Iter F-count        f(x)      Step-size  optimality
    0      8      27955.2            1
    1     17      10121.6       0.4744     5.68e+04
    2     26       3127.5       0.3845     1.24e+04
    3     35      872.577       0.4293     2.81e+03
    4     44      238.548       0.5156          618
    5     53      71.5731       0.4939          147
    6     62      16.9301       0.4222         44.3
    7     71      1.82188       0.3019         11.5
    8     80    0.0426814       0.1356         1.35
    9     89   0.00113417      0.02555        0.243
   10     98  0.000247412     0.008296      0.00764
Local minimum possible.

lsqnonlin stopped because the final change in the sum of squares relative to
its initial value is less than the value of the function tolerance.

vOpt(1,1) =

       Name: 'Ta'
      Value: 0.0500
    Minimum: 0.0100
    Maximum: 1
       Free: 1
      Scale: 0.5000
       Info: [1x1 struct]


vOpt(2,1) =

       Name: 'Md'
      Value: -6.8849
    Minimum: -10
    Maximum: 0
       Free: 1
      Scale: 1
       Info: [1x1 struct]


vOpt(3,1) =

       Name: 'Zd'
      Value: -63.9989
    Minimum: -100
    Maximum: 0
       Free: 1
      Scale: 128
```

```
       Info: [1x1 struct]


vOpt(4,1) =

       Name: 'sdoAircraftEstimation/Actuator...'
      Value: 1.3254e-04
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 1
    dxValue: 0
     dxFree: 1
       Info: [1x1 struct]


4x1 param.Continuous
```

Compare the Measured Output and the Final Simulated Output

Update the experiments with the estimated parameter values.

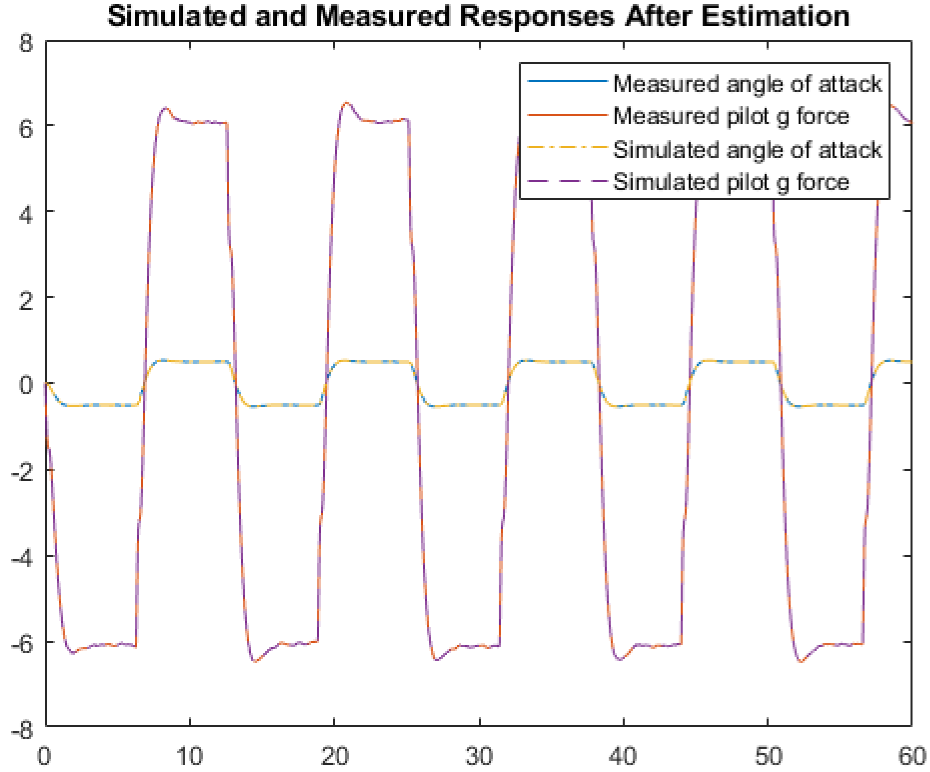
```
Exp = setEstimatedValues(Exp,vOpt);
```

Simulate the model using the updated experiment and compare the simulated output with the experimental data.

The model response using the estimated parameter values closely matches the experiment output data.

```
Simulator    = createSimulator(Exp,Simulator);
Simulator    = sim(Simulator);
SimLog       = find(Simulator.LoggedData,get_param('sdoAircraftEstimation','SignalLoggingName'));
PilotGSignal = find(SimLog,'PilotG');
AoASignal    = find(SimLog,'AngleOfAttack');

plot(time, iodata, ...
    AoASignal.Values.Time,AoASignal.Values.Data,'-.', ...
    PilotGSignal.Values.Time,PilotGSignal.Values.Data,'--')
title('Simulated and Measured Responses After Estimation')
legend('Measured angle of attack',  'Measured pilot g force', ...
    'Simulated angle of attack', 'Simulated pilot g force');
```



Update the Model Parameter Values

Update the model with the estimated actuator parameter values. Do not update the model actuator initial state (fourth element of `vOpt`) as it is dependent on the experiment.

```
sdo.setValueInModel('sdoAircraftEstimation',vOpt(1:3));
```

Related Examples

To learn how to estimate model parameters using the **Parameter Estimator** app, see “Estimate Model Parameter Values (GUI)” on page 2-144.

Close the model.

```
bdclose('sdoAircraftEstimation')
```

Estimate Model Parameters and Initial States (Code)

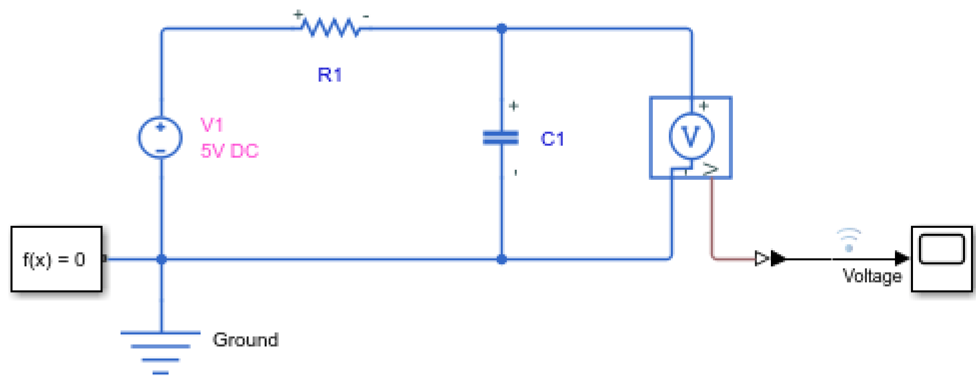
This example shows how to estimate the initial state and parameters of a model.

This example requires Simscape™ software.

RC Circuit Model

The Simulink® model, `sdoRCCircuit`, models a simple resistor-capacitor (RC) circuit.

```
open_system('sdoRCCircuit');
```



Estimation Problem

You use the measured data to estimate the RC model parameter and state values.

Measured output data:

- Capacitor voltage, output of the PS-Simulink Converter block

Parameter:

- Capacitance, `C1`, used by the C1 block

State:

- Initial voltage of the capacitor

Define the Estimation Experiment

Get the measured data.

```
load sdoRCCircuit_ExperimentData
```

The variables `time` and `data` are loaded into the workspace, where `data` is the measured capacitor voltage for times `time`.

Create an experiment object to store the experimental voltage data.

```
Exp = sdo.Experiment('sdoRCCircuit');
```

Create an object to store the measured capacitor voltage output.

```
Voltage = Simulink.SimulationData.Signal;
Voltage.Name      = 'Voltage';
Voltage.BlockPath = 'sdoRCCircuit/PS-Simulink Converter';
Voltage.PortType  = 'outport';
Voltage.PortIndex = 1;
Voltage.Values    = timeseries(data,time);
```

Add the measured capacitor data to the experiment as the expected output data.

```
Exp.OutputData = Voltage;
```

Compare the Measured Output and the Initial Simulated Output

Create a simulation scenario using the experiment and obtain the simulated output.

```
Simulator    = createSimulator(Exp);
Simulator    = sim(Simulator);
```

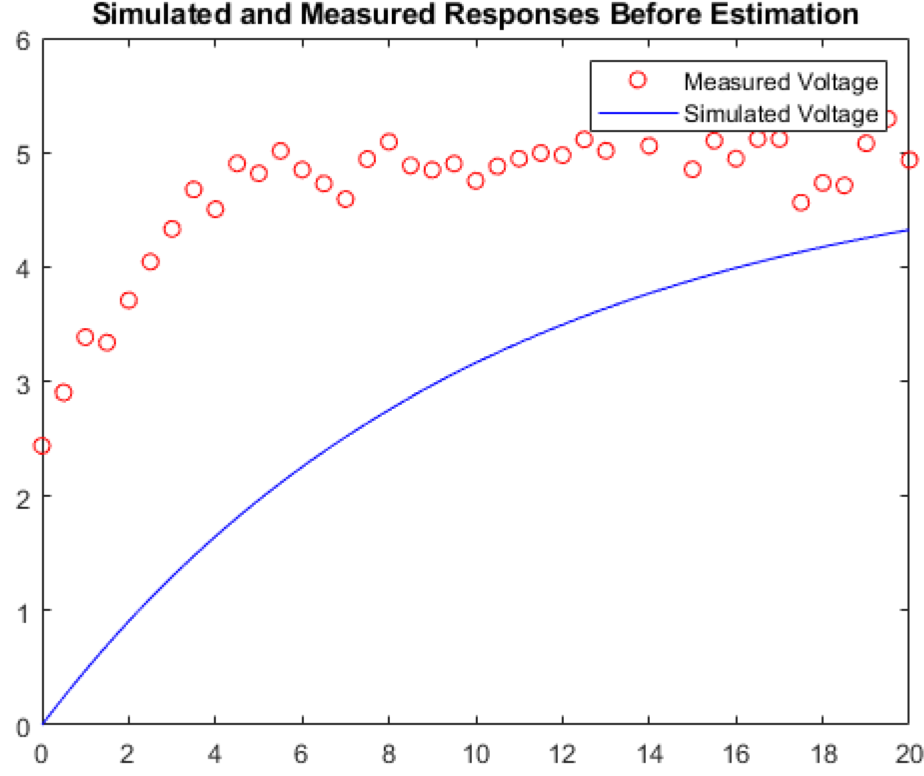
Search for the voltage signal in the logged simulation data.

```
SimLog       = find(Simulator.LoggedData,get_param('sdoRCCircuit','SignalLoggingName'));
Voltage      = find(SimLog,'Voltage');
```

Plot the measured and simulated data.

The model response does not match the experimental output data.

```
plot(time,data,'ro',Voltage.Values.Time,Voltage.Values.Data,'b')
title('Simulated and Measured Responses Before Estimation')
legend('Measured Voltage','Simulated Voltage')
```



Specify the Parameters to Estimate

Select the capacitance parameter from the model. Specify an initial guess for the capacitance value (460 uF) and a minimum bound (0 F).

```
p = sdo.getParameterFromModel('sdoRCCircuit','C1');
p.Value   = 460e-6;
p.Minimum = 0;
```

Define the Estimation Objective Function

Create an estimation objective function to evaluate how closely the simulation output, generated using the estimated parameter value, matches the measured data.

Use an anonymous function with one input argument that calls the `sdoRCCircuit_Objective` function. Pass the anonymous function to `sdo.optimize`, which evaluates the function at each optimization iteration.

```
estFcn = @(v) sdoRCCircuit_Objective(v,Simulator,Exp);
```

The `sdoRCCircuit_Objective` function:

- Has one input argument that specifies the estimated circuit capacitance value.
- Has one input argument that specifies the experiment object containing the measured data.
- Returns a vector of errors between simulated and experimental outputs.

The sdoRCCircuit_Objective function requires two inputs, but sdo.optimize requires a function with one input argument. To work around this, estFcn is an anonymous function with one input argument, v, but it calls sdoRCCircuit_Objective using two input arguments, v and Exp.

For more information regarding anonymous functions, see “Anonymous Functions”.

The optimization solver minimizes the residual errors. For more details on how to write an objective/constraint function to use with the sdo.optimize command, type help sdoExampleCostFunction at the MATLAB® command prompt.

To examine the estimation object function in more detail, type edit sdoRCCircuit_Objective at the MATLAB command prompt.

```
type sdoRCCircuit_Objective
```

```
function vals = sdoRCCircuit_Objective(v,Simulator,Exp)
%SDORCCIRCUIT_OBJECTIVE
%
%    The sdoRCCircuit_Objective function is used to compare model
%    outputs against experimental data.
%
%    vals = sdoRCCircuit_Objective(v,Exp)
%
%    The |v| input argument is a vector of estimated model parameter values
%    and initial states.
%
%    The |Simulator| input argument is a simulation object used
%    simulate the model with the estimated parameter values.
%
%    The |Exp| input argument contains the estimation experiment data.
%
%    The |vals| return argument contains information about how well the
%    model simulation results match the experimental data and is used by
%    the |sdo.optimize| function to estimate the model parameters.
%
%    See also sdo.optimize, sdoExampleCostFunction, sdoRCCircuit_cmddemo
%

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%%
% Define a signal tracking requirement to compute how well the model output
% matches the experiment data. Configure the tracking requirement so that
% it returns the tracking error residuals (rather than the
% sum-squared-error) and does not normalize the errors.
%
r = sdo.requirements.SignalTracking;
r.Type      = '==';
r.Method    = 'Residuals';
r.Normalize = 'off';

%%
% Update the experiments with the estimated parameter values.
%
Exp  = setEstimatedValues(Exp,v);

%%
```

```
% Simulate the model and compare model outputs with measured experiment
% data.
%
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);

SimLog  = find(Simulator.LoggedData,get_param('sdoRCCircuit','SignalLoggingName'));
Voltage = find(SimLog,'Voltage');

VoltageError = evalRequirement(r,Voltage.Values,Exp.OutputData(1).Values);

%%
% Return the residual errors to the optimization solver.
%
vals.F = VoltageError(:);
end
```

Estimate the Parameters

Use the `sdo.optimize` function to estimate the capacitance value.

Specify the optimization options. The estimation function `sdoRCCircuit_Objective` returns the error residuals between simulated and experimental data and does not include any constraints, making this problem ideal for the |lsqnonlin|solver.

```
opt = sdo.OptimizeOptions;
opt.Method = 'lsqnonlin';
```

Estimate the parameters.

```
pOpt = sdo.optimize(estFcn,p,opt)
```

```
 Optimization started 01-Sep-2022 14:19:20

                                             First-order
 Iter F-count        f(x)      Step-size  optimality
    0      3      55.0017            1
    1      6      21.0148       0.2124        17.3
    2      9      11.5069       0.1272         6.1
    3     12      9.56554      0.06554           2
    4     15      9.27804       0.0275        0.43
    5     18      9.27316     0.006987      0.0788
Local minimum possible.

lsqnonlin stopped because the final change in the sum of squares relative to
its initial value is less than the value of the function tolerance.

pOpt =

       Name: 'C1'
      Value: 1.1346e-04
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 0.0020
       Info: [1x1 struct]
```

```
1x1 param.Continuous
```

Compare the Measured Output and the Simulated Output

Update the experiment with the estimated capacitance value.

```
Exp = setEstimatedValues(Exp,pOpt);
```

Create a simulation scenario using the experiment and obtain the simulated output.

```
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);
```

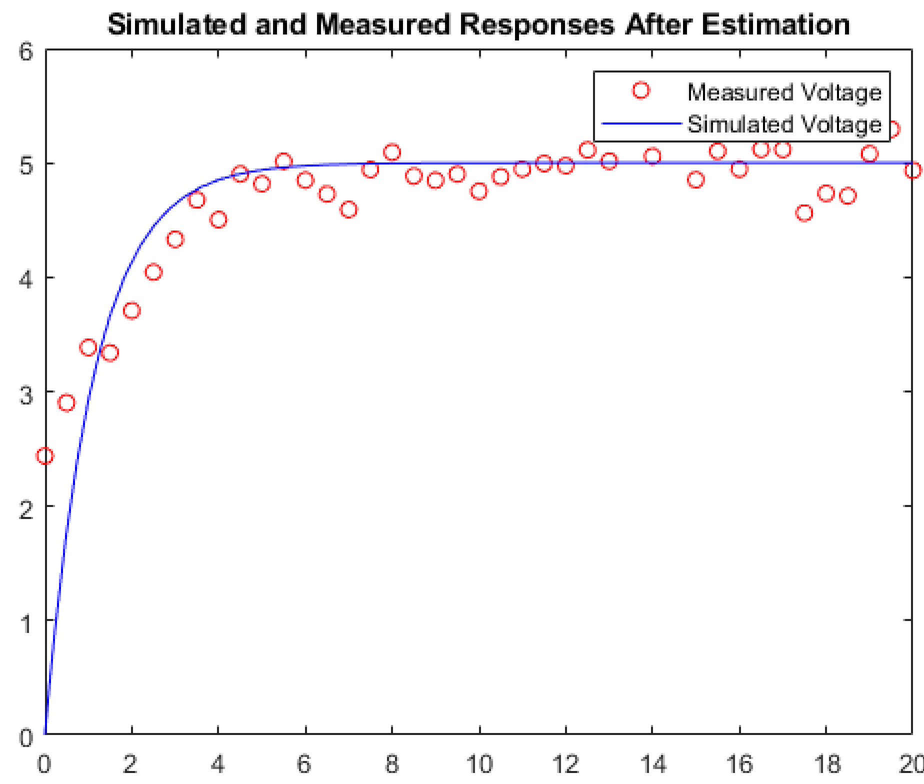
Search for the voltage signal in the logged simulation data.

```
SimLog  = find(Simulator.LoggedData,get_param('sdoRCCircuit','SignalLoggingName'));
Voltage = find(SimLog,'Voltage');
```

Plot the measured and simulated data.

The simulated and measured signals match well, except for near time zero. This mismatch is because the capacitor initial voltage defined in the model does not match the initial voltage from the experiment.

```
plot(time,data,'ro',Voltage.Values.Time,Voltage.Values.Data,'b')
title('Simulated and Measured Responses After Estimation')
legend('Measured Voltage','Simulated Voltage')
```



Estimate the Initial State

Add the capacitor initial voltage for the C1 block to the experiment. Set its initial guess value to 1 V.

```
Exp.InitialStates = sdo.getStateFromModel('sdoRCCircuit','C1');
Exp.InitialStates.Value = 1;
```

Recreate the estimation function to use the experiment with initial state estimation

```
estFcn = @(v) sdoRCCircuit_Objective(v,Simulator,Exp);
```

Get the initial state and capacitance value that is to be estimated from the experiment.

```
v = getValuesToEstimate(Exp);
```

Estimate the parameters.

```
vOpt = sdo.optimize(estFcn,v,opt)
```

```
 Optimization started 01-Sep-2022 14:20:08

                                              First-order
 Iter F-count        f(x)      Step-size  optimality
    0      5      4.74867            1
    1     10       2.1196        1.537         22.7
    2     15      1.34958       0.1262       0.0713
    3     20      1.34365      0.05718        0.129
    4     25      1.34363     0.001378     0.000765
Local minimum found.

Optimization completed because the size of the gradient is less than
the value of the optimality tolerance.

vOpt(1,1) =

       Name: 'sdoRCCircuit/C1:sdoRCCircuit.C1.vc'
      Value: 2.3597
    Minimum: -Inf
    Maximum: Inf
       Free: 1
      Scale: 1
    dxValue: 0
     dxFree: 1
       Info: [1x1 struct]


vOpt(2,1) =

       Name: 'C1'
      Value: 2.2638e-04
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 0.0020
       Info: [1x1 struct]
```

```
2x1 param.Continuous
```

Compare the Measured Output and the Final Simulated Output

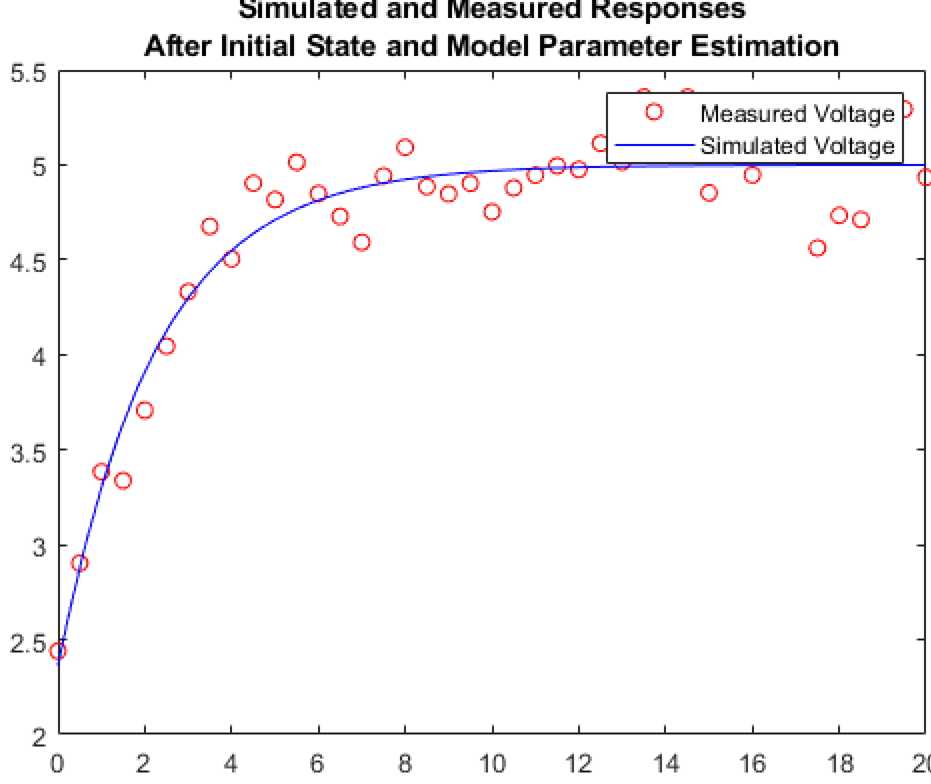
Update the experiment with the estimated capacitance and capacitor initial voltage values.

```
Exp = setEstimatedValues(Exp,vOpt);
```

Simulate the model with the estimated initial-state and parameter values and compare the simulated output with the experiment data.

```
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);
SimLog    = find(Simulator.LoggedData,get_param('sdoRCCircuit','SignalLoggingName'));
Voltage   = find(SimLog,'Voltage');

plot(time,data,'ro',Voltage.Values.Time,Voltage.Values.Data,'b')
title({'Simulated and Measured Responses';...
    'After Initial State and Model Parameter Estimation'})
legend('Measured Voltage','Simulated Voltage')
```



Update the Model Parameter Values

Update the model with the estimated capacitance value. Do not update the model capacitor initial voltage (first element of `vOpt`) as it is dependent on the experiment.

```
sdo.setValueInModel('sdoRCCircuit',vOpt(2));
```

Related Examples

To learn how to estimate model parameters using the `sdo.optimize` command, see “Estimate Model Parameters and Initial States (GUI)” on page 2-169.

Close the model

```
bdclose('sdoRCCircuit')
```

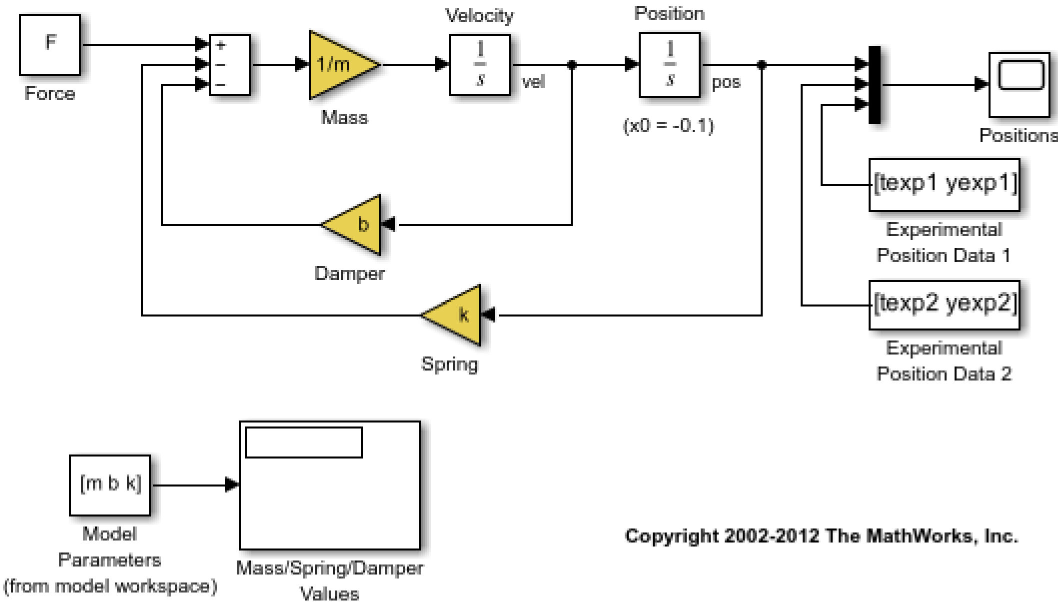
Estimate Model Parameters Using Multiple Experiments (Code)

This example shows how to estimate model parameters from multiple sets of experimental data. You estimate the parameters of a mass-spring-damper system.

Open the Model and Get Experimental Data

This example uses the `sdoMassSpringDamper` model. The model includes two integrators to model the velocity and position of a mass in a mass-spring-damper system.

```
open_system('sdoMassSpringDamper');
```



Load the experiment data.

```
load sdoMassSpringDamper_ExperimentData
```

The variables `texp1`, `yexp1`, `texp2`, and `yexp2` are loaded into the workspace. `yexp1` and `yexp2` describe the mass position for times `texp1` and `texp2`, respectively.

Define the Estimation Experiments

Create a 2-element array of experiment objects to store the measured data for the two experiments.

Create an experiment object for the first experiment.

```
Exp = sdo.Experiment('sdoMassSpringDamper');
```

Create an object to store the measured mass position output.

```
MeasuredPos           = Simulink.SimulationData.Signal;
MeasuredPos.Values    = timeseries(yexp1,texp1);
MeasuredPos.BlockPath = 'sdoMassSpringDamper/Position';
```

```
MeasuredPos.PortType  = 'outport';
MeasuredPos.PortIndex = 1;
MeasuredPos.Name      = 'Position';
```

Add the measured mass position data to the experiment as the expected output data.

```
Exp.OutputData = MeasuredPos;
```

Create an object to specify the initial state for the `Velocity` block. The initial velocity of the mass is 0 m/s.

```
sVel       = sdo.getStateFromModel('sdoMassSpringDamper','Velocity');
sVel.Value = 0;
sVel.Free  = false;
```

`sVel.Free` is set to `false` because the initial velocity is known and does not need to be estimated.

Create an object to specify the initial state for the `Position` block. Specify a guess for the initial mass position. Set the `Free` field of the initial position object to `true` so that it is estimated.

```
sPos       = sdo.getStateFromModel('sdoMassSpringDamper','Position');
sPos.Free  = true;
sPos.Value = -0.1;
```

Add the initial states to the experiment.

```
Exp.InitialStates = [sVel;sPos];
```

Create a two-element array of experiments. As the two experiments are identical except for the expected output data, copy the first experiment twice.

```
Exp = [Exp; Exp];
```

Modify the expected output data of the second experiment object in `Exp`.

```
Exp(2).OutputData.Values  = timeseries(yexp2,texp2);
```

Compare the Measured Output and the Initial Simulated Output

Create a simulation scenario using the first experiment and obtain the simulated output.

```
Simulator = createSimulator(Exp(1));
Simulator = sim(Simulator);
```

Search for the position signal in the logged simulation data.

```
SimLog   = find(Simulator.LoggedData,get_param('sdoMassSpringDamper','SignalLoggingName'));
Position = find(SimLog,'Position');
```

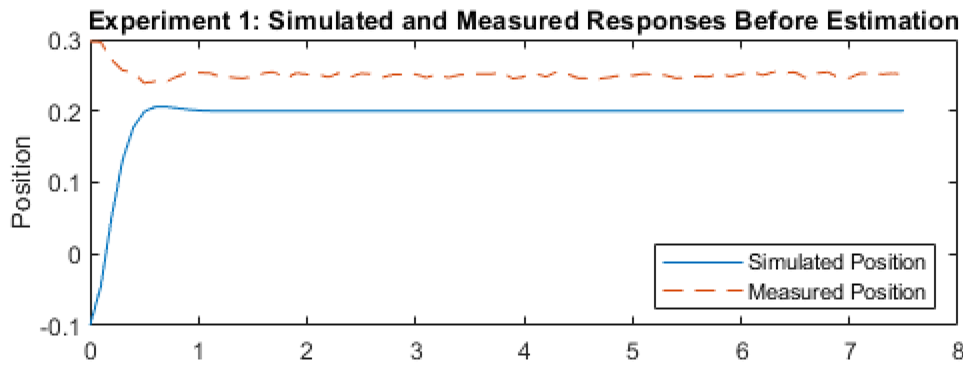
Obtain the simulated position signal for the second experiment.

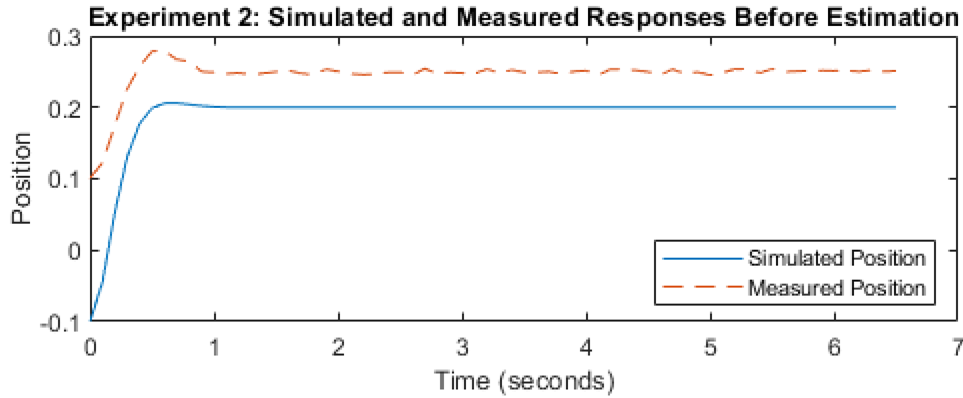
```
Simulator   = createSimulator(Exp(2),Simulator);
Simulator   = sim(Simulator);
SimLog      = find(Simulator.LoggedData,get_param('sdoMassSpringDamper','SignalLoggingName'));
Position(2) = find(SimLog,'Position');
```

Plot the measured and simulated data.

The model response does not match the experimental output data.

```
subplot(211)
plot(...
    Position(1).Values.Time,Position(1).Values.Data, ...
    Exp(1).OutputData.Values.Time, Exp(1).OutputData.Values.Data,'--')
title('Experiment 1: Simulated and Measured Responses Before Estimation')
ylabel('Position')
legend('Simulated Position','Measured Position','Location','SouthEast')
subplot(212)
plot(...
    Position(2).Values.Time,Position(2).Values.Data, ...
    Exp(2).OutputData.Values.Time, Exp(2).OutputData.Values.Data,'--')
title('Experiment 2: Simulated and Measured Responses Before Estimation')
xlabel('Time (seconds)')
ylabel('Position')
legend('Simulated Position','Measured Position','Location','SouthEast')
```





Specify Parameters to Estimate

Select the mass m, spring constant k, and damping coefficient b parameters from the model. Specify that the estimated values for these parameters must be positive.

```
p = sdo.getParameterFromModel('sdoMassSpringDamper', {'b', 'k', 'm'});
p(1).Minimum = 0;
p(2).Minimum = 0;
p(3).Minimum = 0;
```

Get the position initial state values to be estimated from the experiment.

```
s = getValuesToEstimate(Exp);
```

`s` contains two initial state objects, both for the `Position` block. Each object corresponds to an experiment in `Exp`.

Group the model parameters and initial states to be estimated together.

```
v = [p;s]
```

```
v(1,1) =

       Name: 'b'
      Value: 100
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 128
       Info: [1x1 struct]


v(2,1) =

       Name: 'k'
      Value: 500
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 512
       Info: [1x1 struct]


v(3,1) =

       Name: 'm'
      Value: 8
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 8
       Info: [1x1 struct]


v(4,1) =

       Name: 'sdoMassSpringDamper/Position'
      Value: -0.1000
    Minimum: -Inf
    Maximum: Inf
       Free: 1
      Scale: 0.1250
    dxValue: 0
     dxFree: 1
       Info: [1x1 struct]


v(5,1) =
```

```
       Name: 'sdoMassSpringDamper/Position'
      Value: -0.1000
    Minimum: -Inf
    Maximum: Inf
       Free: 1
      Scale: 0.1250
    dxValue: 0
     dxFree: 1
       Info: [1x1 struct]


5x1 param.Continuous
```

Define the Estimation Objective

Create an estimation objective function to evaluate how closely the simulation output, generated using the estimated parameter values, matches the measured data.

Use an anonymous function with one input argument that calls the `sdoMassSpringDamper_Objective` function. Pass the anonymous function to `sdo.optimize`, which evaluates the function at each optimization iteration.

```
estFcn = @(v) sdoMassSpringDamper_Objective(v,Simulator,Exp);
```

The `sdoMassSpringDamper_Objective` function:

- Has one input argument that specifies the mass, spring constant and damper values as well as the initial mass position.
- Has one input argument that specifies the experiment object containing the measured data.
- Returns a vector of errors between simulated and experimental outputs.

The `sdoMassSpringDamper_Objective` function requires two inputs, but `sdo.optimize` requires a function with one input argument. To work around this, `estFcn` is an anonymous function with one input argument, `v`, but it calls `sdoMassSpringDamper_Objective` using two input arguments, `v` and `Exp`.

For more information regarding anonymous functions, see “Anonymous Functions”.

The `sdo.optimize` command minimizes the return argument of the anonymous function `estFcn`, that is, the residual errors returned by `sdoMassSpringDamper_Objective`. For more details on how to write an objective/constraint function to use with the `sdo.optimize` command, type `help sdoExampleCostFunction` at the MATLAB® command prompt.

To examine the estimation objective function in more detail, type `edit sdoMassSpringDamper_Objective` at the MATLAB command prompt.

```
type sdoMassSpringDamper_Objective
```

```
function vals = sdoMassSpringDamper_Objective(v,Simulator,Exp)
%SDOMASSSPRINGDAMPER_OBJECTIVE
%
%    The sdoMassSpringDamper_Objective function is used to compare model
%    outputs against experimental data.
```

```
%
%    vals = sdoMassSpringDamper_Objective(v,Exp)
%
%    The |v| input argument is a vector of estimated model parameter values
%    and initial states.
%
%    The |Simulator| input argument is a simulation object used
%    simulate the model with the estimated parameter values.
%
%    The |Exp| input argument contains the estimation experiment data.
%
%    The |vals| return argument contains information about how well the
%    model simulation results match the experimental data and is used by
%    the |sdo.optimize| function to estimate the model parameters.
%
%    see also sdo.optimize, sdoExampleCostFunction
%

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%%
% Define a signal tracking requirement to compute how well the model output
% matches the experiment data. Configure the tracking requirement so that
% it returns the tracking error residuals (rather than the
% sum-squared-error) and does not normalize the errors.
%
r = sdo.requirements.SignalTracking;
r.Type      = '==';
r.Method    = 'Residuals';
r.Normalize = 'off';

%%
% Update the experiments with the estimated parameter values.
%
Exp  = setEstimatedValues(Exp,v);

%%
% Simulate the model and compare model outputs with measured experiment
% data.
%
Error = [];
for ct=1:numel(Exp)

    Simulator = createSimulator(Exp(ct),Simulator);
    Simulator = sim(Simulator);

    SimLog  = find(Simulator.LoggedData,get_param('sdoMassSpringDamper','SignalLoggingName'));
    Position = find(SimLog,'Position');

    PositionError = evalRequirement(r,Position.Values,Exp(ct).OutputData.Values);

    Error = [Error; PositionError(:)];
end

%%
% Return the residual errors to the optimization solver.
%
```

```
vals.F = Error(:);
end
```

Estimate the Parameters

Use the `sdo.optimize` function to estimate the actuator parameter values and initial state.

Specify the optimization options. The estimation function `sdoMassSpringDamper_Objective` returns the error residuals between simulated and experimental data and does not include any constraints, making this problem ideal for the `lsqnonlin` solver.

```
opt = sdo.OptimizeOptions;
opt.Method = 'lsqnonlin';
```

Estimate the parameters. Notice that the initial mass position is estimated twice, once for each experiment.

```
vOpt = sdo.optimize(estFcn,v,opt)
```

```
 Optimization started 01-Sep-2022 14:21:47

                                                First-order
 Iter F-count        f(x)      Step-size  optimality
    0     11     0.777696           1
    1     22   0.00413099       3.696      0.00648
    2     33   0.00118327      0.3194      0.00243
    3     44    0.0011106     0.06718     5.09e-05
Local minimum found.

Optimization completed because the size of the gradient is less than
the value of the optimality tolerance.

vOpt(1,1) =

       Name: 'b'
      Value: 58.1959
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 128
       Info: [1x1 struct]


vOpt(2,1) =

       Name: 'k'
      Value: 399.9452
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 512
       Info: [1x1 struct]


vOpt(3,1) =

       Name: 'm'
```

```
      Value: 9.7225
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 8
       Info: [1x1 struct]


vOpt(4,1) =

       Name: 'sdoMassSpringDamper/Position'
      Value: 0.2995
    Minimum: -Inf
    Maximum: Inf
       Free: 1
      Scale: 0.1250
    dxValue: 0
     dxFree: 1
       Info: [1x1 struct]


vOpt(5,1) =

       Name: 'sdoMassSpringDamper/Position'
      Value: 0.0994
    Minimum: -Inf
    Maximum: Inf
       Free: 1
      Scale: 0.1250
    dxValue: 0
     dxFree: 1
       Info: [1x1 struct]


5x1 param.Continuous
```

Compare the Measured Output and the Final Simulated Output

Update the experiments with the estimated parameter values.

```
Exp  = setEstimatedValues(Exp,vOpt);
```

Obtain the simulated output for the first experiment.

```
Simulator   = createSimulator(Exp(1),Simulator);
Simulator   = sim(Simulator);
SimLog      = find(Simulator.LoggedData,get_param('sdoMassSpringDamper','SignalLoggingName'));
Position(1) = find(SimLog,'Position');
```

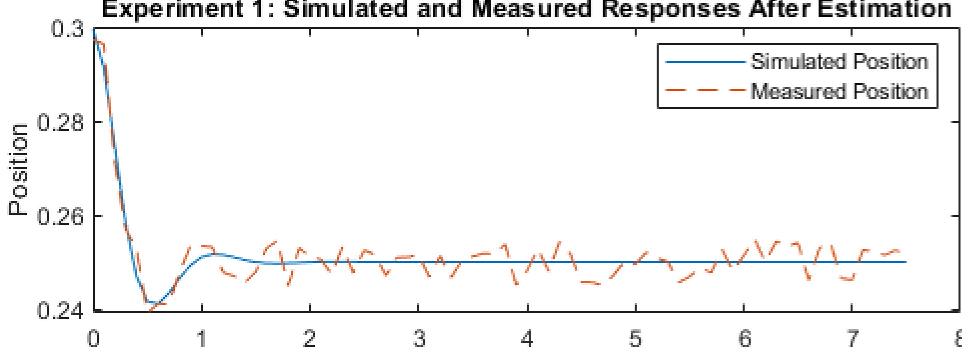
Obtain the simulated output for the second experiment.

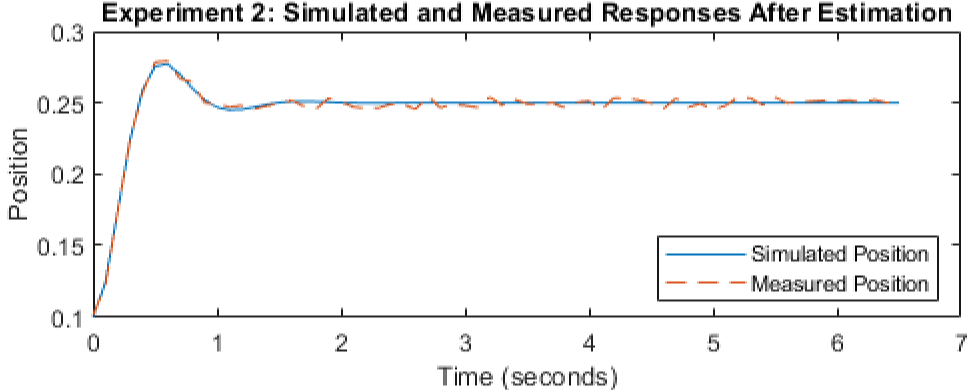
```
Simulator   = createSimulator(Exp(2),Simulator);
Simulator   = sim(Simulator);
SimLog      = find(Simulator.LoggedData,get_param('sdoMassSpringDamper','SignalLoggingName'));
Position(2) = find(SimLog,'Position');
```

Plot the measured and simulated data.

The model response using the estimated parameter values matches the output data for the experiments.

```
subplot(211)
plot(...
    Position(1).Values.Time,Position(1).Values.Data, ...
    Exp(1).OutputData.Values.Time, Exp(1).OutputData.Values.Data,'--')
title('Experiment 1: Simulated and Measured Responses After Estimation')
ylabel('Position')
legend('Simulated Position','Measured Position','Location','NorthEast')
subplot(212)
plot(...
    Position(2).Values.Time,Position(2).Values.Data, ...
    Exp(2).OutputData.Values.Time, Exp(2).OutputData.Values.Data,'--')
title('Experiment 2: Simulated and Measured Responses After Estimation')
xlabel('Time (seconds)')
ylabel('Position')
legend('Simulated Position','Measured Position','Location','SouthEast')
```





Update the Model Parameter Values

Update the model `m`, `k`, and `b` parameter values. Do not update the model initial position value as this is dependent on the experiment.

```
sdo.setValueInModel('sdoMassSpringDamper',vOpt(1:3));
```

Close the model

```
bdclose('sdoMassSpringDamper')
```

Estimate Model Parameters Per Experiment (Code)

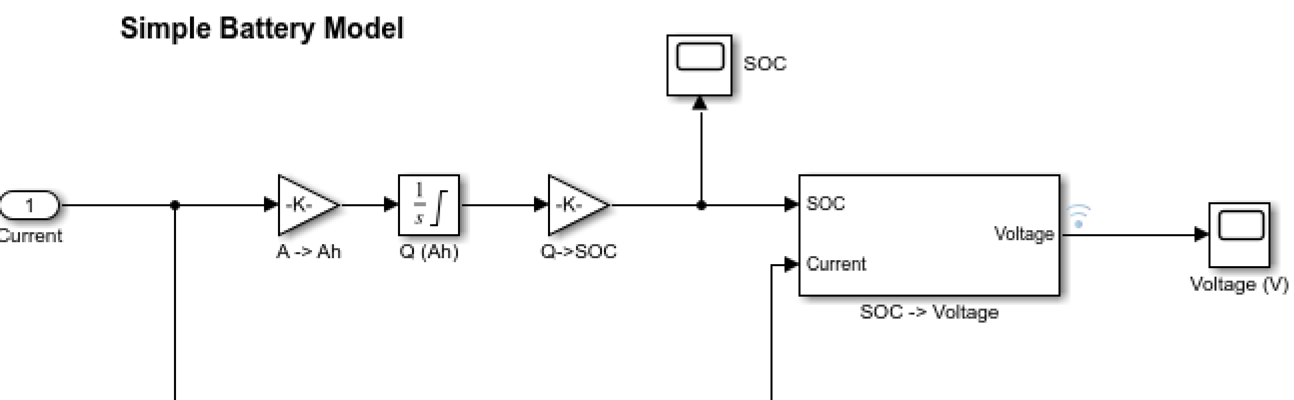
This example shows how to use multiple experiments to estimate a mix of model parameter values; some that are estimated using all the experiments and others that are estimated using individual experiments. The example also shows how to configure estimation experiments with experiment dependent parameter values.

You estimate the parameters of a rechargeable battery based on data collected in experiments that discharge and charge the battery.

Open the Model and Get Experimental Data

This example estimates parameters of a simple, rechargeable battery model, `sdoBattery`. The model input is the battery current and the model output, the battery terminal voltage, is computed from the battery state-of-charge.

```
open_system('sdoBattery');
```



The model is based on the equation

$$E = (1 - \text{Loss})V - KQ_{\text{max}}\frac{1 - s}{s}$$

In the equation:

E is the battery terminal voltage in Volts.

V is the battery constant voltage in Volts.

K is the battery polarization resistance in Ohms.

Q_{max} is the maximum battery capacity in Ampere-hours.

s is the battery charge state, with 1 being fully charged and 0 discharged. The battery state-of-charge is computed from the integral of the battery current with a positive current indicating discharge and

a negative current indicating charging. The battery initial state-of-charge is specified by Q_0 in Ampere-hours.

Loss is the voltage drop when charging, expressed as a fraction of the battery constant voltage. When the battery is discharging this value is zero.

`V`, `K`, `Qmax`, `Q0`, and `Loss` are variables defined in the model workspace.

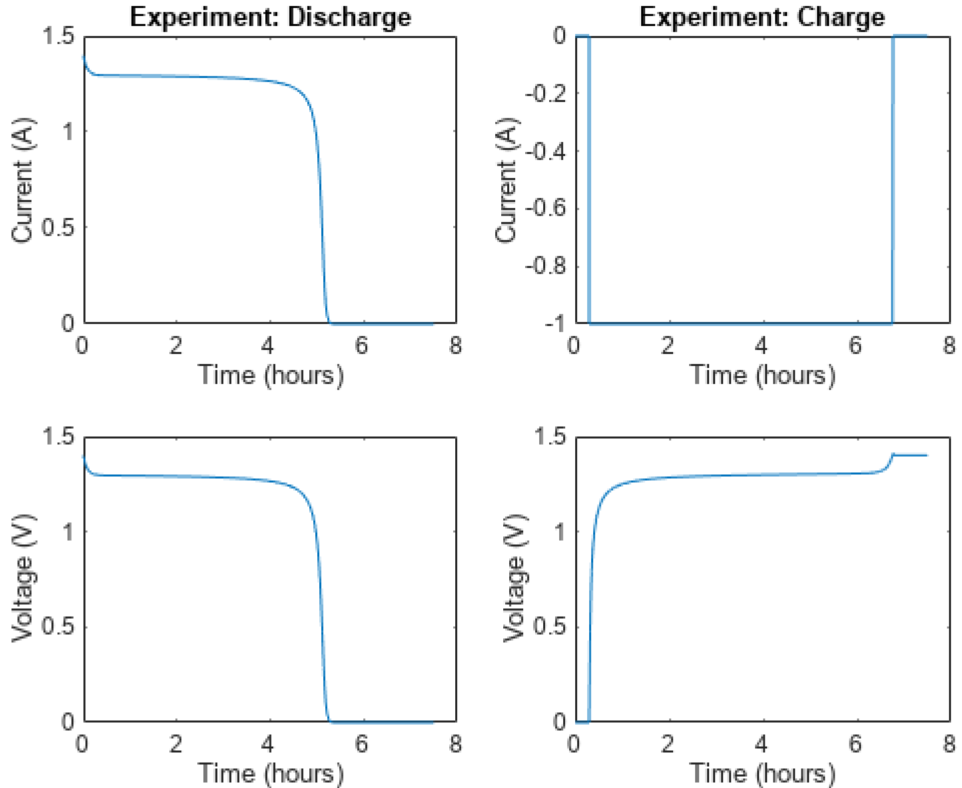
Load the experiment data. A 1.2V (6500mAh) battery was subjected to a discharge experiment and a charging experiment.

```
load sdoBattery_ExperimentData
```

The variables `Charge_Data` and `DCharge_Data` are loaded into the workspace. The first column of `Charge_Data` contains time data. The second and third columns of `Charge_Data` describe the current and voltage during a battery charging experiment. `DCharge_Data` is similarly structured and contains data for a battery discharging experiment.

Plot the Experiment Data

```
subplot(221),
plot(DCharge_Data(:,1)/3600,DCharge_Data(:,2))
title('Experiment: Discharge')
xlabel('Time (hours)')
ylabel('Current (A)')
subplot(223)
plot(DCharge_Data(:,1)/3600,DCharge_Data(:,3))
xlabel('Time (hours)')
ylabel('Voltage (V)')
subplot(222),
plot(Charge_Data(:,1)/3600,Charge_Data(:,2))
title('Experiment: Charge')
xlabel('Time (hours)')
ylabel('Current (A)')
subplot(224)
plot(Charge_Data(:,1)/3600,Charge_Data(:,3))
xlabel('Time (hours)')
ylabel('Voltage (V)')
```



Define the Estimation Experiments

Create a 2-element array of experiment objects to specify the measured data for the two experiments.

Create an experiment object for the battery discharge experiment. The measured current data is specified as a timeseries in the experiment object.

```
DCharge_Exp = sdo.Experiment('sdoBattery');
```

Specify the input data (current) as a timeseries object.

```
DCharge_Exp.InputData = timeseries(DCharge_Data(:,2),DCharge_Data(:,1));
```

Create an object to specify the measured voltage output data.

```
VoltageSig = Simulink.SimulationData.Signal;
VoltageSig.Name      = 'Voltage';
VoltageSig.BlockPath = 'sdoBattery/SOC -> Voltage';
VoltageSig.PortType  = 'outport';
VoltageSig.PortIndex = 1;
VoltageSig.Values    = timeseries(DCharge_Data(:,3),DCharge_Data(:,1));
```

Add the voltage signal to the discharge experiment as the expected output data.

```
DCharge_Exp.OutputData = VoltageSig;
```

Specify the battery initial charge state for the experiment. The battery charge state is modeled by the `Q (Ah)` block and it's initial value is specified by the variable `Q0`. Create a parameter for the `Q0`

variable and add the parameter to the experiment. Q0 is experiment dependent and assumes different values in the discharging and charging experiments.

```
Q0 = sdo.getParameterFromModel('sdoBattery','Q0');
Q0.Value = 6.5;
Q0.Free  = false;
```

Q0.Free is set to false because the initial battery charge is known and does not need to be estimated.

Add the Q0 parameter to the experiment.

```
DCharge_Exp.Parameters = Q0;
```

Create an experiment object to store the charging experiment data. Add the measured current input and measured voltage output data to the object.

```
Charge_Exp = sdo.Experiment('sdoBattery');
Charge_Exp.InputData  = timeseries(Charge_Data(:,2),Charge_Data(:,1));
VoltageSig.Values     = timeseries(Charge_Data(:,3),Charge_Data(:,1));
Charge_Exp.OutputData = VoltageSig;
```

Add the battery initial charge and charging loss fraction parameters to the experiment. For this experiment, the initial charge (Q0) is known (0 Ah), but the value of the charging loss fraction (Loss) is not known.

```
Q0.Value = 0;

Loss = sdo.getParameterFromModel('sdoBattery','Loss');
Loss.Free    = true;
Loss.Minimum = 0;
Loss.Maximum = 0.5;

Charge_Exp.Parameters = [Q0;Loss];
```

Loss.Free is set to true so that the value of Loss is estimated.

Collect both experiments into one vector.

```
Exp = [DCharge_Exp; Charge_Exp];
```

Compare the Measured Output and the Initial Simulated Output

Create a simulation scenario using the first (discharging) experiment and obtain the simulated output.

```
Simulator  = createSimulator(Exp(1));
Simulator  = sim(Simulator);
```

Search for the voltage signal in the logged simulation data.

```
SimLog     = find(Simulator.LoggedData,get_param('sdoBattery','SignalLoggingName'));
Voltage(1) = find(SimLog,'Voltage');
```

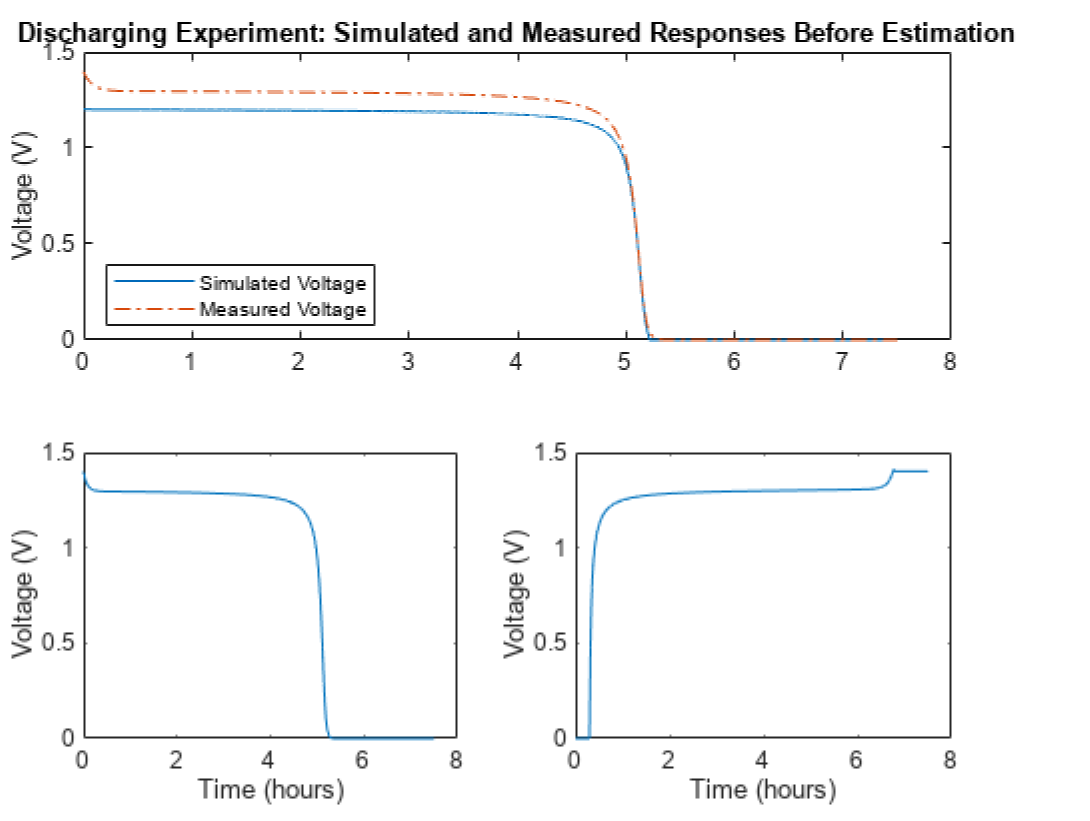
Obtain the simulated voltage signal for the second (charging) experiment.

```
Simulator  = createSimulator(Exp(2),Simulator);
Simulator  = sim(Simulator);
```

```
SimLog      = find(Simulator.LoggedData,get_param('sdoBattery','SignalLoggingName'));
Voltage(2) = find(SimLog,'Voltage');
```

Plot the measured and simulated data. The model response does not match the experimental output data.

```
subplot(211)
plot(...
    Voltage(1).Values.Time/3600,Voltage(1).Values.Data, ...
    Exp(1).OutputData.Values.Time/3600, Exp(1).OutputData.Values.Data,'-.')
title('Discharging Experiment: Simulated and Measured Responses Before Estimation')
ylabel('Voltage (V)')
legend('Simulated Voltage','Measured Voltage','Location','SouthWest')
```




```
subplot(212)
plot(...
    Voltage(2).Values.Time/3600,Voltage(2).Values.Data, ...
    Exp(2).OutputData.Values.Time/3600, Exp(2).OutputData.Values.Data,'-.')
title('Charging Experiment: Simulated and Measured Responses Before Estimation')
xlabel('Time (hours)')
ylabel('Voltage (V)')
legend('Simulated Voltage','Measured Voltage','Location','SouthEast')
```

Specify Parameters to Estimate

Estimate the values of the battery voltage V, the battery polarization resistance K, and the charging loss fraction Loss. The V and K parameters are estimated using all the experiment data while the Loss parameter is estimated using only the charging data.

Select the battery voltage V and the battery polarization resistance K parameters from the model. Specify minimum and maximum bounds for these parameters.

```
p = sdo.getParameterFromModel('sdoBattery',{'V','K'});

p(1).Minimum = 0;
p(1).Maximum = 2;

p(2).Minimum = 1e-6;
p(2).Maximum = 1e-1;
```

Get the experiment-specific `Loss` parameter from the experiment.

```
s = getValuesToEstimate(Exp);
```

Group all the parameters to be estimated.

```
v = [p;s]
```

```
v(1,1) =

       Name: 'V'
      Value: 1.2000
    Minimum: 0
    Maximum: 2
       Free: 1
      Scale: 2
       Info: [1x1 struct]


v(2,1) =

       Name: 'K'
      Value: 1.0000e-03
    Minimum: 1.0000e-06
    Maximum: 0.1000
       Free: 1
      Scale: 0.0020
       Info: [1x1 struct]


v(3,1) =

       Name: 'Loss'
      Value: 0.0100
    Minimum: 0
    Maximum: 0.5000
       Free: 1
      Scale: 0.0156
       Info: [1x1 struct]


3x1 param.Continuous
```

Define the Estimation Objective

Create an estimation objective function to evaluate how closely the simulation output, generated using the estimated parameter values, matches the measured data.

Use an anonymous function with one input argument that calls the `sdoBattery_Objective` function. We pass the anonymous function to `sdo.optimize`, which evaluates the function at each optimization iteration.

```
estFcn = @(v) sdoBattery_Objective(v,Simulator,Exp);
```

The `sdoBattery_Objective` function:

- Has one input argument that specifies the estimated battery parameter values.
- Has one input argument that specifies the experiment object containing the measured data.
- Returns a vector of errors between simulated and experimental outputs.

The `sdoBattery_Objective` function requires two inputs, but `sdo.optimize` requires a function with one input argument. To work around this, `estFcn` is an anonymous function with one input argument, `v`, but it calls `sdoBattery_Objective` using two input arguments, `v` and `Exp`.

For more information regarding anonymous functions, see “Anonymous Functions”.

The `sdo.optimize` command minimizes the return argument of the anonymous function `estFcn`, that is, the residual errors returned by `sdoBattery_Objective`. For more details on how to write an objective/constraint function to use with the `sdo.optimize` command, type `help sdoExampleCostFunction` at the MATLAB® command prompt.

To examine the estimation objective function in more detail, type `edit sdoBattery_Objective` at the MATLAB command prompt.

```
type sdoBattery_Objective
```

```
function vals = sdoBattery_Objective(v,Simulator,Exp)
%SDOBATTERY_OBJECTIVE
%
%    The sdoBattery_Objective function is used to compare model
%    outputs against experimental data.
%
%    vals = sdoBattery_Objective(v,Exp)
%
%    The |v| input argument is a vector of estimated model parameter values
%    and initial states.
%
%    The |Simulator| input argument is a simulation object used
%    simulate the model with the estimated parameter values.
%
%    The |Exp| input argument contains the estimation experiment data.
%
%    The |vals| return argument contains information about how well the
%    model simulation results match the experimental data and is used by
%    the |sdo.optimize| function to estimate the model parameters.
%
%    See also sdo.optimize, sdoExampleCostFunction
%
```

```
% Copyright 2012-2015 The MathWorks, Inc.

%%
% Define a signal tracking requirement to compute how well the model output
% matches the experiment data. Configure the tracking requirement so that
% it returns the tracking error residuals (rather than the
% sum-squared-error) and does not normalize the errors.
%
r = sdo.requirements.SignalTracking;
r.Type      = '==';
r.Method    = 'Residuals';
r.Normalize = 'off';

%%
% Update the experiments with the estimated parameter values.
%
Exp  = setEstimatedValues(Exp,v);

%%
% Simulate the model and compare model outputs with measured experiment
% data.
%
Error = [];
for ct=1:numel(Exp)

    Simulator = createSimulator(Exp(ct),Simulator);
    Simulator = sim(Simulator);

    SimLog  = find(Simulator.LoggedData,get_param('sdoBattery','SignalLoggingName'));
    Voltage = find(SimLog,'Voltage');

    VoltageError = evalRequirement(r,Voltage.Values,Exp(ct).OutputData(1).Values);

    Error = [Error; VoltageError(:)];
end

%%
% Return the residual errors to the optimization solver.
%
vals.F = Error(:);
end
```

Estimate the Parameters

Use the `sdo.optimize` function to estimate the battery parameter values.

Specify the optimization options. The estimation function `sdoBattery_Objective` returns the error residuals between simulated and experimental data and does not include any constraints, making this problem ideal for the 'lsqnonlin' solver.

```
opt = sdo.OptimizeOptions;
opt.Method = 'lsqnonlin';
```

Estimate the parameters.

```
vOpt = sdo.optimize(estFcn,v,opt)
```

```
 Optimization started 01-Sep-2022 13:40:26
```

```
                                                    First-order
 Iter F-count        f(x)      Step-size  optimality
    0      7      3272.22            1
    1     14      619.356       0.1634     3.15e+05
    2     21      411.131       0.2175         28.7
    3     28      405.529       0.3838     2.16e+03
    4     35      403.727       0.2767         15.2
    5     42      403.379       0.1645     1.14e+03
Local minimum possible.

lsqnonlin stopped because the final change in the sum of squares relative to
its initial value is less than the value of the function tolerance.

vOpt(1,1) =

       Name: 'V'
      Value: 1.3083
    Minimum: 0
    Maximum: 2
       Free: 1
      Scale: 2
       Info: [1x1 struct]


vOpt(2,1) =

       Name: 'K'
      Value: 0.0010
    Minimum: 1.0000e-06
    Maximum: 0.1000
       Free: 1
      Scale: 0.0020
       Info: [1x1 struct]


vOpt(3,1) =

       Name: 'Loss'
      Value: 5.1801e-05
    Minimum: 0
    Maximum: 0.5000
       Free: 1
      Scale: 0.0156
       Info: [1x1 struct]


3x1 param.Continuous
```

Compare the Measured Output and the Final Simulated Output

Update the experiments with the estimated parameter values.

```
Exp  = setEstimatedValues(Exp,vOpt);
```

Obtain the simulated output for the first (discharging) experiment.

```
Simulator  = createSimulator(Exp(1),Simulator);
Simulator  = sim(Simulator);
```

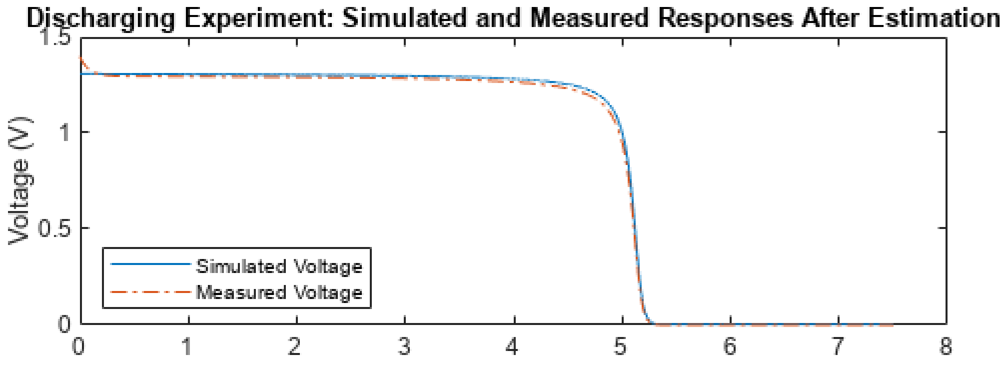
```
SimLog     = find(Simulator.LoggedData,get_param('sdoBattery','SignalLoggingName'));
Voltage(1) = find(SimLog,'Voltage');
```

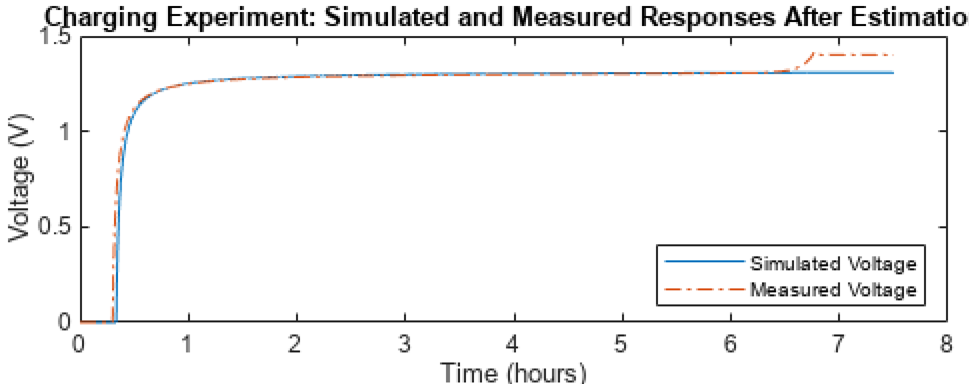
Obtain the simulated output for the second (charging) experiment.

```
Simulator  = createSimulator(Exp(2),Simulator);
Simulator  = sim(Simulator);
SimLog     = find(Simulator.LoggedData,get_param('sdoBattery','SignalLoggingName'));
Voltage(2) = find(SimLog,'Voltage');
```

Plot the measured and simulated data. The simulation results match the experimental data well except in the regions when the battery is fully charged. This is not unexpected as the simple battery model does not model the exponential voltage drop when the battery is fully charged.

```
subplot(211)
plot(...
    Voltage(1).Values.Time/3600,Voltage(1).Values.Data, ...
    Exp(1).OutputData.Values.Time/3600, Exp(1).OutputData.Values.Data,'-.')
title('Discharging Experiment: Simulated and Measured Responses After Estimation')
ylabel('Voltage (V)')
legend('Simulated Voltage','Measured Voltage','Location','SouthWest')
subplot(212)
plot(...
    Voltage(2).Values.Time/3600,Voltage(2).Values.Data, ...
    Exp(2).OutputData.Values.Time/3600, Exp(2).OutputData.Values.Data,'-.')
title('Charging Experiment: Simulated and Measured Responses After Estimation')
xlabel('Time (hours)')
ylabel('Voltage (V)')
legend('Simulated Voltage','Measured Voltage','Location','SouthEast')
```





Update the Model Parameter Values

Update the model `V`, `K`, and `Loss` parameter values.

```
sdo.setValueInModel('sdoBattery',vOpt);
```

Related Examples

To learn how to estimate the battery parameters using the **Parameter Estimator**, see “Estimate Model Parameters Per Experiment (GUI)” on page 2-155.

Close the model

```
bdclose('sdoBattery')
```

Set Model to Steady-State When Estimating Parameters (Code)

This example shows how to set a model to steady-state in the process of parameter estimation. Setting a model to steady-state is important in many applications such as power systems and aircraft dynamics. This example uses a population dynamics model.

This example requires Simulink® Control Design™ software.

Model Description

The Simulink model `sdoPopulationInflux` models a simple ecology where an organism population growth is limited by the carrying capacity of the environment.

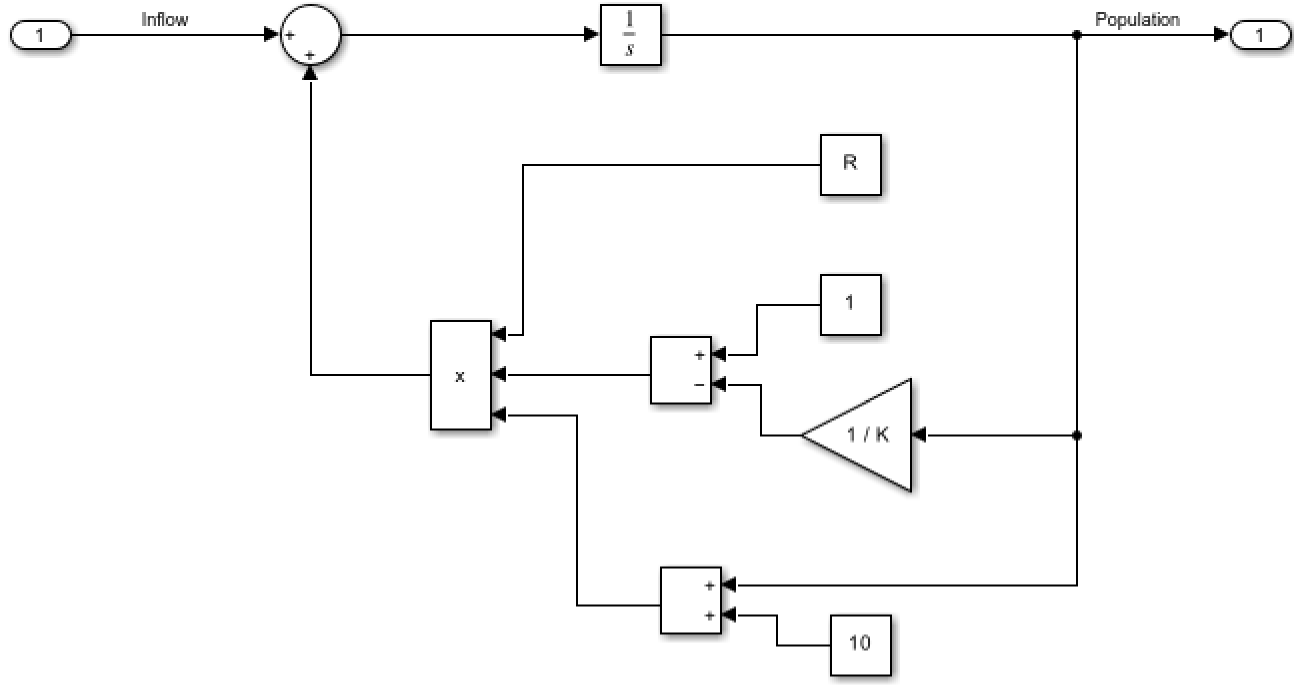
$$\frac{dy}{dt} = R(1 - \frac{y}{K})(y + 10)$$

- R is the inherent growth rate of the organism population.
- K is the carrying capacity of the environment.

There is also an influx of other members of the organism from a neighboring environment. The model uses normalized units.

Open the model.

```
modelName = 'sdoPopulationInflux';
open_system(modelName)
```



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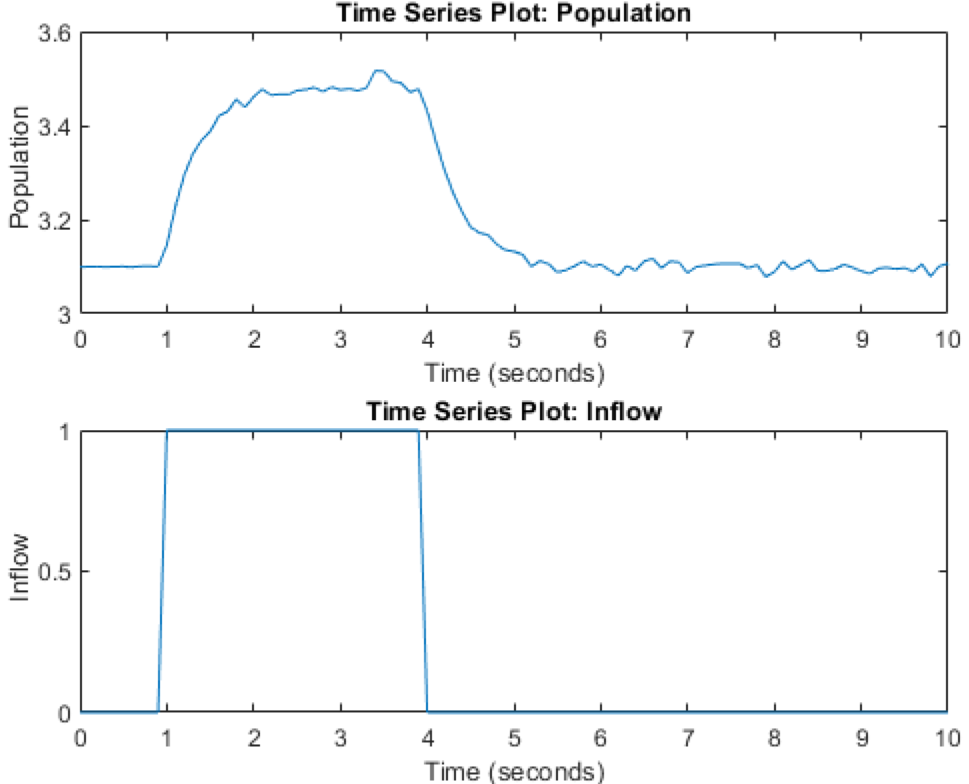
The file sdoPopulationInflux_Data.mat contains data of the population in the environment as well as the influx of additional organisms from the neighboring environment.

```
load sdoPopulationInflux_Data.mat;   % Time series:  Population_ts  Inflow_ts
hFig = figure;
subplot(2,1,1);
plot(Population_ts)
subplot(2,1,2);
plot(Inflow_ts)
```



The population starts in a steady state. After some time, there is an influx of organisms from the neighboring environment. Based on the measured data, you can estimate values for the model parameters.

The parameter R represents the inherent growth rate of the organism. Use 1 as the initial guess for this parameter. It is non-negative.

```
R = sdo.getParameterFromModel(modelName, 'R');
R.Value = 1;
R.Minimum = 0;
```

The parameter K represents the carrying capacity of the environment. Use 2 as the initial guess for this parameter. It is known to be at least 0.1.

```
K = sdo.getParameterFromModel(modelName, 'K');
K.Value = 2;
K.Minimum = 0.1;
```

Collect these parameters into a vector.

```
v = [R K];
```

Compare Measured Data to Initial Simulated Output

Create an Experiment object.

```
Exp = sdo.Experiment(modelName);
```

Associate `Population_ts` with model output.

```
Population = Simulink.SimulationData.Signal;
Population.Name = 'Population';
Population.BlockPath = [modelName  '/Integrator'];
Population.PortType = 'outport';
Population.PortIndex = 1;
Population.Values = Population_ts;
```

Add `Population` to the experiment.

```
Exp.OutputData = Population;
```

Associate `Inflow_ts` with model input.

```
Inflow = Simulink.SimulationData.Signal;
Inflow.Name = 'Population';
Inflow.BlockPath = [modelName  '/In1'];
Inflow.PortType = 'outport';
Inflow.PortIndex = 1;
Inflow.Values = Inflow_ts;
```

Add `Inflow` to the experiment.

```
Exp.InputData = Inflow;
```

Create a simulation scenario using the experiment, and obtain the simulated output.

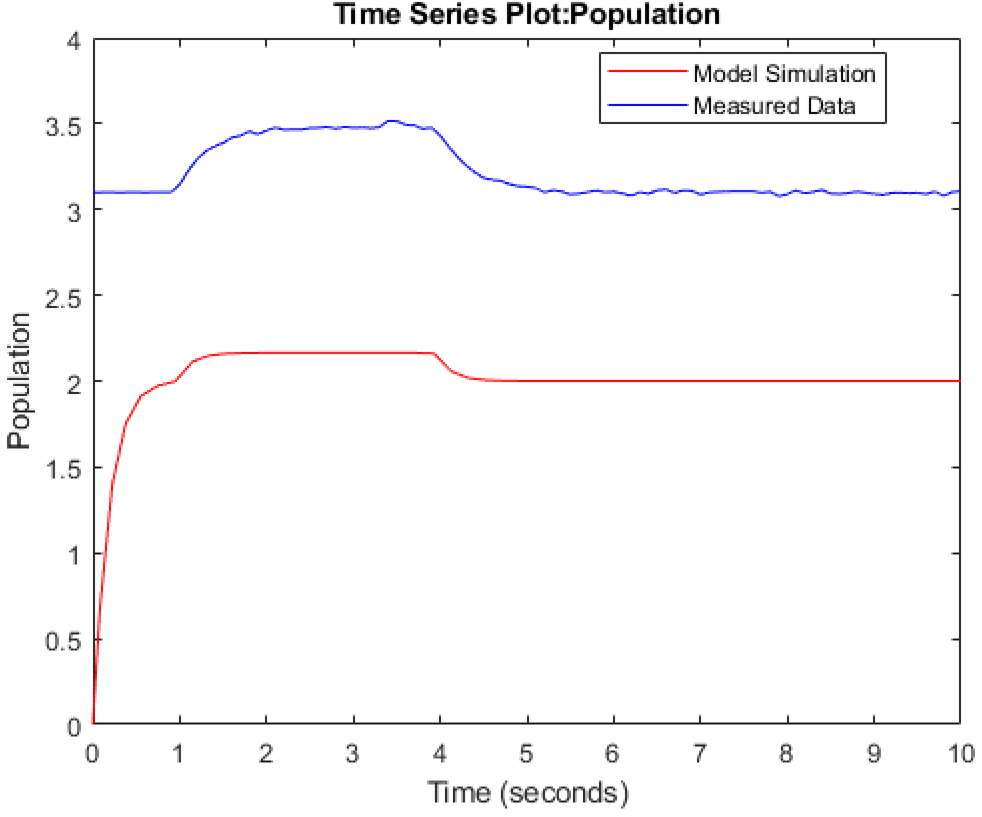
```
Exp = setEstimatedValues(Exp, v);   % use vector of parameters/states
Simulator = createSimulator(Exp);
Simulator = sim(Simulator);
```

Search for the model output signal in the logged simulation data.

```
SimLog = find(Simulator.LoggedData,  ...
    get_param(modelName, 'SignalLoggingName') );
PopulationSim = find(SimLog, 'Population');
```

The model output does not match the data very well, indicating a need to compute better estimates of the model parameters.

```
clf;
plot(PopulationSim.Values, 'r');
hold on;
plot(Population_ts, 'b');
legend('Model Simulation', 'Measured Data',  'Location', 'best');
```



Estimate Parameters

To estimate parameters, define an objective function to compute the sum squared error between model simulation and measured data.

```
estFcn = @(v) sdoPopulationInflux_Objective(v, Simulator, Exp);
type sdoPopulationInflux_Objective.m
```

```
function vals = sdoPopulationInflux_Objective(v, Simulator, Exp, OpPointSetup)
% Compare model output with data
%
%    Inputs:
%       v            - vector of parameters and/or states
%       Simulator    - used to simulate the model
%       Exp          - Experiment object
%       OpPointSetup - Object to set up computation of steady-state
%                      operating point

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%Parse inputs
if nargin < 4
    OpPointSetup = [];
end

% Requirement setup
req = sdo.requirements.SignalTracking;
```

```
req.Type = '==';
req.Method = 'Residuals';

% Simulate the model
Exp = setEstimatedValues(Exp, v);   % use vector of parameters/states
Simulator = createSimulator(Exp,Simulator);
strOT = mat2str(Exp.OutputData(1).Values.Time);
if isempty(OpPointSetup)
    Simulator = sim(Simulator, 'OutputOption', 'AdditionalOutputTimes', 'OutputTimes', strOT);
else
    Simulator = sim(Simulator, 'OutputOption', 'AdditionalOutputTimes', 'OutputTimes', strOT, ..
        'OperatingPointSetup', OpPointSetup);
end

% Compare model output with data
SimLog = find(Simulator.LoggedData,  ...
    get_param(Exp.ModelName, 'SignalLoggingName') );
OutputModel = find(SimLog, 'Population');
Model_Error = evalRequirement(req, OutputModel.Values, Exp.OutputData.Values);
vals.F = Model_Error;

%Define options for the optimization.
%
opts = sdo.OptimizeOptions;
opts.Method = 'lsqnonlin';
```

Estimate the parameters.

```
vOpt = sdo.optimize(estFcn, v, opts);
disp(vOpt)
```

```
 Optimization started 01-Sep-2022 14:45:32

                                          First-order
 Iter F-count        f(x)      Step-size  optimality
    0      5       12.485            1
    1     10      1.09824        1.184        0.244
    2     15       0.9873        1.088       0.0259
    3     20     0.952948        1.217      0.00624
    4     25     0.946892       0.9151      0.00197
    5     30     0.946484       0.3541      0.00153
Local minimum possible.

lsqnonlin stopped because the final change in the sum of squares relative to
its initial value is less than the value of the function tolerance.

(1,1) =

       Name: 'R'
      Value: 5.5942
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 1
       Info: [1x1 struct]
```

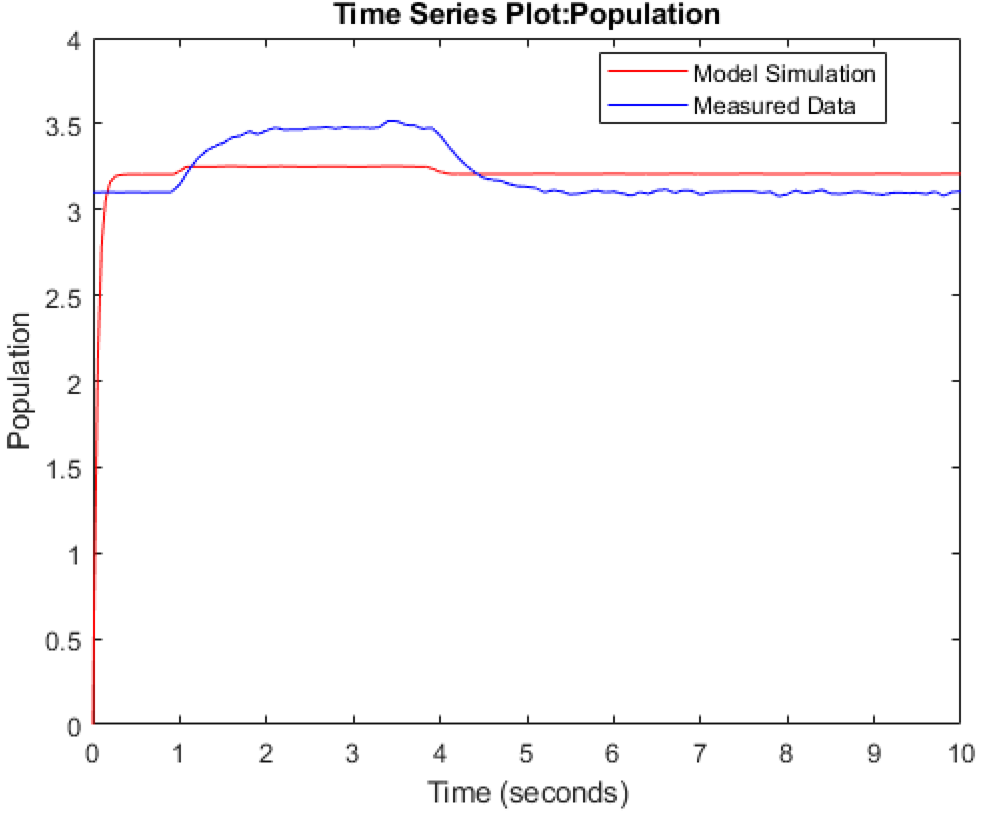
```
(1,2) =

       Name: 'K'
      Value: 3.2061
    Minimum: 0.1000
    Maximum: Inf
       Free: 1
      Scale: 2
       Info: [1x1 struct]


1x2 param.Continuous
```

Use the estimated parameter values in the model, and obtain the model response. Search for the model output signal in the logged simulation data.

```
Exp = setEstimatedValues(Exp, vOpt);
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);
SimLog = find(Simulator.LoggedData,  ...
    get_param(modelName, 'SignalLoggingName') );
PopulationSim = find(SimLog, 'Population');
```

Comparing the measured population data with the optimized model response shows that they still do not match well. There is a transient at the beginning of the model response, where it is markedly different from the measured data.

```
clf;
plot(PopulationSim.Values, 'r');
hold on;
plot(Population_ts, 'b');
legend('Model Simulation', 'Measured Data',  'Location', 'best');
```



Put Model in Steady-State During Estimation

To improve the fit between the model and measured data, the model needs to be set to steady-state when parameters are estimated. Define an operating point specification. The input is known from experimental data. Therefore, (1) it should not be treated as a free variable when computing the steady-state operating point, and (2) after the operating point is found, its input should not be used when simulating the model. On the other hand, all the states found when computing the operating point should be used when simulating the model. Create an `sdo.OperatingPointSetup` object to collect the operating point specification, inputs to use, and states to use, so this information can be passed to the objective function and used when simulating the model. You can also provide a fourth argument to `sdo.OperatingPointSetup` to specify options for computing the operating point. For example, the option `'graddescent-proj'` is often used to find the operating point for systems that use physical modeling.

```
opSpec = operspec(modelName);
opSpec.Inputs(1).Known = true;
inputsToUse = [];
statesToUse = 1:numel(opSpec.States);
OpPointSetup = sdo.OperatingPointSetup(opSpec, inputsToUse, statesToUse);
```

Estimate the parameters, setting the model to steady-state in the process.

```
estFcn = @(v) sdoPopulationInflux_Objective(v, Simulator, Exp, OpPointSetup);
vOpt = sdo.optimize(estFcn, v, opts);
disp(vOpt)
```

```
 Optimization started 01-Sep-2022 14:46:08

                                                First-order
 Iter F-count        f(x)      Step-size  optimality
    0      5      11.1517            1
    1     10     0.025674       0.5732        0.045
    2     15   0.00239293       0.3451        0.357
    3     20  0.000692478       0.0148      0.00301
    4     25   0.00069236    6.539e-05     1.16e-07
Local minimum found.

Optimization completed because the size of the gradient is less than
the value of the optimality tolerance.

(1,1) =

       Name: 'R'
      Value: 0.5953
    Minimum: 0
    Maximum: Inf
       Free: 1
      Scale: 1
       Info: [1x1 struct]


(1,2) =

       Name: 'K'
      Value: 3.0988
    Minimum: 0.1000
    Maximum: Inf
       Free: 1
      Scale: 2
       Info: [1x1 struct]


1x2 param.Continuous
```

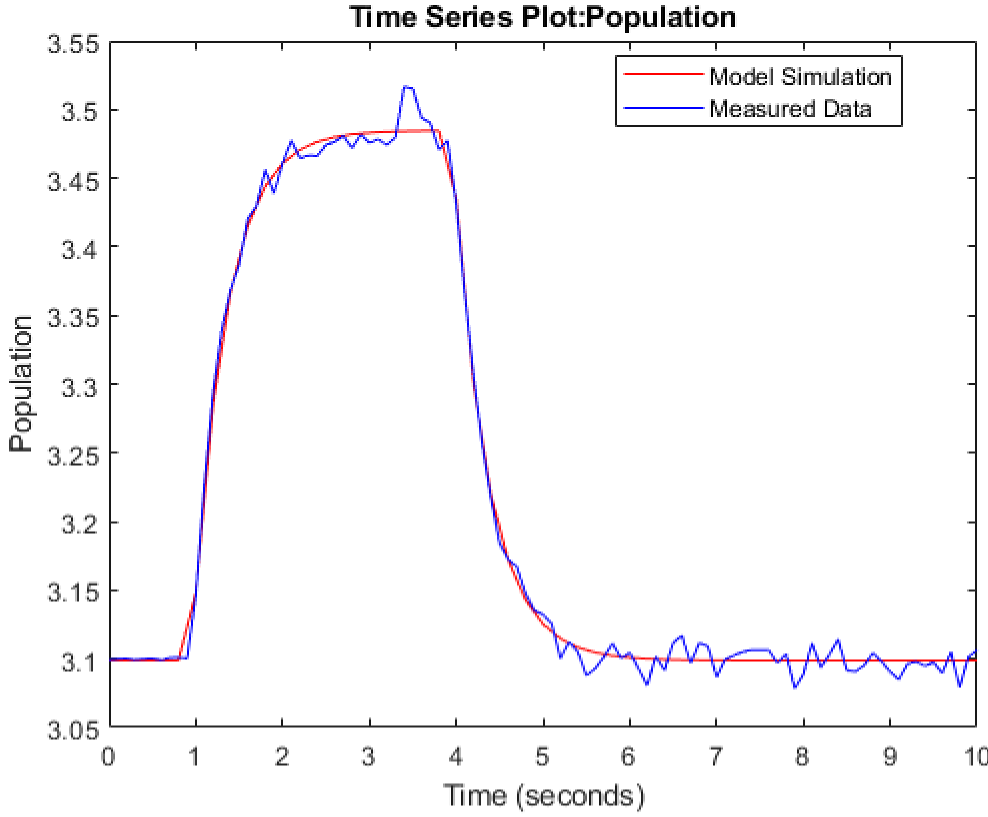
Use the estimated parameter values in the model, and obtain the model response. Search for the model output signal in the logged simulation data.

```
Exp = setEstimatedValues(Exp, vOpt);
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator, 'OperatingPointSetup', OpPointSetup);
SimLog = find(Simulator.LoggedData,  ...
    get_param(modelName, 'SignalLoggingName') );
PopulationSim = find(SimLog, 'Population');
```

There is no more transient at the beginning of the model response, and there is a much better match between the model response and measured data, which is also reflected by the lower objective/cost function value in the second optimization. All these indicate that a good set of parameter values was found.

```
clf;
plot(PopulationSim.Values, 'r');
hold on;
```

```
plot(Population_ts, 'b');
legend('Model Simulation', 'Measured Data',  'Location', 'best');
```



Related Examples

To learn how to put models in a steady state using the **Parameter Estimator** app, see “Set Model to Steady-State When Estimating Parameters (GUI)” on page 2-118.

Close the model and figure.

```
bdclose(modelName)
close(hFig)
```

Parameter Estimation for Power Plant Excitation System Starting at Steady-State (GUI)

This example shows how to perform parameter estimation while starting the system in steady state using the example of an excitation system model for a power plant electric generator.

Need for Parameter Estimation in Power Systems

Parameter estimation is a powerful tool for power system operations where the accuracy of models is critical and may be required by regulation. There are several reasons why one might need to perform parameter estimation in power systems, including:

- The system parameters may have been unknown from the start. For instance, if some or all of the parameters were not provided by the supplier.
- Even if the system parameters were known in the past, these parameters may drift with time due to wear on components in the system.
- Some settings may be changed for the system causing unknown effects on the system parameters. Parameter estimation can be used to account for these settings changes.
- The system may need to be fit to some standardized model. For instance, in this example we are fitting the IEEE DC1A standard model for excitation systems to our system.

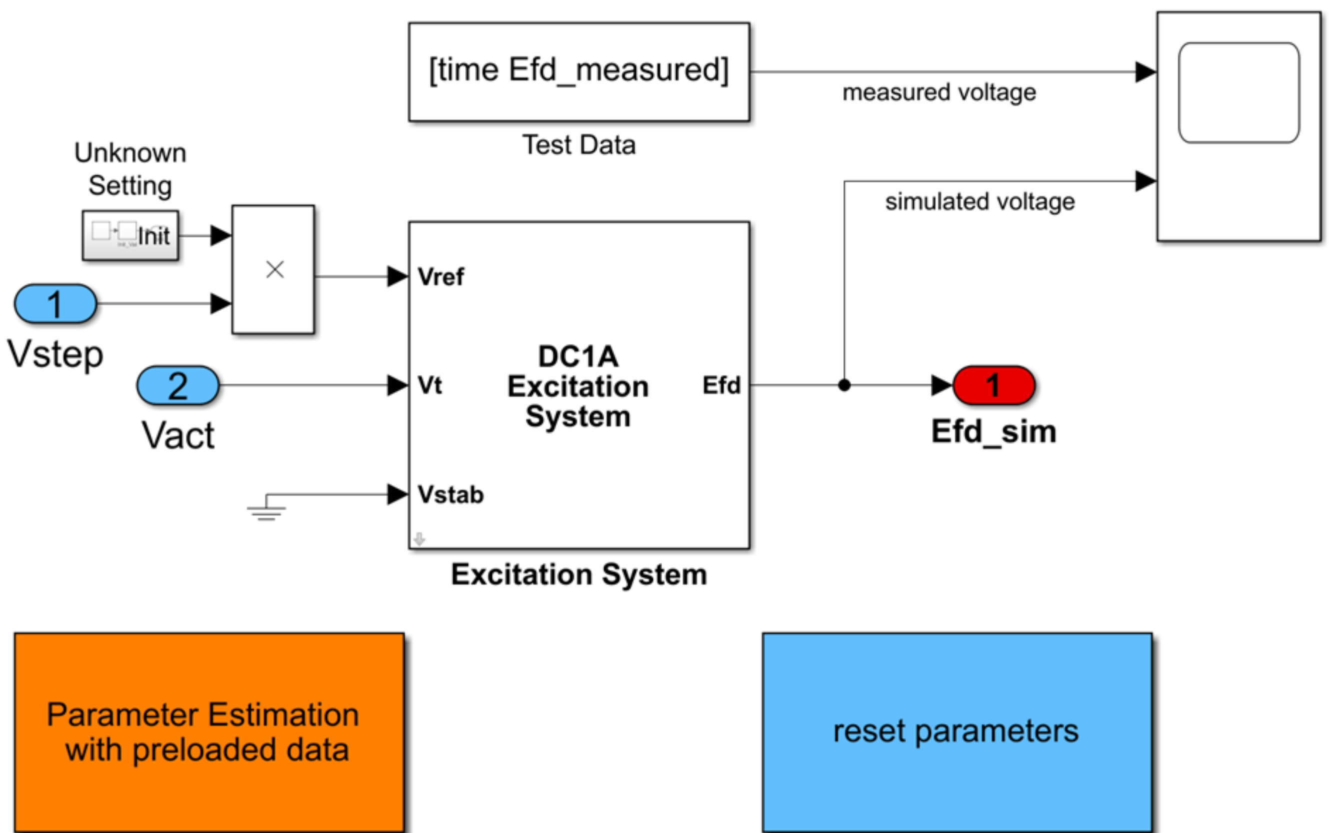
Excitation System Model Description

Generators create power by rotating a magnetic field and coiled wires relative to one another to induce an electric current. For generators that use electromagnets, an excitation system supplies current to the generator's field coils to create the magnetic field. By controlling the strength of the magnetic field inside the generator, the exciter system can control the generator's output voltage.

The Simulink® model `spe_exciter` models an excitation system in an offline step test. In this test, the generator is taken offline, then a step voltage input is applied to the exciter, and the output voltage is measured for system characterization purposes. This model includes the subsystem labeled "DC1A Excitation System" which follows the model structure for an excitation system outlined in the IEEE DC1A standard. The block contains several parameters, such as gains and time constants, that define the system's behavior and need to be fit to our system. The voltage inputs and outputs are in p.u. (per unit).

You can open the model with the following command:

```
open_system('spe_exciter');
```

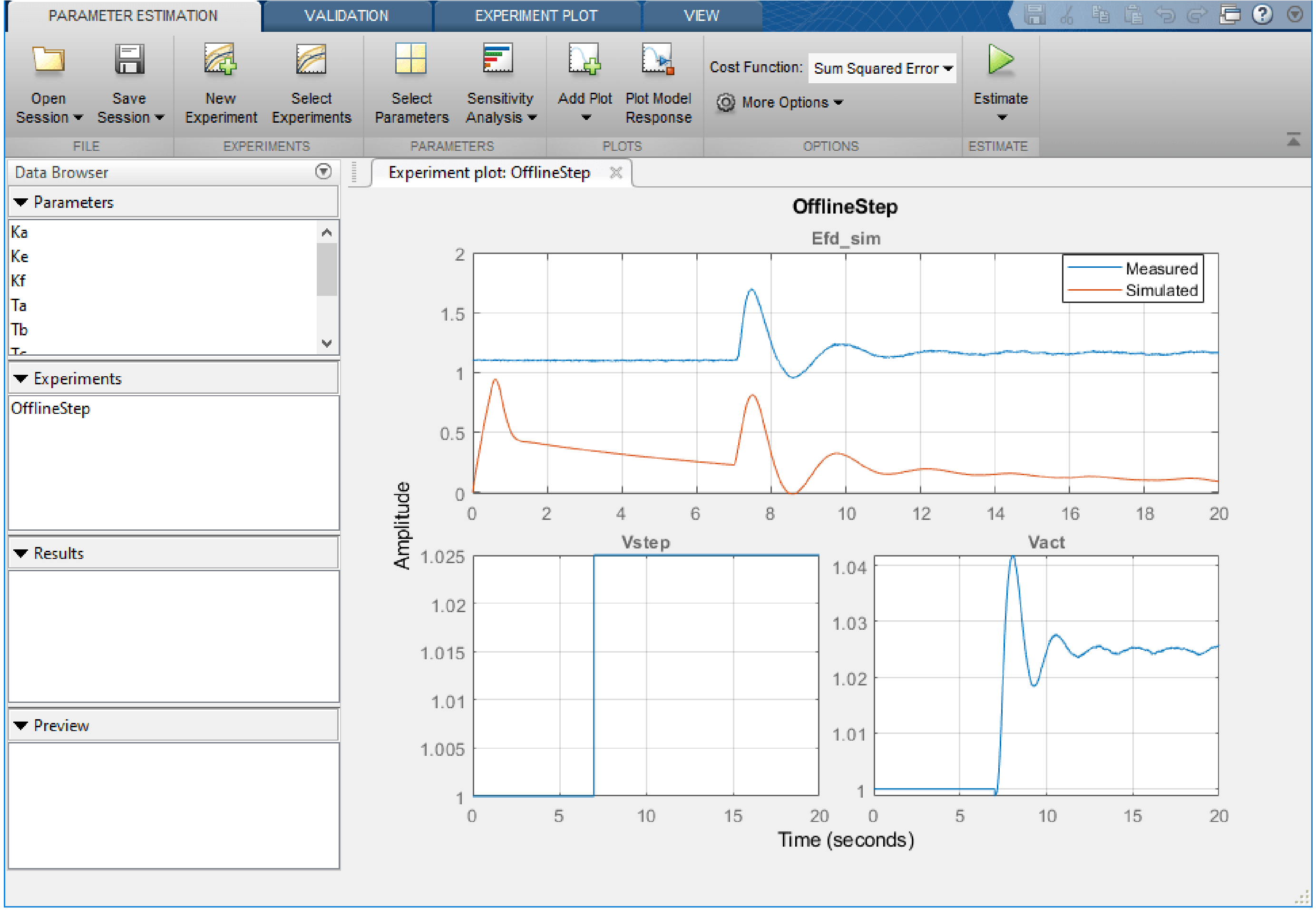


Open Parameter Estimator App

Double-click the orange block labeled `Parameter Estimation with preloaded data` in the lower left corner of the model. This will launch a Parameter Estimation session pre-loaded with data for this project, including the experimental data from the offline step test.

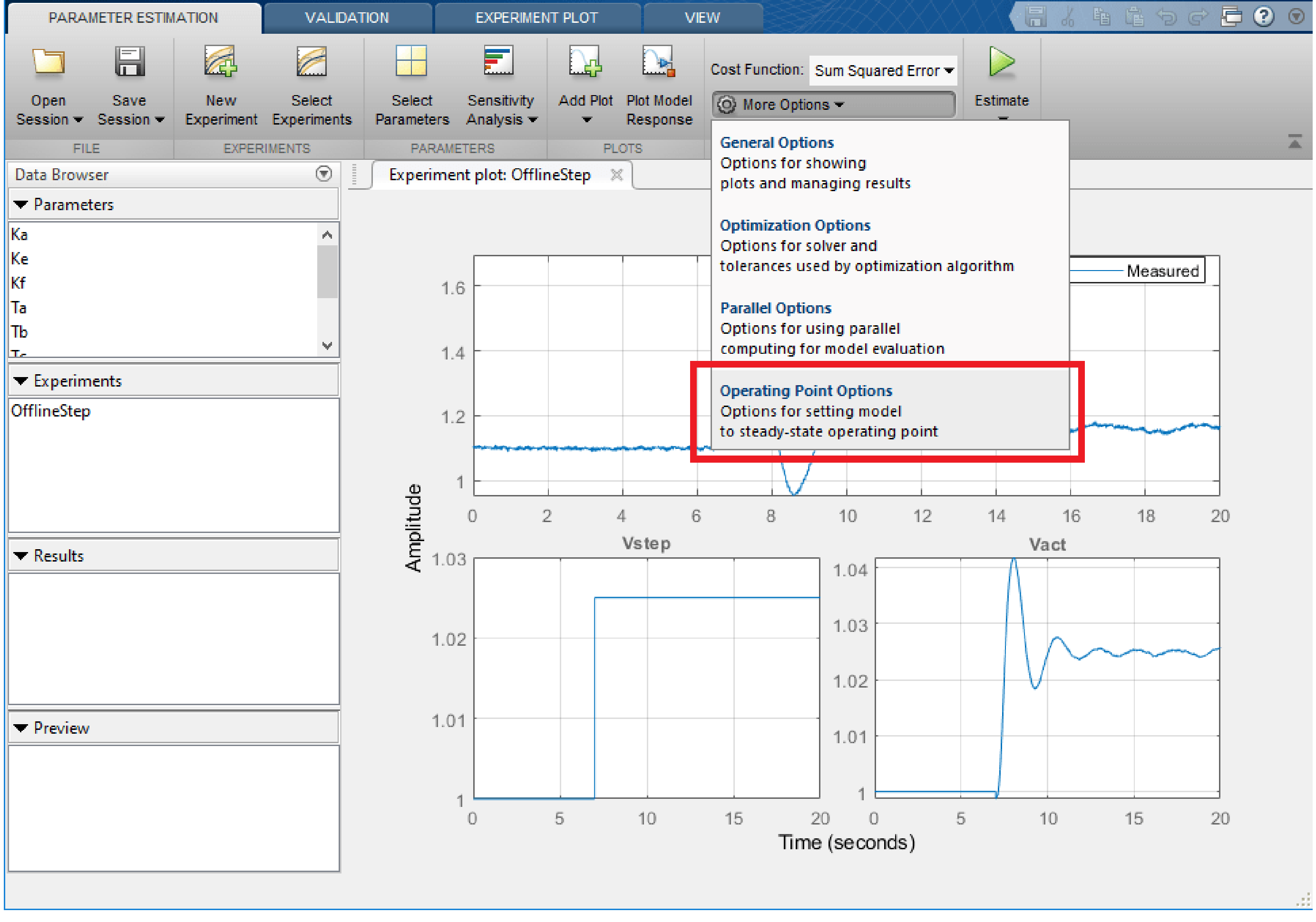
The Parameter Estimation session is loaded with the system parameters which were determined to need tuning due to any of the reasons noted previously. These parameters include the gains `Ka`, `Ke`, and `Kf`; and time constants `Ta`, `Tb`, `Tc`, `Te`, `Tf`, and `Tr`. These parameters are bound to use only positive values during estimation.

To plot the model's response against the experimental data, click the **Plot Model Response** button in the toolbar. Notice that the initial conditions for the states in our model are currently incorrect, which causes the initial dynamic in the simulated response and the offset between the simulated and measured response. In the next step we will update the options in the **Parameter Estimator** app to solve for the correct initial conditions in our model.

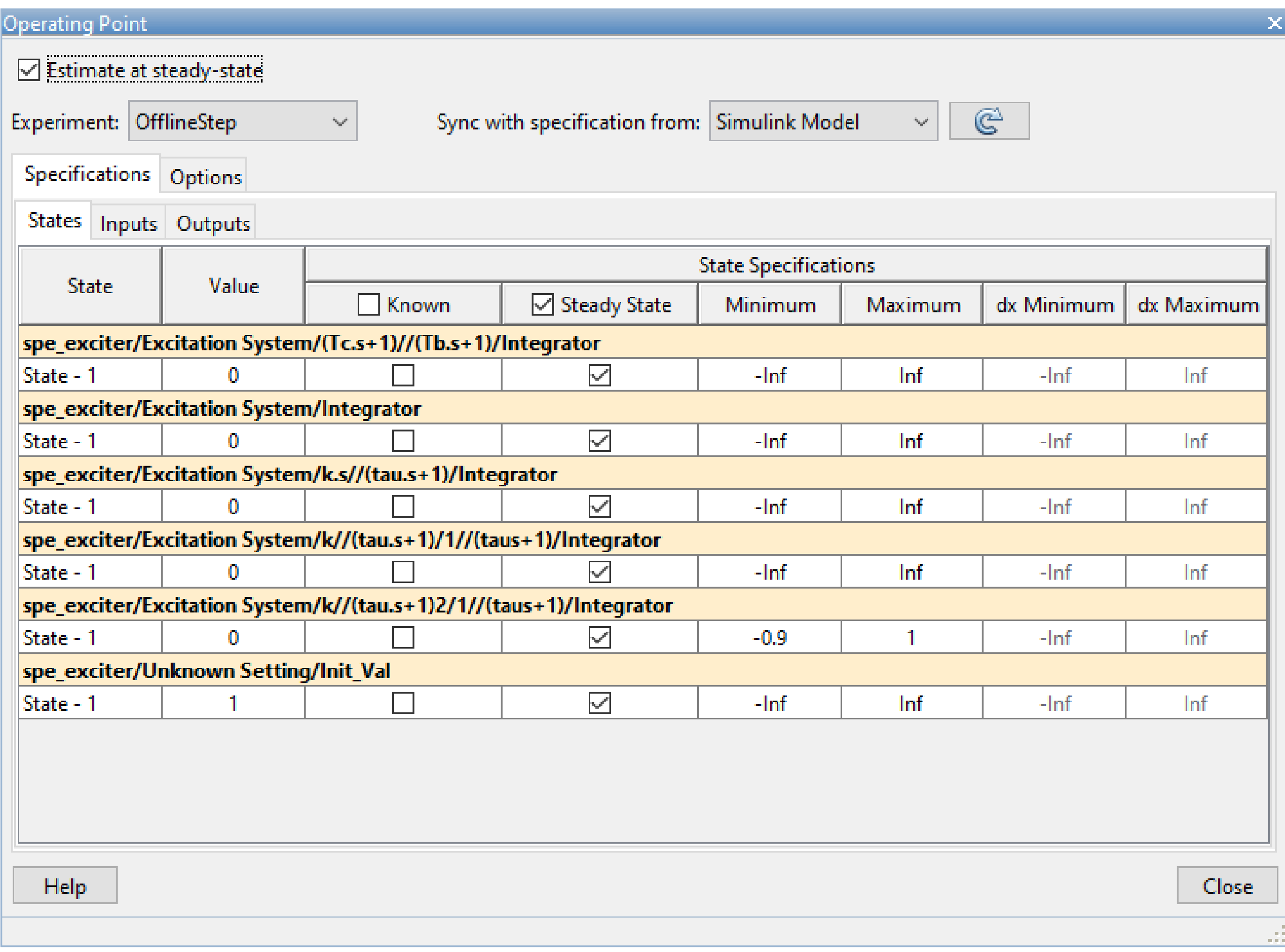


Compute Steady-State Operating Point During Parameter Estimation

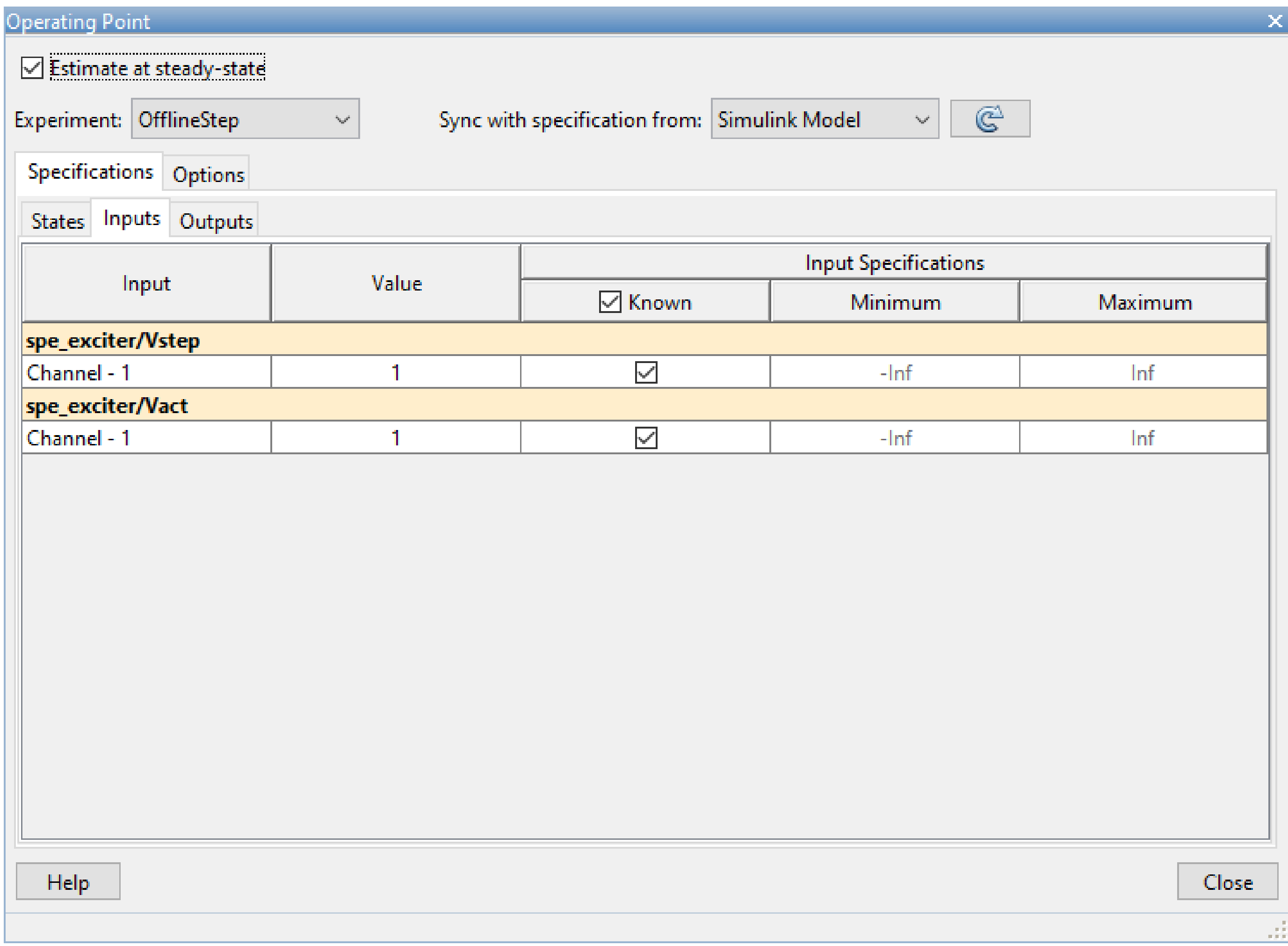
In the experimental step test that produced the measured response, the excitation system was in steady state and outputting around 1.1 p.u. before the test measurements began. To match these conditions in our parameter estimation, we will specify that the model should start at a steady-state operating point during parameter estimation. Click **More Options** and select **Operating Point Options**.



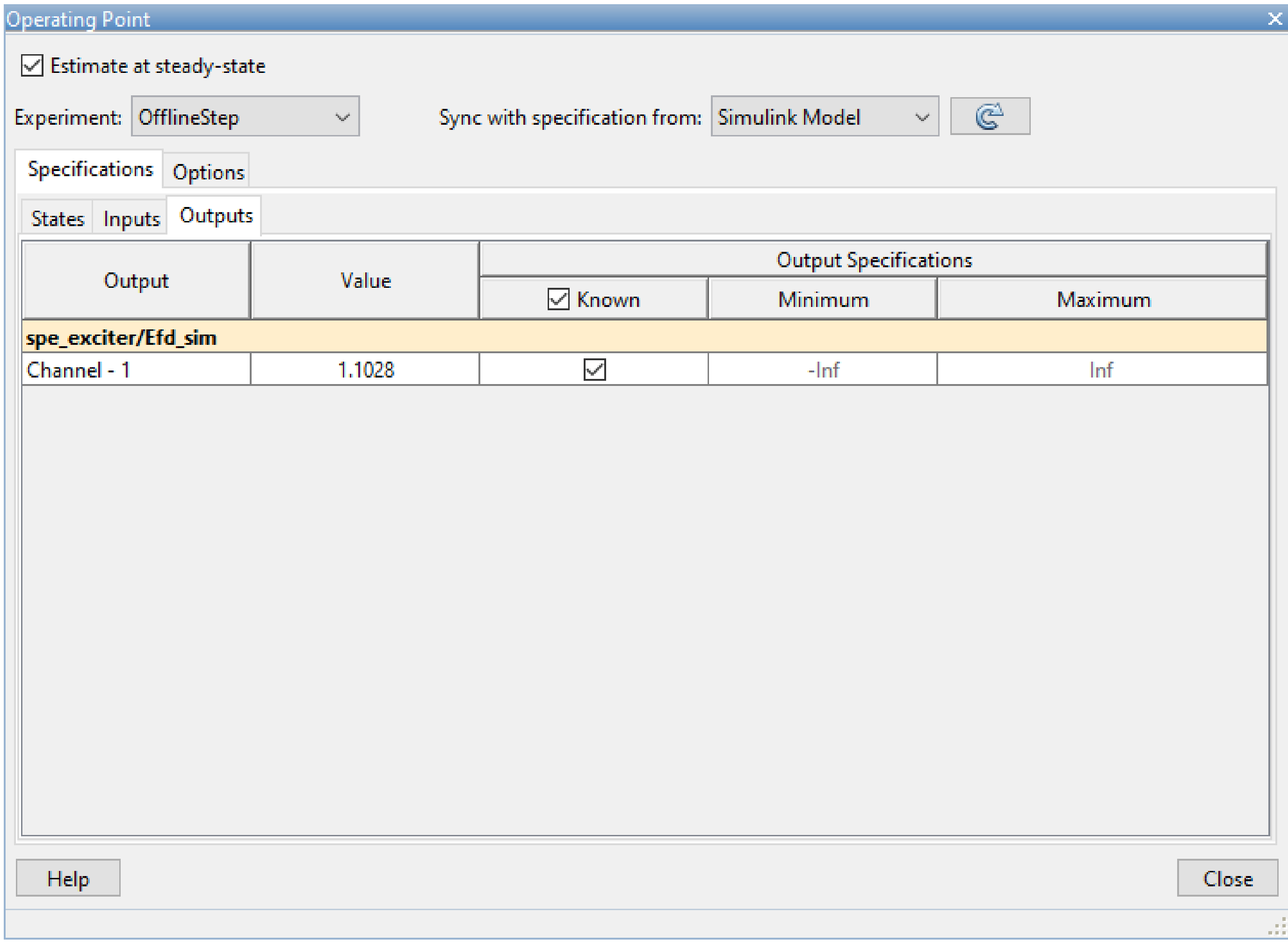
This shows a dialog where you can specify how steady-state operating points should be computed during parameter estimation. Open the dialog and select the check box `Estimate at steady-state` so that the **Parameter Estimator** will put the model into steady-state each time it varies parameters and runs the model. There are seven states in this model, by default they will be set to unknown and marked as states to be set to steady-state. This matches our system, so we will keep these options unchanged.



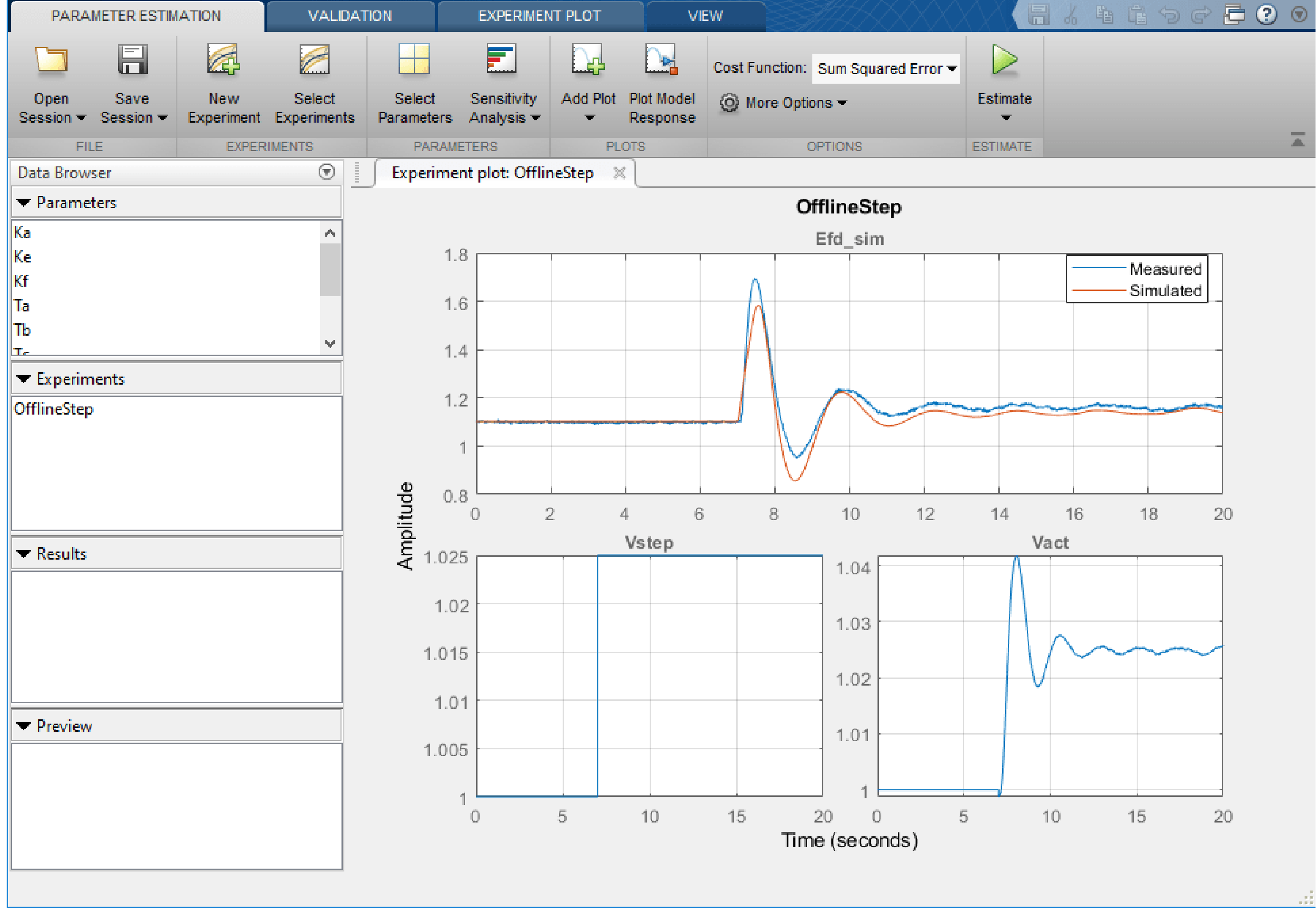
The inputs to the model (terminal voltage and reference voltage) are known from the offline step test. Switching to the **Inputs** tab under **Specifications**, we can specify these conditions. We can see that the inputs are marked as known by default with a value of one. These come from the starting value in the measured data, and we will leave these values unchanged.



Switching to the **Outputs** tab under **Specifications**, we mark the output (field voltage) of our system as known by checking the “Known” checkbox, and set its “Value” to 1.1028, which is the first value of our measured field voltage test data.

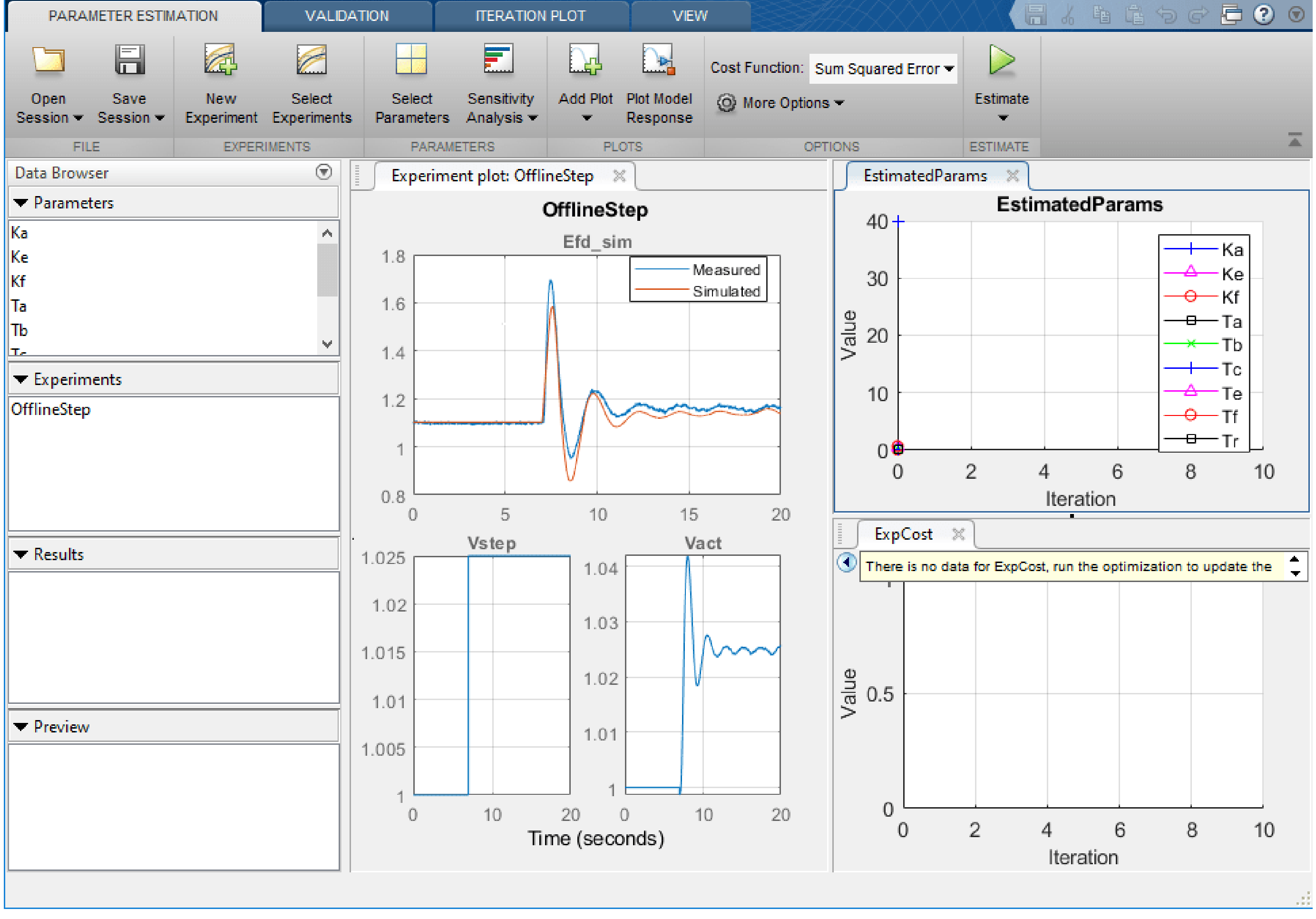


With the options we have now set up, before running each model simulation, Parameter Estimation will solve for a set of initial conditions that will place all the specified states in steady-state at the specified input and output levels. To see the result of these changes, click **Plot Model Response** again and see that the simulated response is now in steady state at the expected initial output.



Set up Parameter Estimation View

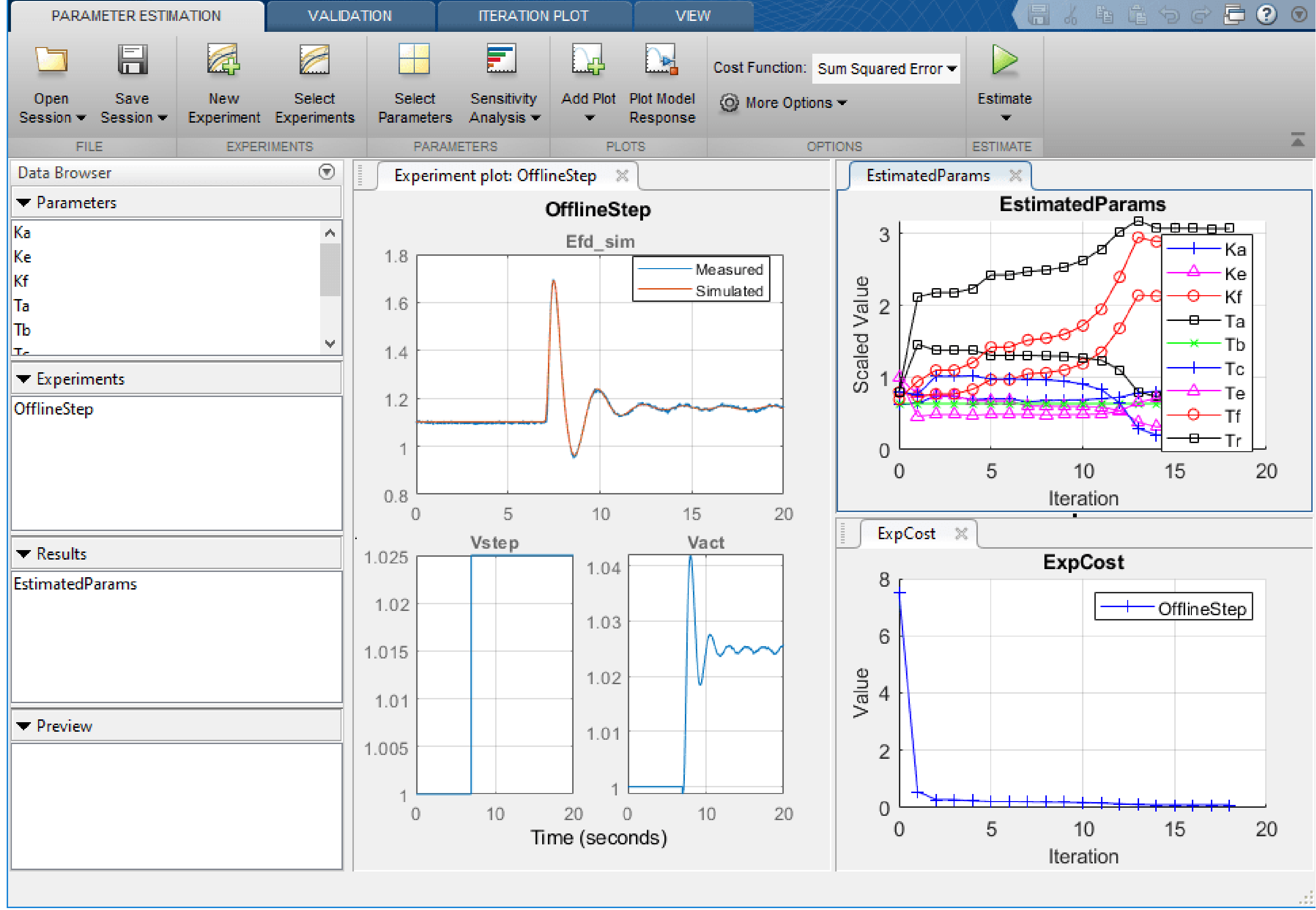
Before estimating parameters, we can use the toolbar to customize the view of Parameter Estimation to display the information we are interested in. Use the **Add Plot** button on the toolbar to add a **Parameter Trajectory** plot and an **Estimation Cost** plot. You can use the **View** tab to adjust the layout and make all plots visible.



Perform Parameter Estimation

Now we are ready to perform parameter estimation. In the **Parameter Estimation** tab, click **Estimate**.. Due to the large number of parameters being estimated in this example, this process may take several minutes.

Once the estimation process has converged, the new model response is shown in the **Experiment Plot**. We see a better match between the model and the measured data, and the error in the **ExpCost** plot decreased significantly. These indicate that a good set of parameters was found. The **EstimatedParams** plot shows how each parameter changed at each iteration. To more clearly see how much each parameter changed relative to its initial value, right click the **EstimatedParams** plot and select `Show scaled values`.



Speed Up Estimation Using Parallel Pool Options

Because of the large number of parameters being estimated, the parameter estimation can take a long time. As the number of parameters increases, the number of times the model must run at each iteration also increases. This leads to an increase in the total computation time required for the parameter estimation to converge.

To speed up our parameter estimation we can set up our options to use a parallel pool. Then our parallel workers can run simulations simultaneously to speed up the parameter estimation process.

To do this you will need **MATLAB Parallel Computing Toolbox**. Before performing parameter estimation, go to **More Options>Parallel Options** in the Parameter Estimation toolbar. Then select `Use parallel pool during estimation`. Click OK, then click **Estimate** in the toolbar.

For a parallel pool with 8 workers, the estimation process for this example was 3.5 times faster to complete. For access to options related to parallel computing like number of workers and cluster setup, see "Specify Your Parallel Preferences" (Parallel Computing Toolbox).

See Also

Parameter Estimator

Related Examples

- “Set Model to Steady-State When Estimating Parameters (GUI)” on page 2-118
- “Set Model to Steady-State When Estimating Parameters (Code)” on page 2-97

More About

- “Specify Steady-State Operating Point for Parameter Estimation” on page 2-47
- “What Is an Operating Point?” (Simulink Control Design)
- “What Is a Steady-State Operating Point?” (Simulink Control Design)

Set Model to Steady-State When Estimating Parameters (GUI)

This example shows how to set a model to steady-state in the process of parameter estimation. Setting a model to steady-state is important in many applications such as power systems and aircraft dynamics. This example uses a population dynamics model.

Model Description

The Simulink® model `sdoPopulationInflux` models a simple ecology where an organism population growth is limited by the carrying capacity of the environment.

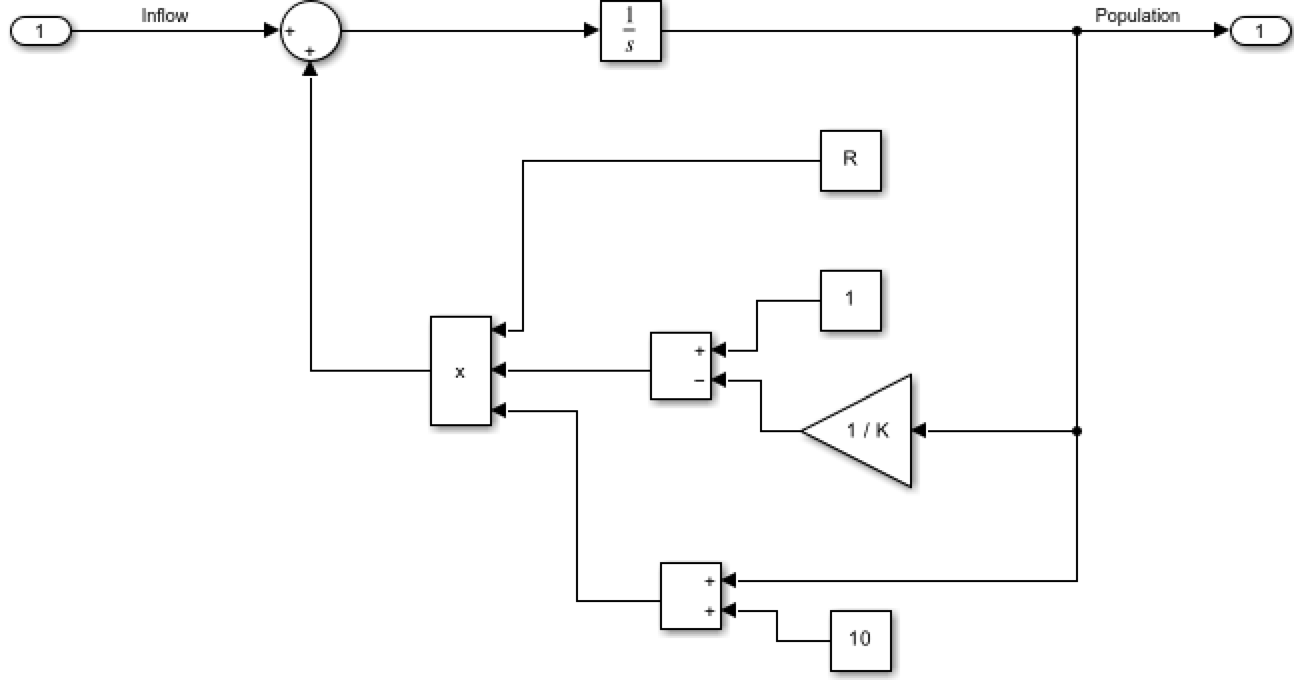
$$\frac{dy}{dt} = R(1 - \frac{y}{K})(y + 10)$$

- R is the inherent growth rate of the organism population.
- K is the carrying capacity of the environment.

There is also an influx of other members of the organism from a neighboring environment. The model uses normalized units.

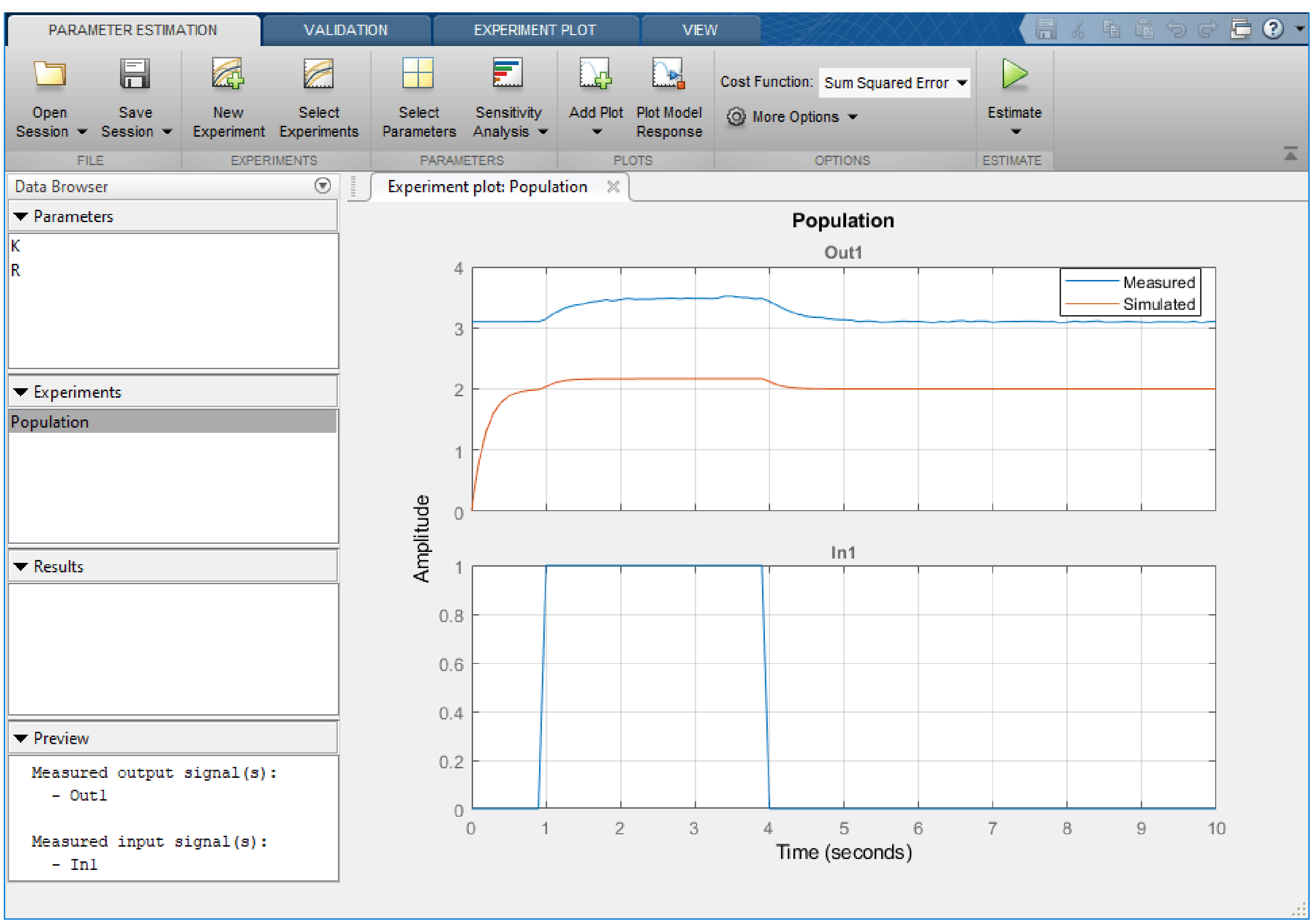
Open the model.

```
open_system('sdoPopulationInflux')
```



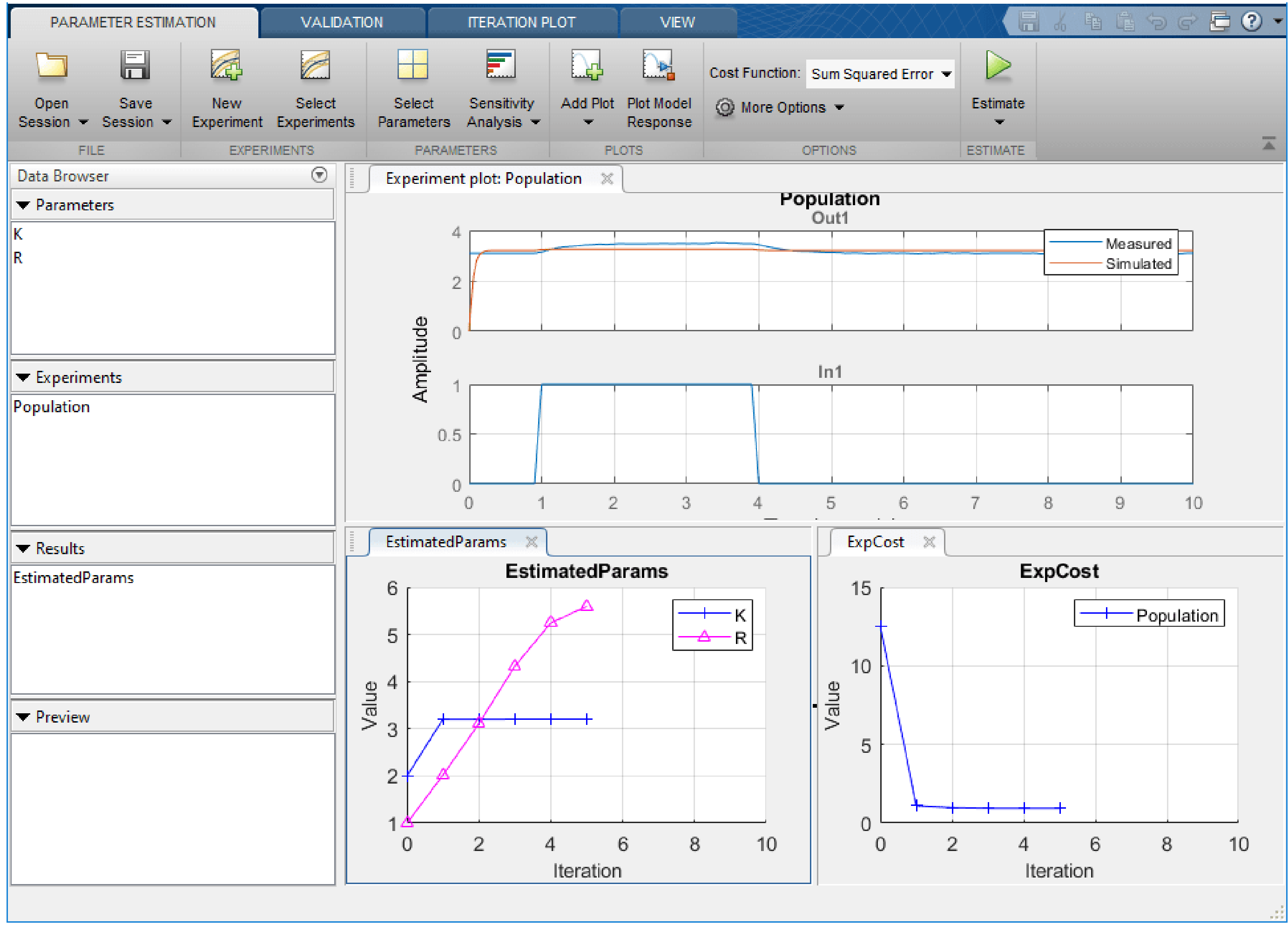
Open Parameter Estimator App

To open the **Parameter Estimator**, in the Simulink model window, in the **Apps** gallery, under **Control Systems**, click **Parameter Estimator**. In **Parameter Estimator**, click **Open Session** and select `Open from model workspace`, and then select `sdoPopulationInflux_spesession` to load a session with population experiment data already loaded. In the toolstrip, click **Plot Model Response** to plot the model response with the model's initial parameter values for R and K. The plot shows that with the model's initial parameter values, the model output is not close to the measured data. You can use the app to compute better estimates of these parameters.



Estimate Parameters

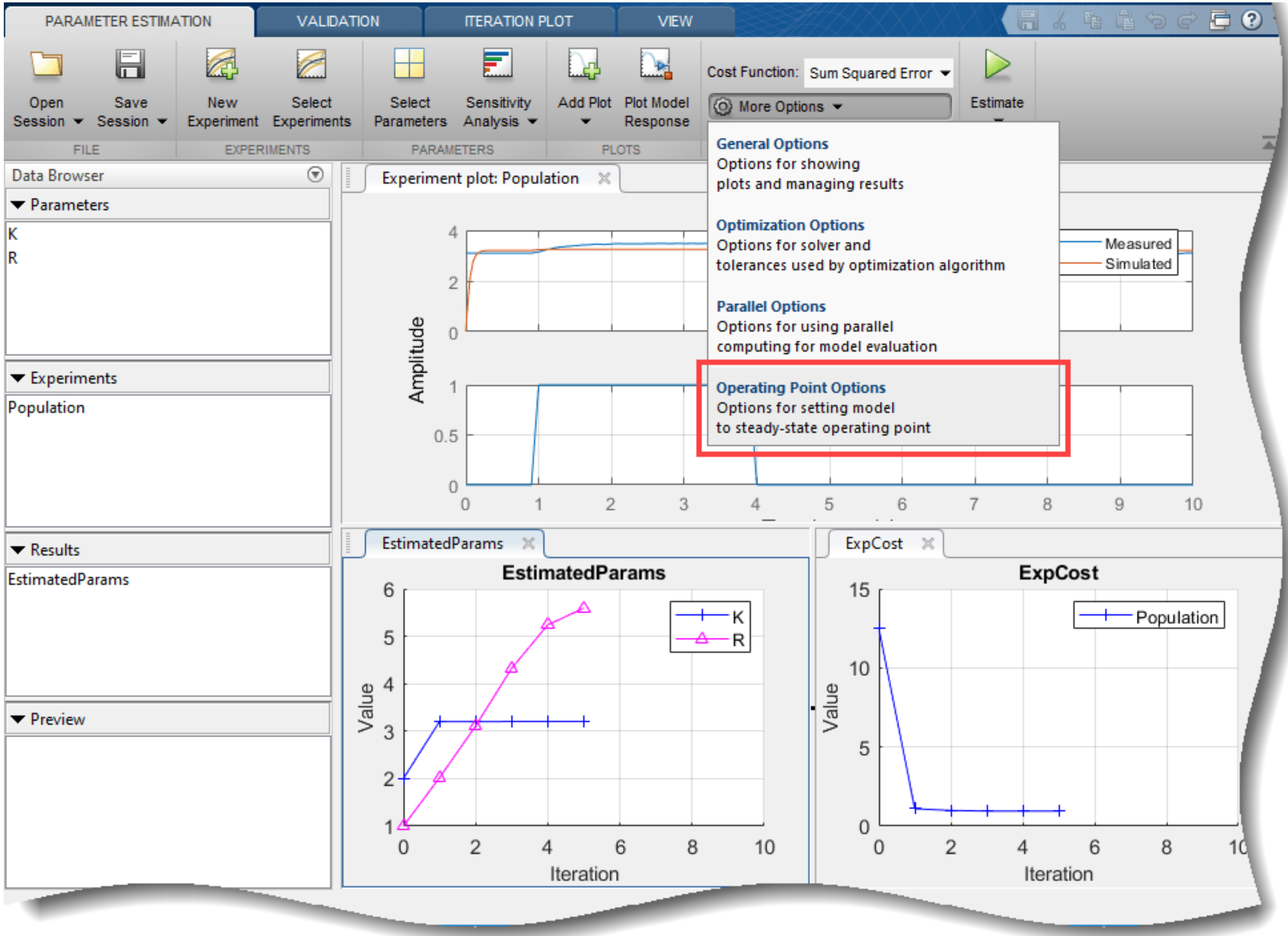
The pre-configured parameter estimation session also specifies that R and K are to be estimated, and that their lower bounds are 0 since the inherent growth rate and environment carrying capacity are not negative. In the toolstrip, click **Add Plot** and add a plot to show the parameter trajectories during estimation, and another plot to show the estimation cost. Use the **View** tab to lay out the plots in a convenient format. Click **Estimate** to estimate parameters R and K. The optimization goes through several iterations, changing the values of the parameters to improve the fit between model response and data.



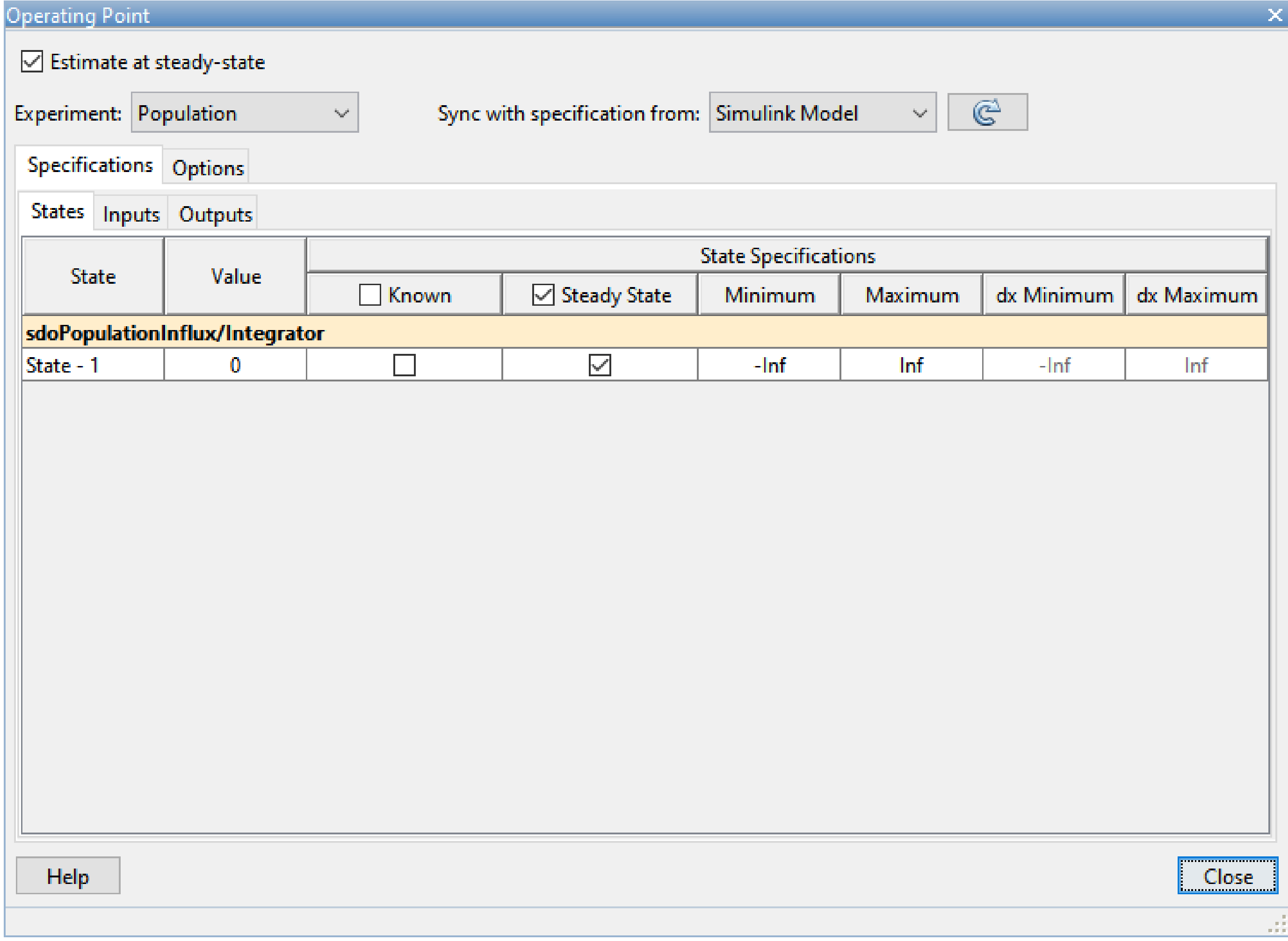
Comparing the measured population data with the optimized model response shows that they still do not match well. There is a transient at the beginning of the model response, where it is markedly different from the measured data.

Compute Steady-State Operating Point During Parameter Estimation

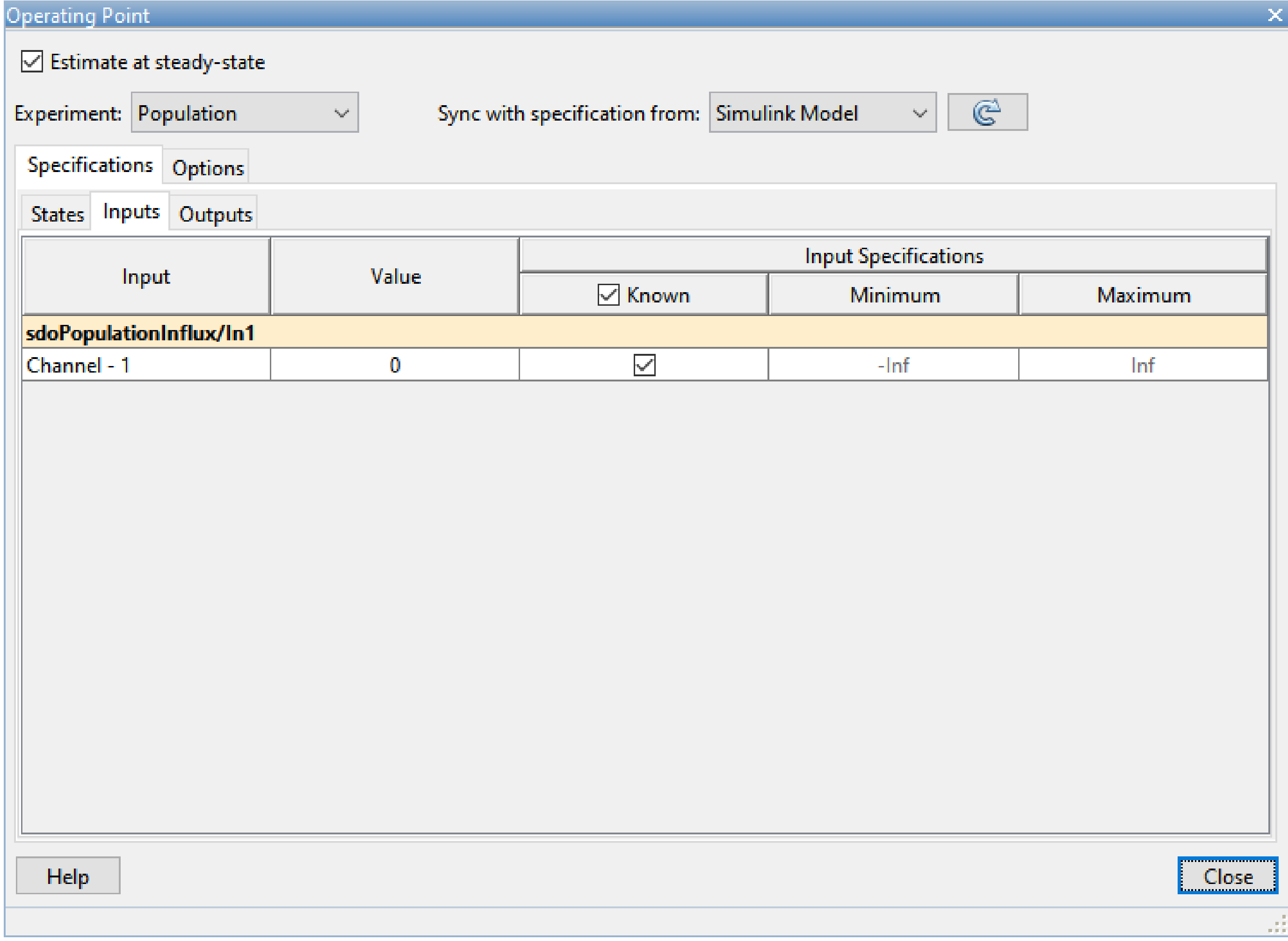
To improve the fit between the model and measured data, the model needs to be set to steady-state when parameters are estimated. In the toolstrip click **More Options** and select `Operating Point Options`.



This shows a dialog where you can specify how to compute steady-state operating points during parameter estimation. There is one state in this model, namely the initial condition of the integrator. Use the operating point dialog to specify that this state should be treated as an unknown, and it should be set to steady state. During parameter estimation, the operating point computation will vary this state to set it at steady-state.

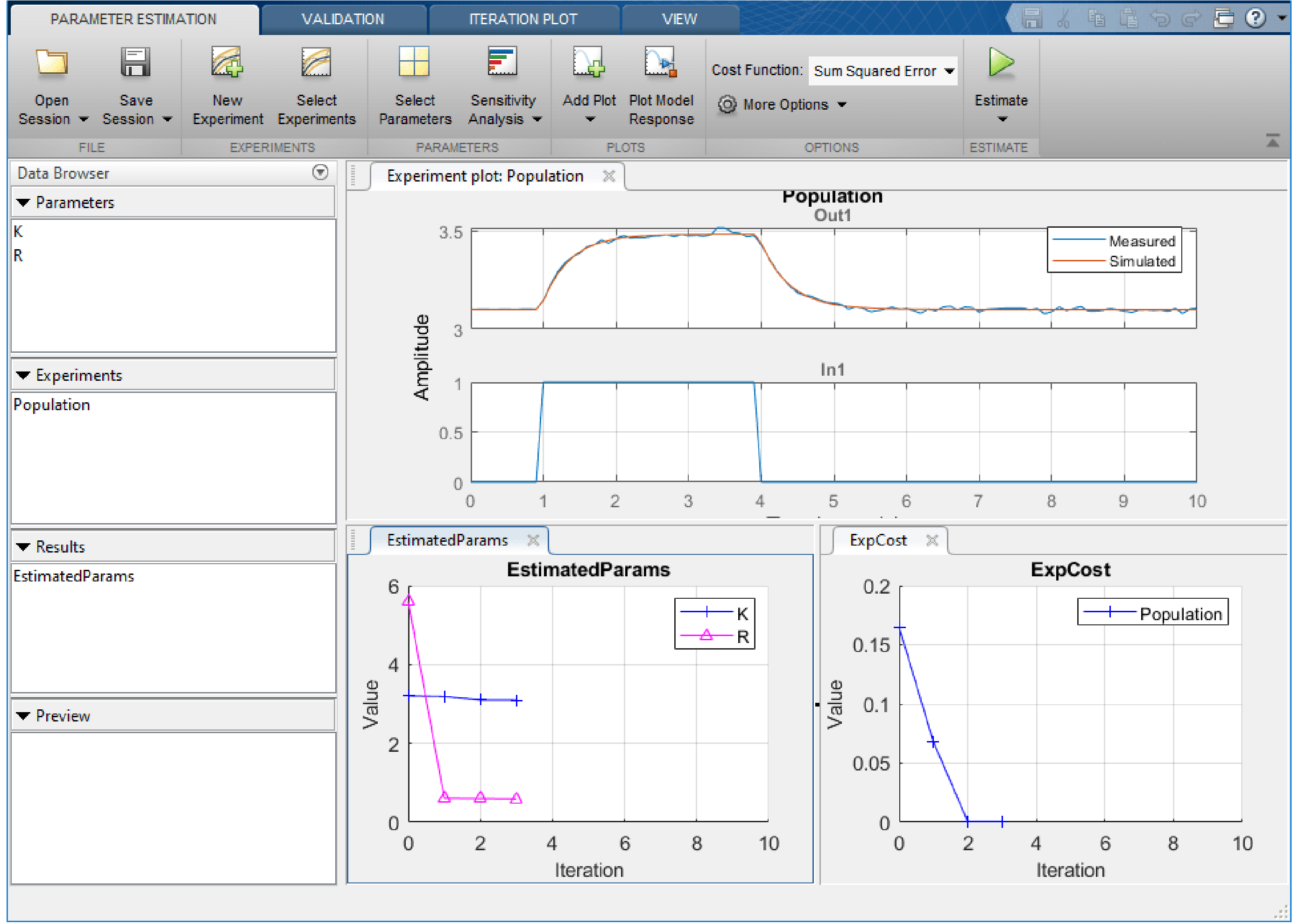


The input to the model is known from the experimental data for the population influx. Use the operating point dialog to specify that this input is known. This input will not be varied by the operating point computation during parameter estimation.



You can also specify options for computing the operating point, by using the options tab in the dialog. For example, the option `Gradient descent with projection` is often used to find the operating point for systems that use physical modeling.

After specifying to compute the operating point, click **Estimate** and perform parameter estimation again. There is no more transient at the beginning of the model response, and there is a much better match between the model response and measured data, which is also reflected by the lower objective/cost function value in the second optimization. This indicates that a good set of parameter values was found.



Related Examples

To learn how to put models in a steady state using the `sdo.optimize` command, see "Set Model to Steady-State When Estimating Parameters (Code)" on page 2-97.

Close the model.

```
bdclose('sdoPopulationInflux')
```

Estimate Model Parameters with Parameter Constraints (Code)

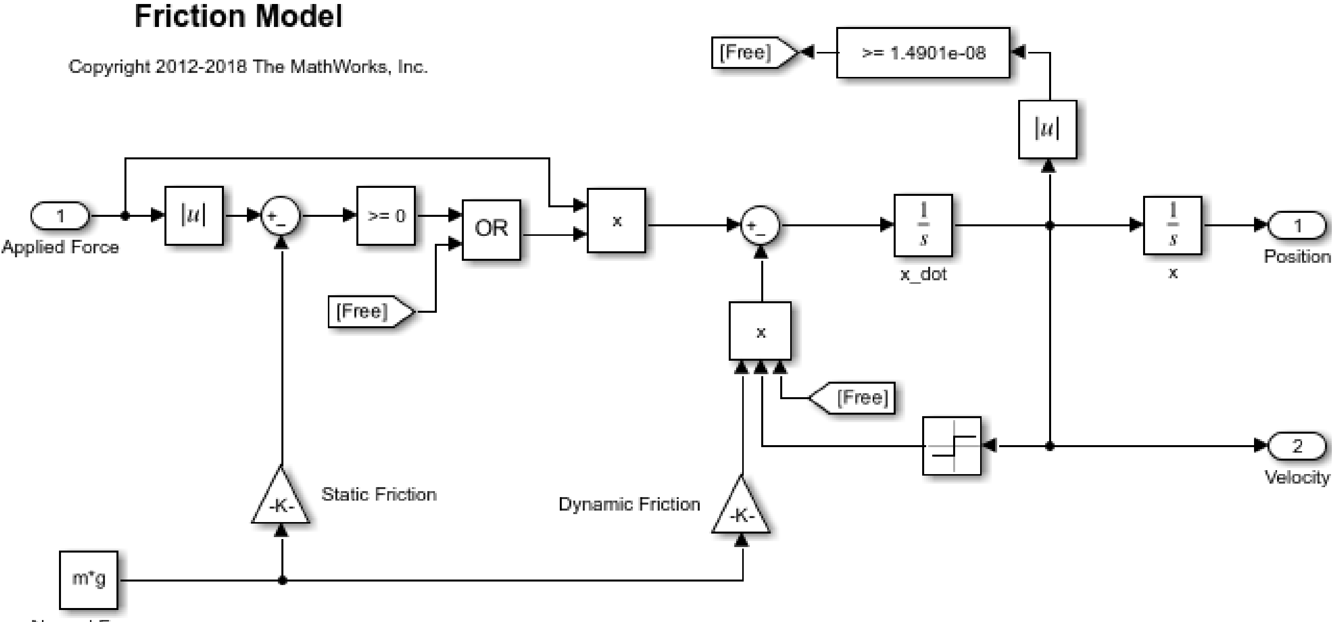
This example shows how to estimate model parameters while imposing constraints on the parameter values.

You estimate dynamic and static friction coefficients of a simple friction system.

Open the Model and Get Experimental Data

This example estimates parameters for a simple friction system, `sdoFriction`. The model input is the force applied to a mass and the model outputs are the mass position and velocity.

```
open_system('sdoFriction');
```



The model is based on a mass sliding on a surface. The mass is subject to a static friction that must be overcome before the mass moves and a dynamic friction once the mass moves. The static friction, `u_static`, is a fraction of the mass normal force; similarly the dynamic friction, `u_dynamic`, is a fraction of the mass normal force.

Load the experiment data. The mass was subjected to an applied force and its position recorded.

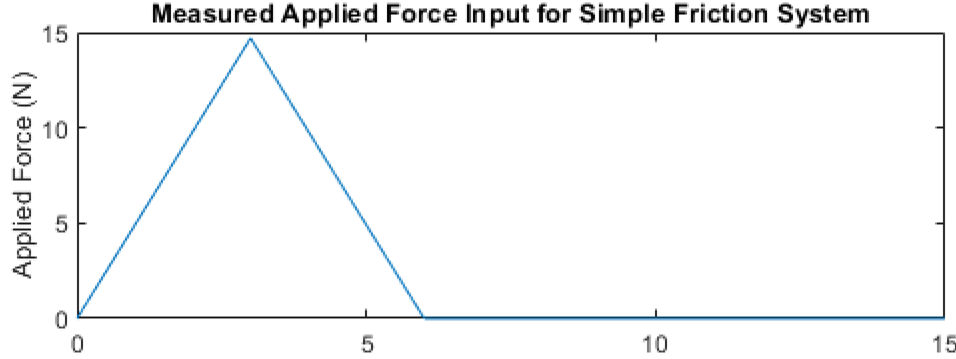
```
load sdoFriction_ExperimentData
```

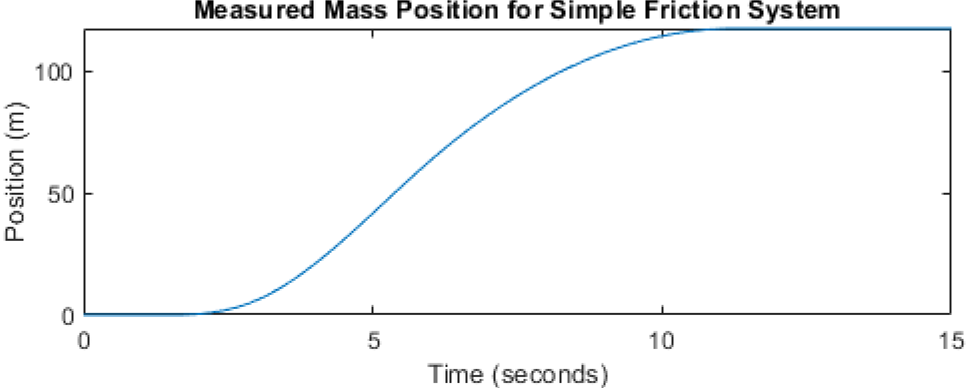
The variables `AppliedForce`, `Position`, and `Velocity` are loaded into the workspace. The first column of each of these variables represents time and the second column represents the measured data. Because velocity is the first derivative of position, only use the position measurements for this example.

Plot the Experiment Data

```
subplot(211),
plot(AppliedForce(:,1),AppliedForce(:,2))
```

```
title('Measured Applied Force Input for Simple Friction System');
ylabel('Applied Force (N)')
subplot(212)
plot(Position(:,1),Position(:,2))
title('Measured Mass Position for Simple Friction System');
xlabel('Time (seconds)')
ylabel('Position (m)')
```





Define the Estimation Experiment

Create an experiment object to specify the experiment data.

```
Exp = sdo.Experiment('sdoFriction');
```

Specify the input data (applied force) as a timeseries object.

```
Exp.InputData = timeseries(AppliedForce(:,2),AppliedForce(:,1));
```

Create an object to specify the measured mass position output.

```
PositionSig = Simulink.SimulationData.Signal;
PositionSig.Name      = 'Position';
PositionSig.BlockPath = 'sdoFriction/x';
PositionSig.PortType  = 'outport';
PositionSig.PortIndex = 1;
PositionSig.Values    = timeseries(Position(:,2),Position(:,1));
```

Add the measured mass position data to the experiment as the expected output data.

```
Exp.OutputData = PositionSig;
```

Compare the Measured Output and the Initial Simulated Output

Create a simulation scenario using the experiment and obtain the simulated output.

```
Simulator    = createSimulator(Exp);
Simulator    = sim(Simulator);
```

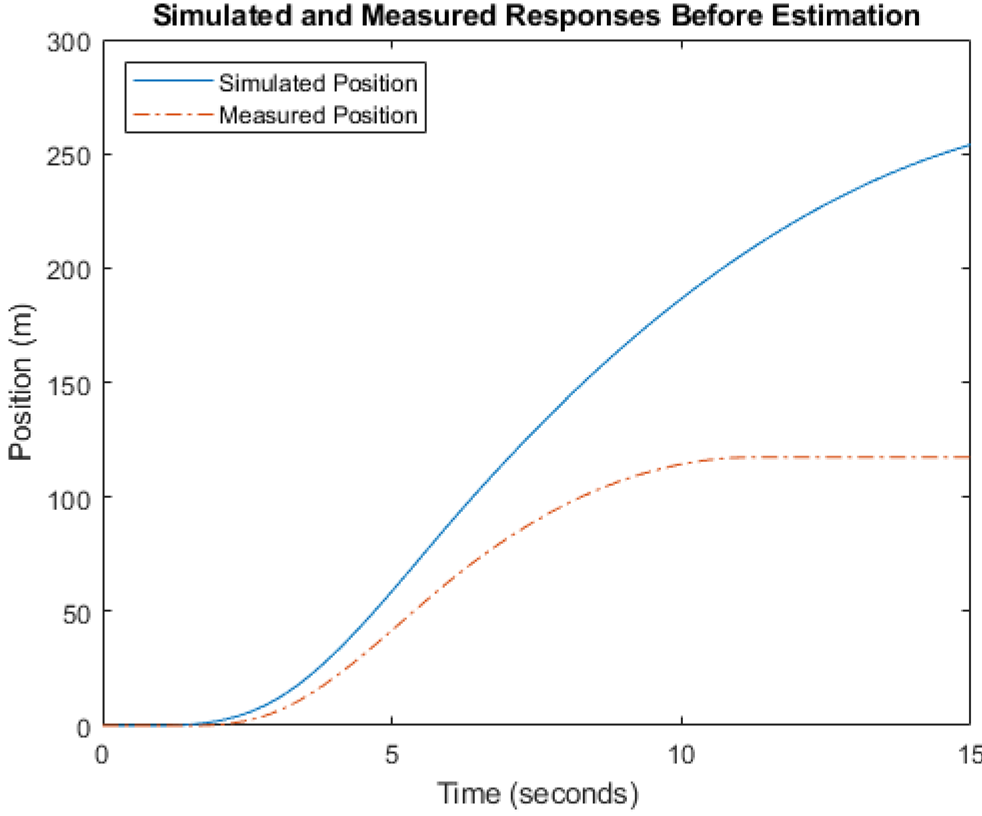
Search for the position signal in the logged simulation data.

```
SimLog     = find(Simulator.LoggedData,get_param('sdoFriction','SignalLoggingName'));
Position   = find(SimLog,'Position');
```

Plot the measured and simulated data.

As expected, the model response does not match the experimental output data.

```
figure
plot(...
    Position.Values.Time,Position.Values.Data, ...
    Exp.OutputData.Values.Time, Exp.OutputData.Values.Data,'-.')
title('Simulated and Measured Responses Before Estimation')
ylabel('Position (m)')
xlabel('Time (seconds)')
legend('Simulated Position','Measured Position','Location','NorthWest')
```



Specify Parameters to Estimate

Estimate the u_static and u_dynamic friction coefficients using the experiment data. These coefficients are used as gains in the Static Friction and Dynamic Friction blocks, respectively. Physics indicates that friction coefficients should be constrained so that u_static ≥ u_dynamic; this parameter constraint is implemented in the estimation objective function.

Select the u_static and u_dynamic model parameters. Specify bounds for the estimated parameter values. Both coefficients are limited to the range [0 1].

```
p = sdo.getParameterFromModel('sdoFriction',{'u_static','u_dynamic'});

p(1).Minimum = 0;
p(1).Maximum = 1;

p(2).Minimum = 0;
p(2).Maximum = 1;
```

Define the Estimation Objective

Create an estimation objective function to evaluate how closely the simulation output, generated using the estimated parameter values, matches the measured data.

Use an anonymous function with one input argument that calls the sdoFriction_Objective function. We pass the anonymous function to sdo.optimize, which evaluates the function at each optimization iteration.

```
estFcn = @(v) sdoFriction_Objective(v,Simulator,Exp);
```

The sdoFriction_Objective function:

- Has one input argument that specifies the estimated friction coefficients.
- Has one input argument that specifies the experiment object containing the measured data.
- Returns the sum-squared-error errors between simulated and experimental outputs, and returns the parameter constraint.

The sdoFriction_Objective function requires two inputs, but sdo.optimize requires a function with one input argument. To work around this, estFcn is an anonymous function with one input argument, v, but it calls sdoFriction_Objective using two input arguments, v and Exp.

For more information regarding anonymous functions, see “Anonymous Functions”.

The sdo.optimize command minimizes the return argument of the anonymous function estFcn, that is, the residual errors returned by sdoFriction_Objective. For more details on how to write an objective/constraint function to use with the sdo.optimize command, type help sdoExampleCostFunction at the MATLAB® command prompt.

To examine the estimation objective function in more detail, type edit sdoFriction_Objective at the MATLAB command prompt.

```
type sdoFriction_Objective
```

```
function vals = sdoFriction_Objective(p,Simulator,Exp)
%SDOFRICTION_OBJECTIVE
```

```
%
%    The sdoFriction_Objective function is used to compare model
%    outputs against experimental data and measure how well constraints are
%    satisfied.
%
%    vals = sdoFriction_Objective(p,Exp)
%
%    The |p| input argument is a vector of estimated model parameter values.
%
%    The |Simulator| input argument is a simulation object used
%    simulate the model with the estimated parameter values.
%
%    The |Exp| input argument contains the estimation experiment data.
%
%    The |vals| return argument contains information about how well the
%    model simulation results match the experimental data and how well
%    constraints are satisfied. The |vals| argument is used by the
%    |sdo.optimize| function to estimate the model parameters.
%
%    See also sdo.optimize, sdoExampleCostFunction, sdoFriction_cmddemo
%

% Copyright 2012-2015 The MathWorks, Inc.

%%
% Define a signal tracking requirement to compute how well the model output
% matches the experiment data. Configure the tracking requirement so that
% it returns the sum-squared-error.
%
r = sdo.requirements.SignalTracking;
r.Type   = '==';
r.Method = 'SSE';

%%
% Update the experiments with the estimated parameter values.
%
Exp  = setEstimatedValues(Exp,p);

%%
% Simulate the model and compare model outputs with measured experiment
% data.
%
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);

SimLog  = find(Simulator.LoggedData,get_param('sdoFriction','SignalLoggingName'));
Position = find(SimLog,'Position');

PositionError = evalRequirement(r,Position.Values,Exp.OutputData(1).Values);

%%
% Measure how well the parameters satisfy the friction coefficient constraint,
% |u_static| >= |u_dynamic|. Note that constraints are returned to the
% optimizer in a c <=0 format. The friction coefficient constraint is
% rewritten accordingly.
PConstr =  p(2).Value - p(1).Value; % u_dynamic - u_static <= 0

%%
```

```
% Return the sum-squared-error and constraint violation to the optimization
% solver.
%
vals.F    = PositionError(:);
vals.Cleq = PConstr;
end
```

The friction coefficient constraint, `u_static` $\geq$ `u_dynamic`, is implemented in the `sdoFriction_Objective` function as `u_dynamic - u_static` ≤ 0. This is because the optimizer requires constraint values in a $c \leq 0$ format. For more information, type `help sdo.optimize` at the MATLAB command prompt.

Estimate the Parameters

Use the `sdo.optimize` function to estimate the friction model parameter values.

Specify the optimization options. The estimation function `sdoFriction_Objective` returns the sum-squared-error between simulated and experimental data and includes a parameter constraint. The default `'fmincon'` solver is ideal for this type of problem.

Estimate the parameters.

```
pOpt = sdo.optimize(estFcn,p)
```

```
 Optimization started 01-Sep-2022 14:24:13

                               max                     First-order 
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      5      27.7267            0
    1     11      22.5643            0         2.21         72.9
    2     15      17.4771            0         0.51           16
    3     22      0.76336            0         1.33         10.7
    4     29     0.408381            0        0.263         3.15
    5     34    0.0255292            0       0.0897         1.22
    6     39   0.00527178            0       0.0295        0.271
    7     44   0.00405706            0         0.02        0.177
    8     49   0.00111788            0        0.109        0.176
    9     63   0.00111788            0      0.00176        0.176
Local minimum possible. Constraints satisfied.

fmincon stopped because the size of the current step is less than
the value of the step size tolerance and constraints are
satisfied to within the value of the constraint tolerance.

pOpt(1,1) =

       Name: 'u_static'
      Value: 0.8224
    Minimum: 0
    Maximum: 1
       Free: 1
      Scale: 0.5000
       Info: [1x1 struct]


pOpt(2,1) =
```

```
       Name: 'u_dynamic'
      Value: 0.3973
    Minimum: 0
    Maximum: 1
       Free: 1
      Scale: 0.2500
       Info: [1x1 struct]


2x1 param.Continuous
```

Compare the Measured Output and the Final Simulated Output

Update the experiments with the estimated parameter values.

```
Exp  = setEstimatedValues(Exp,pOpt);
```

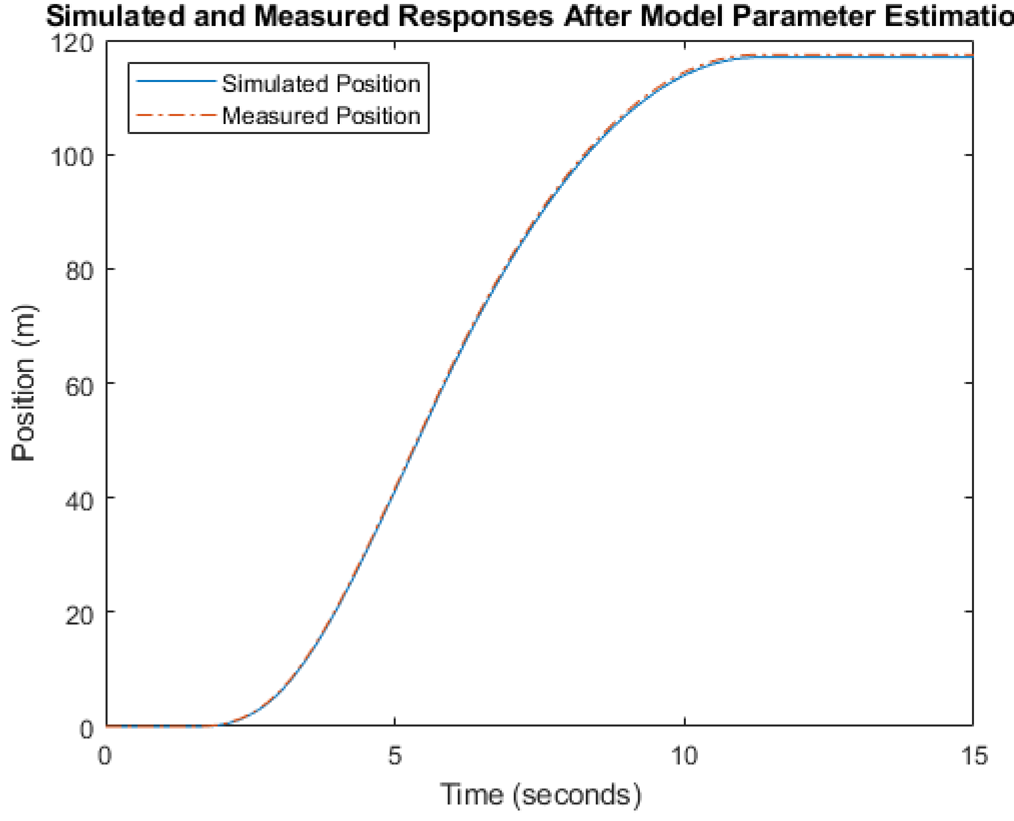
Obtain the simulated output for the experiment.

```
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);
SimLog    = find(Simulator.LoggedData,get_param('sdoFriction','SignalLoggingName'));
Position  = find(SimLog,'Position');
```

Plot the measured and simulated data.

It can be seen that the model response using the estimated parameter values nicely matches the experiment output data.

```
plot(...
    Position.Values.Time,Position.Values.Data, ...
    Exp.OutputData.Values.Time, Exp.OutputData.Values.Data,'-.')
title('Simulated and Measured Responses After Model Parameter Estimation')
ylabel('Position (m)')
xlabel('Time (seconds)')
legend('Simulated Position','Measured Position','Location','NorthWest')
```



Update the Model Parameter Values

Update the model `u_static` and `u_dynamic` parameter values.

```
sdo.setValueInModel('sdoFriction',pOpt);
```

Close the model.

```
bdclose('sdoFriction')
```

Importing and Preprocessing Experiment Data (GUI)

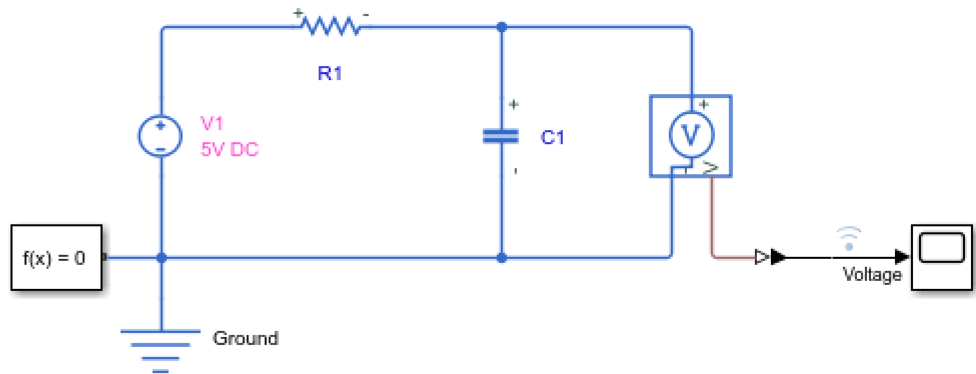
This example shows how to create an estimation experiment from measured data stored in a file and how to preprocess the measured data. You use the imported data to estimate the parameters of a simple RC circuit.

This example requires Simscape™ software.

RC Circuit Model

The Simulink® model, `sdoRCCircuit`, models a simple resistor-capacitor (RC) circuit.

```
open_system('sdoRCCircuit');
```



You use measured data to estimate the RC model parameter and state values.

Measured output data:

- Capacitor voltage, output of the PS-Simulink Converter block

Parameter:

- Capacitance, `C1`, used by the C1 block

State:

- Initial voltage of the capacitor

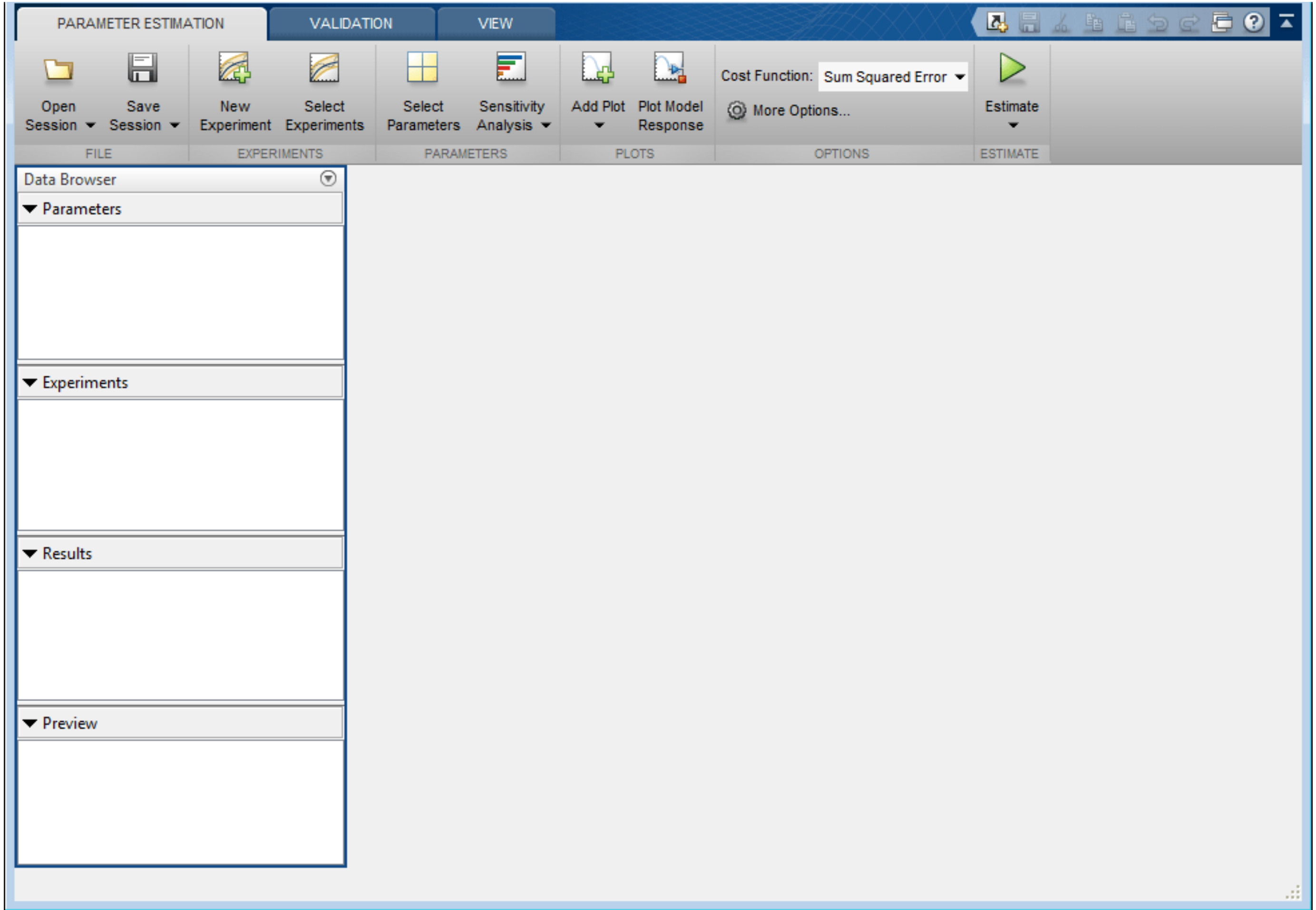
Define the Estimation Experiment

In this example, you load the measured data from a saved MATLAB® file. The data is also stored in a comma separated variable (csv) text file. You can also load the measured data directly from text or Excel® files.

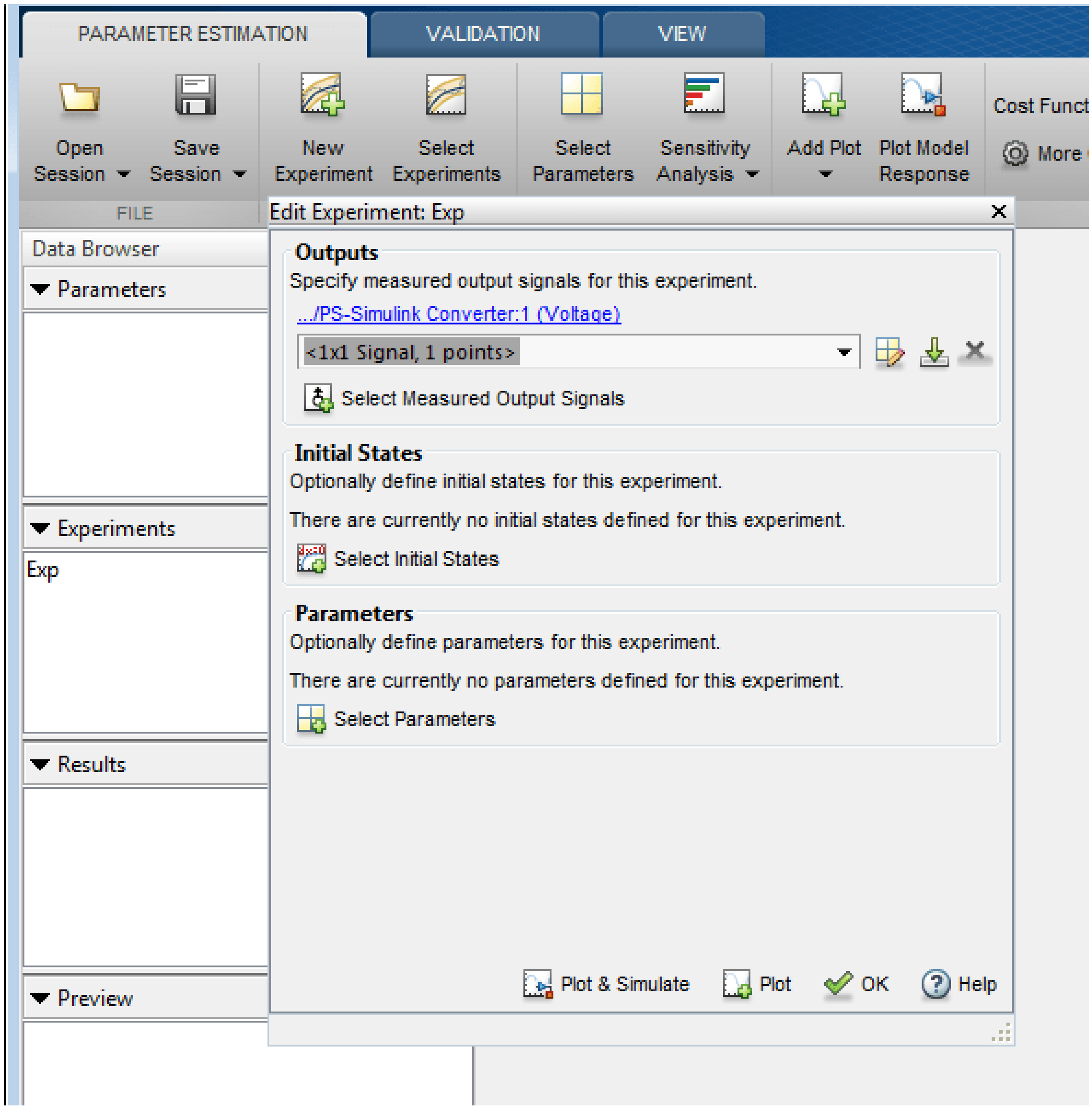
First load the measured data from the MATLAB file, the file defines two variables, `time` and `data` that specify the measured capacitor voltage.

```
load sdoRCCircuit_ExperimentData
```

To launch the **Parameter Estimator**, in the Simulink model window, in the **Apps** gallery, under **Control Systems**, click **Parameter Estimator**.



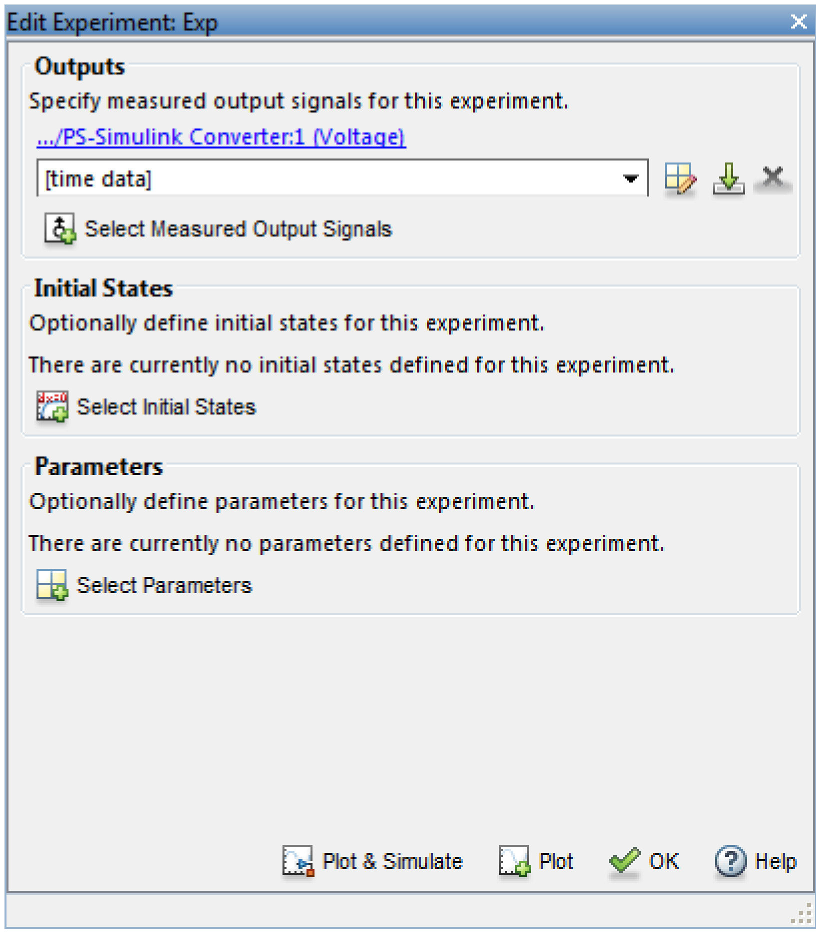
Click **New Experiment** to create an estimation experiment that contains the measured data. A variable Exp is created in the **Parameter Estimator** and a dialog to edit the experiment opens.



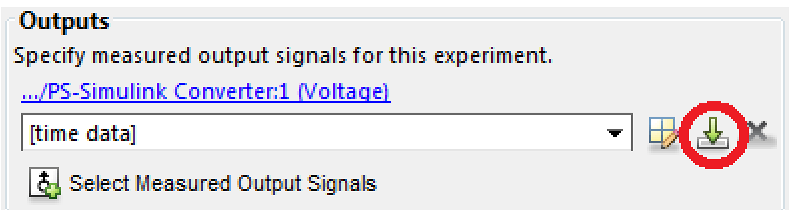
The experiment editor contains sections to specify measured output data and sections to optionally specify experiment initial states and parameters.

The experiment editor automatically adds measured output signals for model root level ports and logged model signals. Click **Select Measured Output Signals** to add additional measured outputs if needed. For this example the capacitor voltage signal is logged in the model and already added to the experiment.

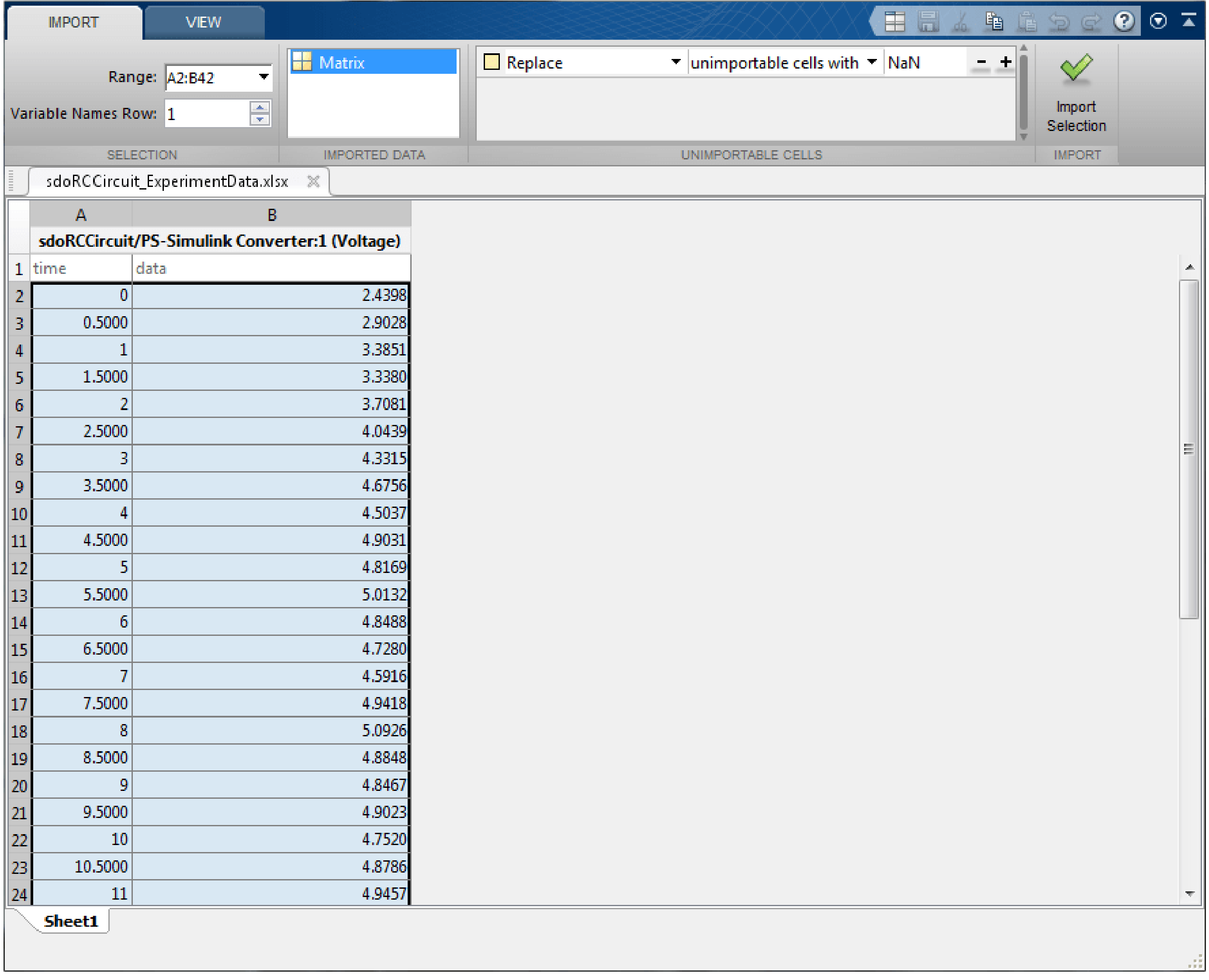
Specify the measured capacitor voltage by typing `[time data]` in the edit field. This uses the MATLAB variables `time` and `data` loaded from file earlier to specify the measured capacitor voltage. Measured data is specified as a matrix where the 1st column is time and subsequent columns signal data.



Alternatively, you can specify the measured capacitor voltage variables by loading the measured data directly from text or Excel files. Click the import button to open a file browser and select `sdoRCCircuit_ExperimentData.csv` file.

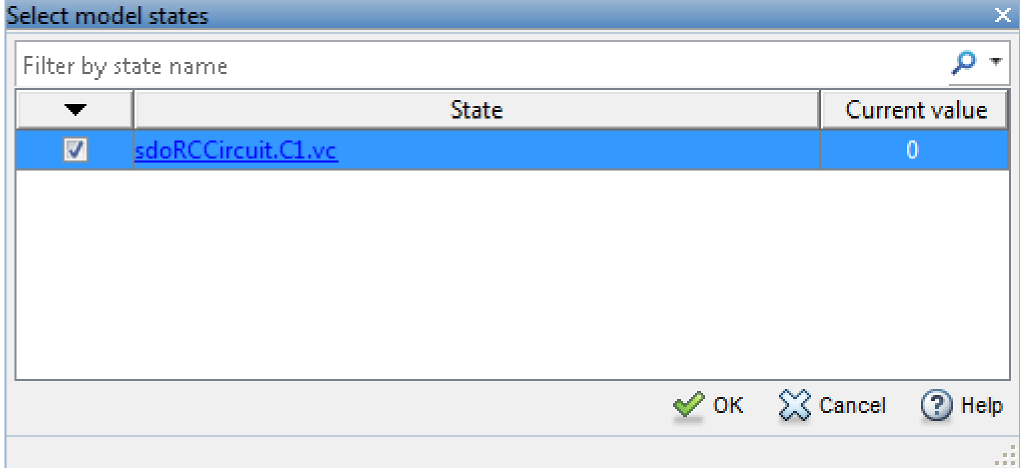


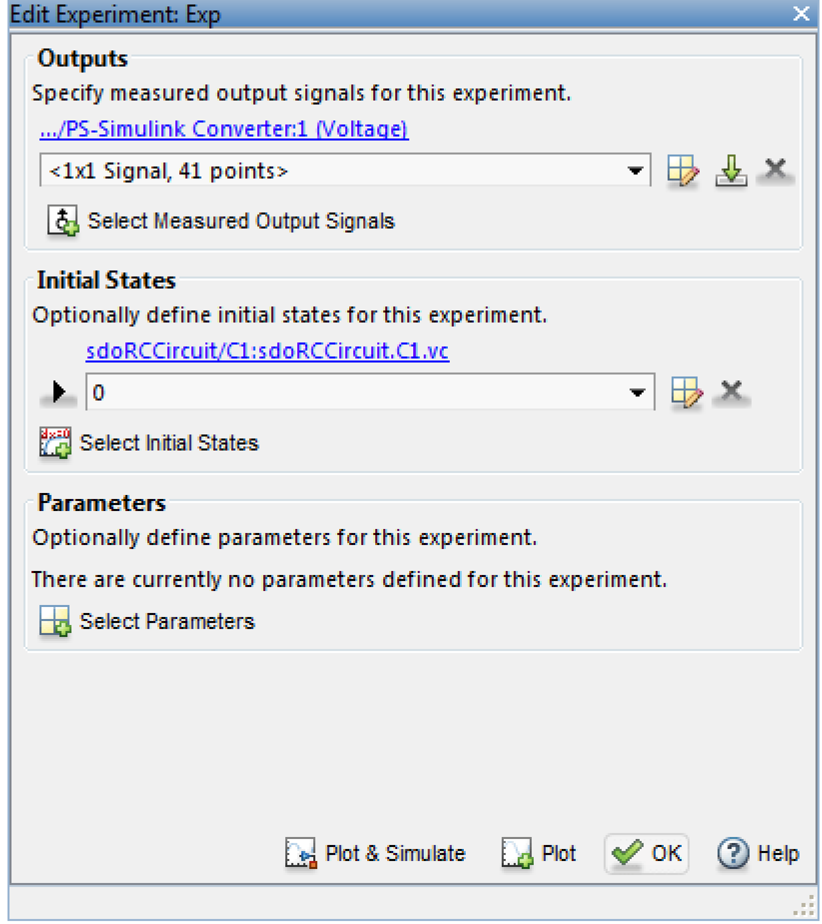
A tool for importing column data from a file opens. The first column selected for import is used to specify the signal time, subsequent columns selected for import are used to specify the signal data. Select the `time` and `data` columns and click **Import Selection**.



In the experiment editor click **Plot & Simulate** to plot the measured experiment data and the simulated model response.

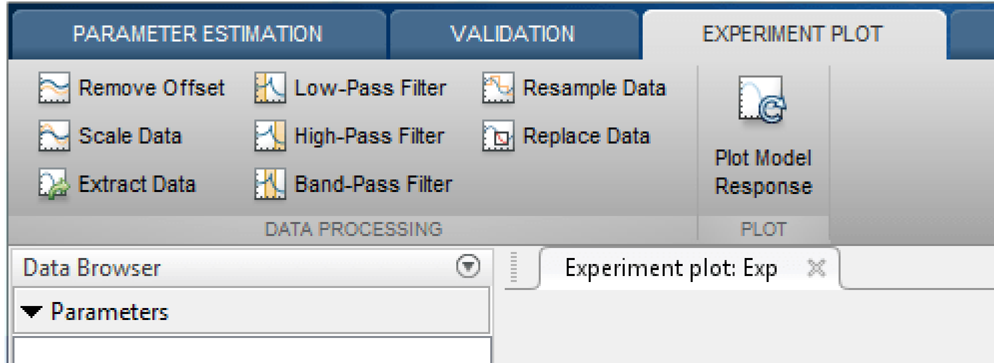
The experiment plot shows that the simulated data does not match the measured data. The plot also shows that the model initial state is not correct and needs to be estimated (the measured and simulated voltages at time 0 are significantly different). From the experiment editor, click **Select Initial States** to open a dialog to select model initial states; select the `sdoRCCircuit.C1.vc` state and click **Ok** to add the state to the experiment.



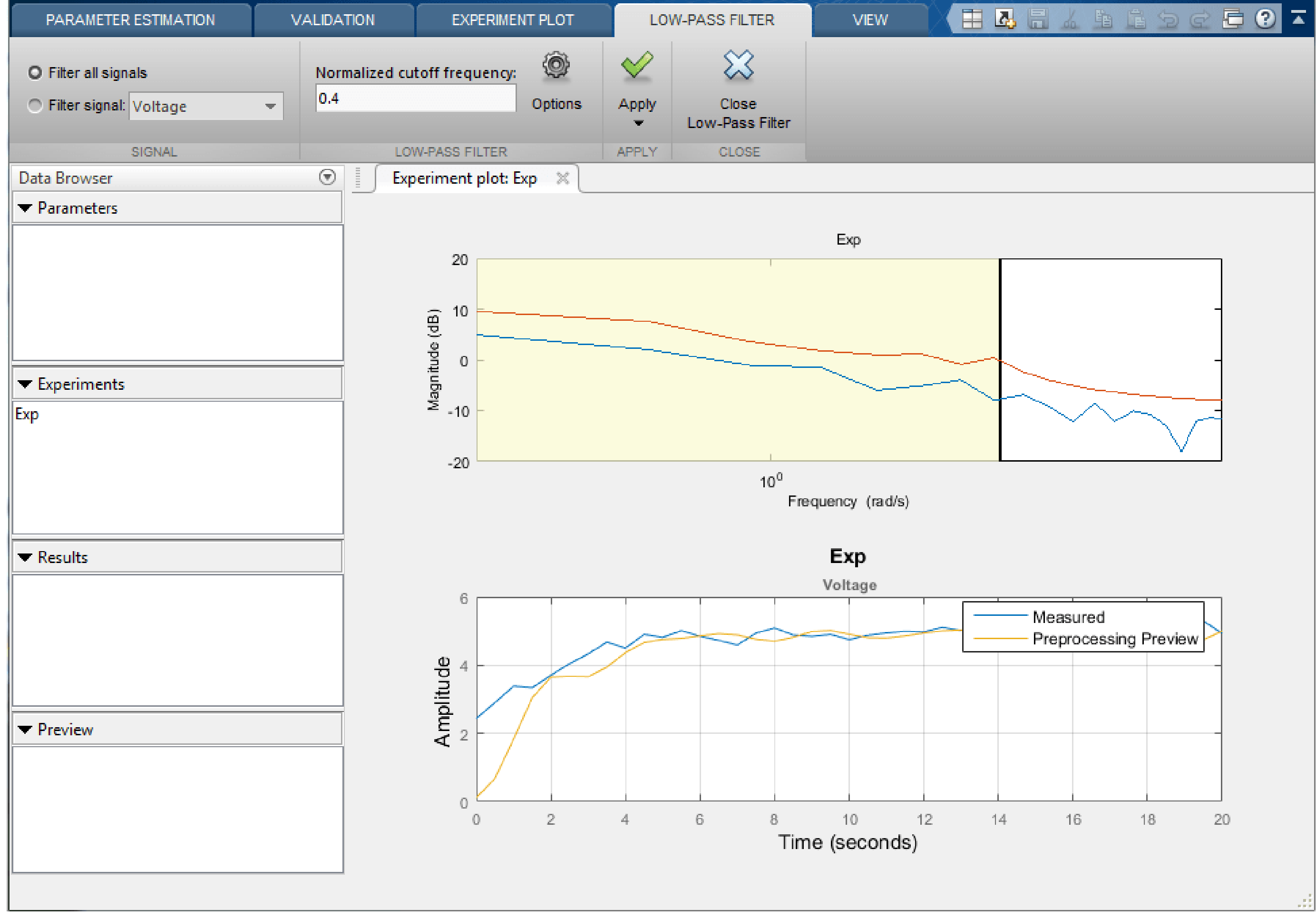


Preprocess the Experiment Data

The measured data contains high frequency noise that you can remove using a low-pass filter. Click the **Experiment Plot** tab and select **Low Pass Filter**.



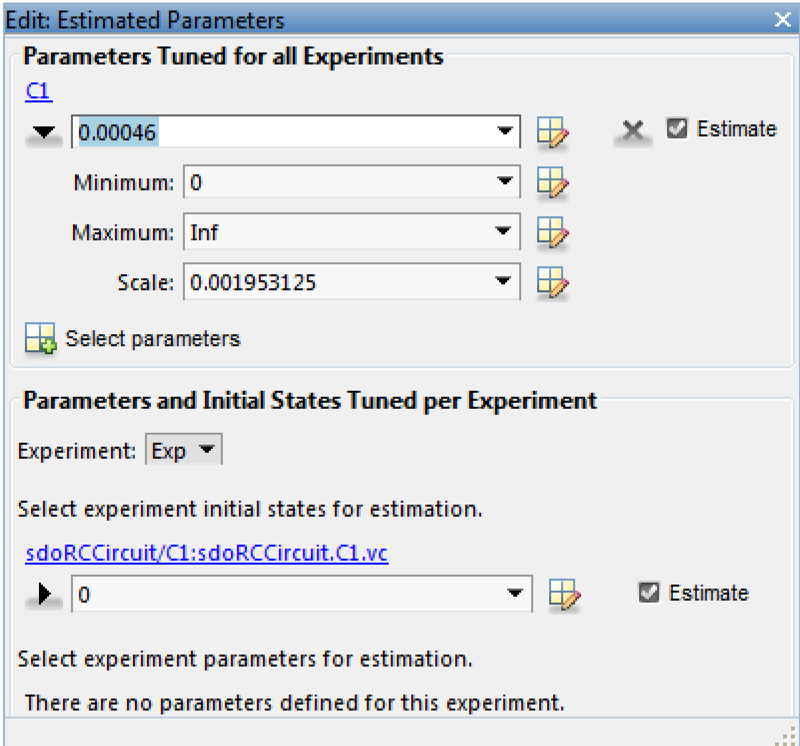
This opens the Low-Pass Filter tool. The upper axis shows the signal FFT, the lower axis shows the signals. The original signal is shown in blue and the filtered signal in red. Adjust the filter bandwidth by either typing a value in the **Normalized cutoff frequency** edit field or clicking and dragging the yellow patch edge. Drag the filter cutoff to 0.4. Click **Options** and select **Zero-phase shift filter** to avoid introducing the filter phase shift into the measured data.



Click **Apply** and **Close Low-Pass Filter** to complete low-pass filtering of the data. The experiment is updated with the filtered signal. You can use other preprocessing tools such as remove offset, scale, and resample to further process the measured data. For this example low-pass filtering is sufficient.

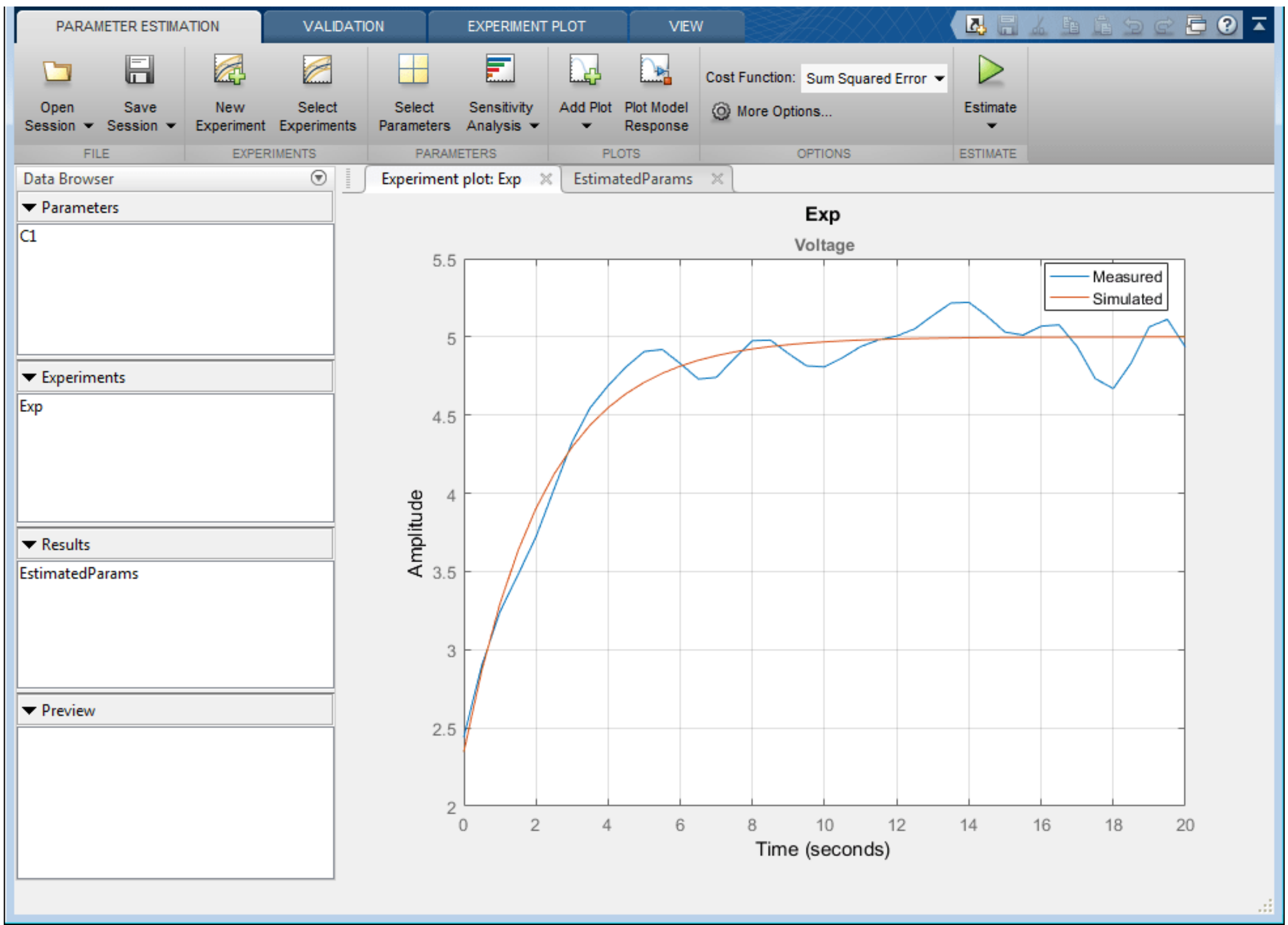
Estimate Model Parameter Values

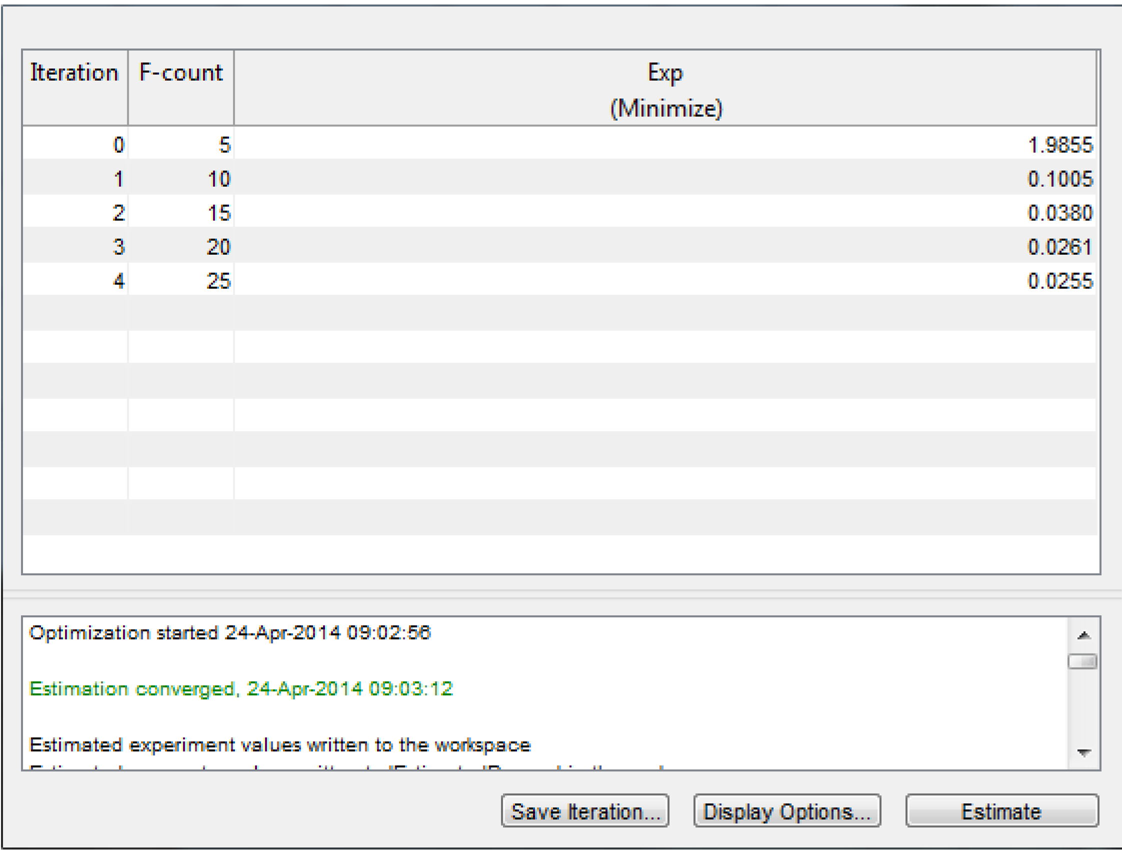
With the experiment data configured and preprocessed you can now run an estimation. First select parameters to estimate. Click the **Parameter Estimation** tab and select **Select Parameters**. A dialog to specify model parameters for estimation opens. Click **Select Parameters** and select, `C1`, the circuit capacitor value. Set the capacitor minimum value to 0 and the initial guess to 460e-6.



Click **Estimate** to start the estimation. You can modify estimation options by setting the **Cost Function** combobox and clicking **More Options**.

While the estimation is running, the plots update and a dialog showing estimation progress appears. The progress dialog shows the estimation iterations, the number of times the model has been evaluated (F-count), and the estimation cost at each iteration.


PARAMETER ESTIMATION
VALIDATION
EXPERIMENT PLOT
VIEW
Open Session
Save Session
New Experiment
Select Experiments
Select Parameters
Sensitivity Analysis
Add Plot
Plot Model Response
Cost Function:
Sum Squared Error
More Options...
Estimate
FILE
EXPERIMENTS
PARAMETERS
PLOTS
OPTIONS
ESTIMATE
Data Browser
Parameters
C1
Experiments
Exp
Results
EstimatedParams
Preview
Experiment plot: Exp
EstimatedParams
Exp
Voltage
Measured
Simulated
Amplitude
Time (seconds)



After a number of iterations the estimation converges and terminates. The model is updated with the estimated parameters and the estimation results are saved in the data browser.

Related Examples

To learn how to estimate model parameters using the `sdo.optimize` command, see “Estimate Model Parameters and Initial States (Code)” on page 2-67.

Close the model.

```
bdclose('sdoRCCircuit')
```

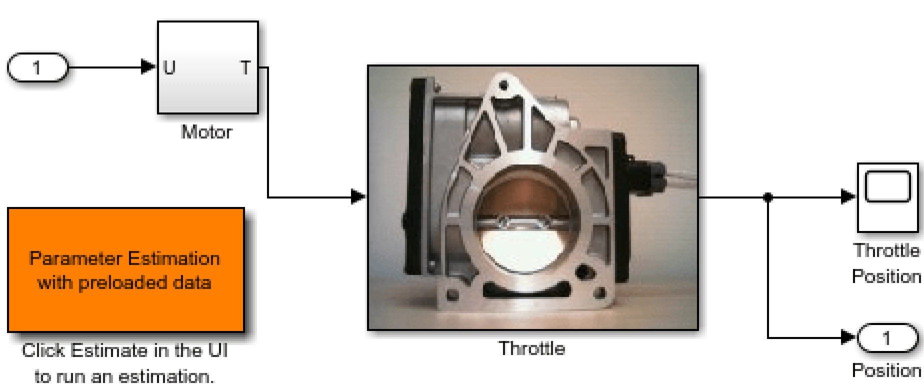
Estimate Model Parameter Values (GUI)

This example shows how to use experiment data to estimate model parameters. You estimate the parameters of an engine throttle system.

Engine Throttle System Model

Open the Simulink® model.

```
open_system('spe_engine_throttle')
```



Throttle Model Description

The throttle controls the air mass flow into the intake manifold of an engine. The throttle body contains a butterfly valve that opens when the driver presses down on the accelerator pedal. This lets more air enter the cylinders and causes the engine to produce more torque.

A DC motor controls the opening angle of the butterfly valve. There is also a spring attached to the valve to return it to its closed position when the DC motor is de-energized. The amount of rotation of the valve is limited to approximately 90 degrees. Therefore, if a large command input is applied to the motor, the valve hits the hard stops preventing it from rotating further.

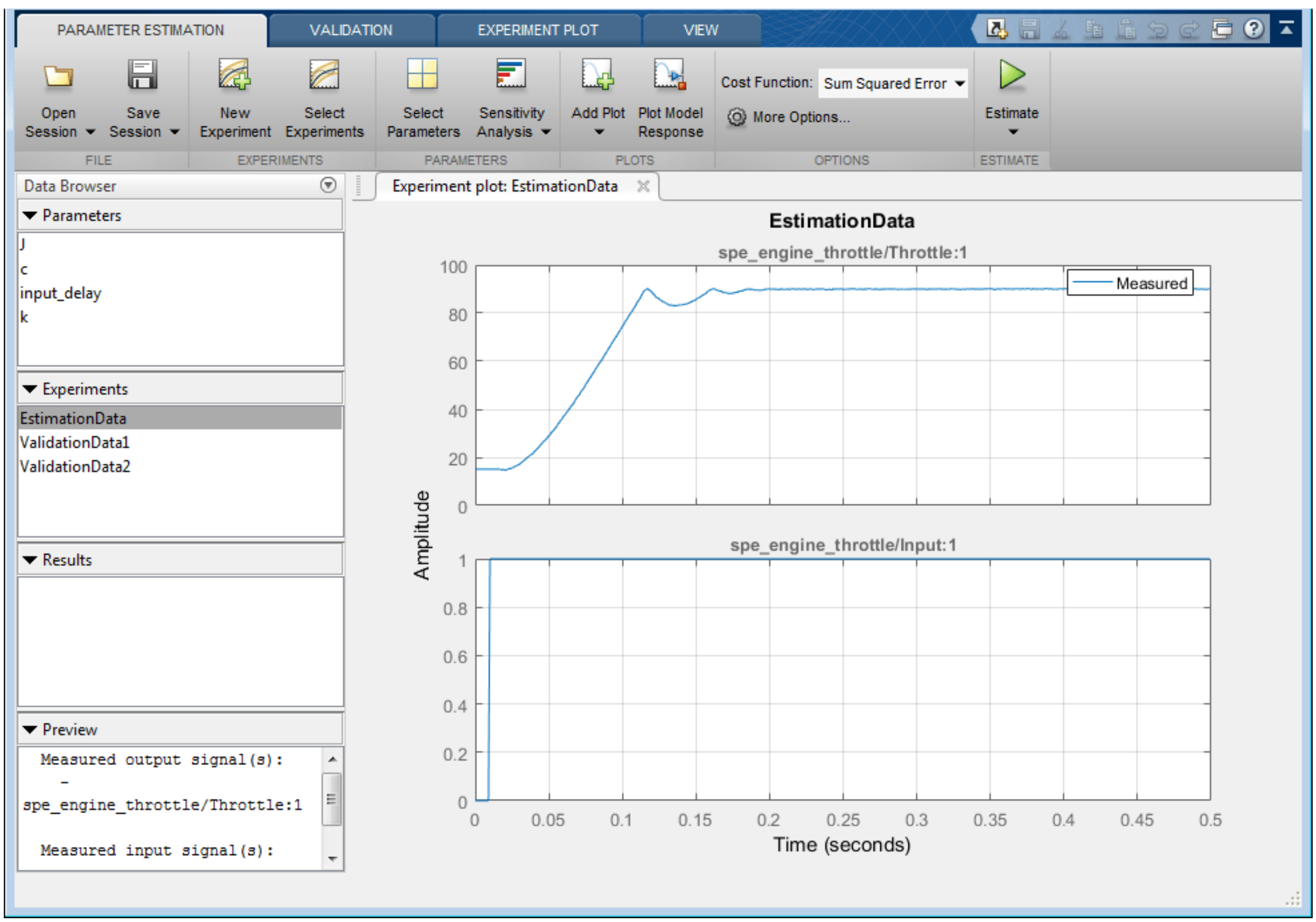
The motor is modeled as a torque gain and a time-delay input with parameters Kt and input_delay. The butterfly valve is modeled as a mass-spring-damper system with parameters J, c and k. This system is augmented with hard stops to limit the valve opening to 90 degrees. The model components are known, however, the parameter values of the system are not known accurately.

Estimation Experiment Data

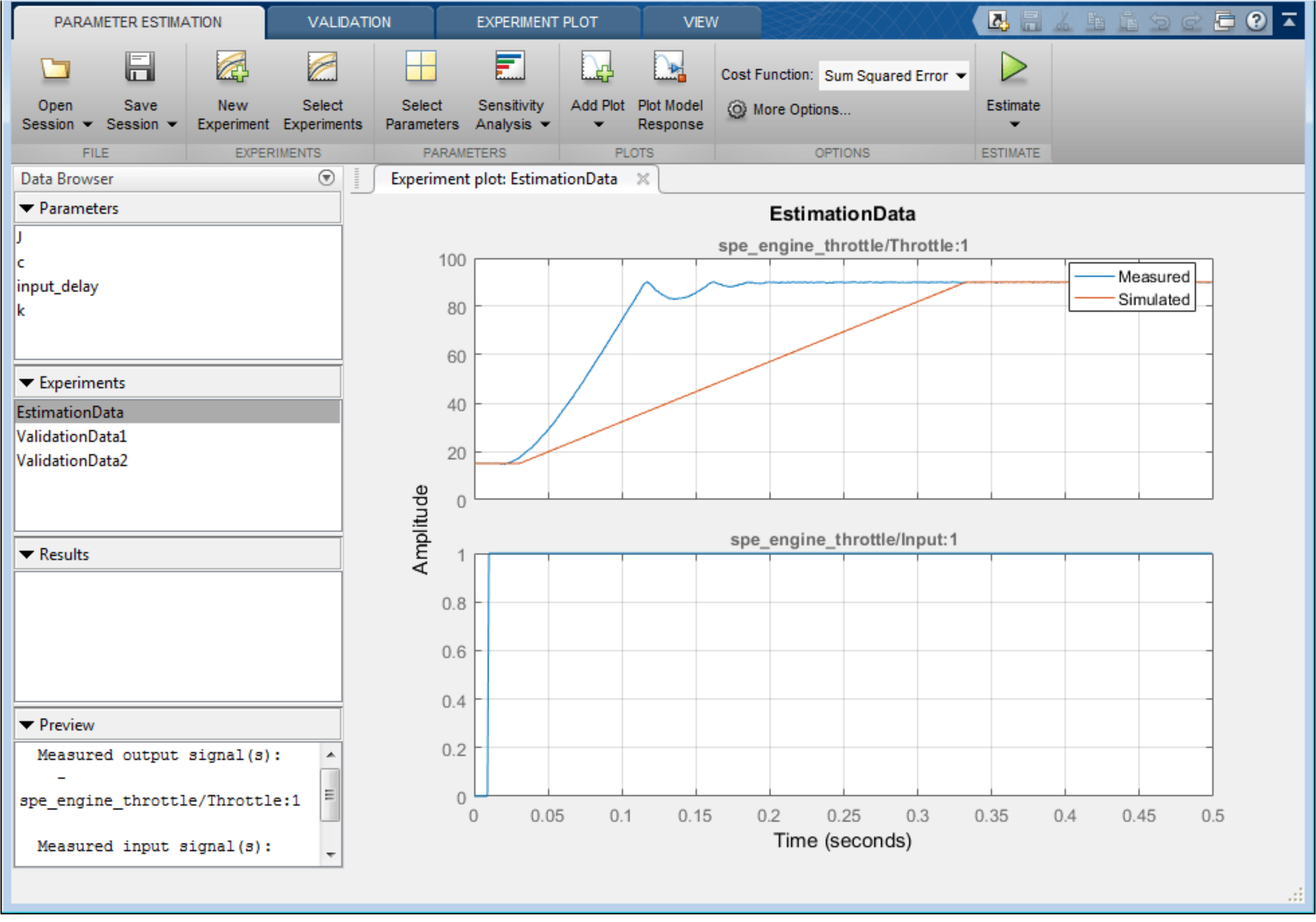
Double-click the Parameter Estimation with preloaded data block in the model to open a pre-configured estimation GUI session.

The saved estimation project defines three experiments; the `EstimationData` experiment is used for parameter estimation, while `ValidationData1`, `ValidationData2` are used for validating the estimated parameters. The `EstimateData` experiment is plotted.

The signal data for the experiments can be imported from various sources including MATLAB® variables, MAT files, Excel® files, or comma-separated-value files. See “Importing and Preprocessing Experiment Data (GUI)” on page 2-133 for more information.



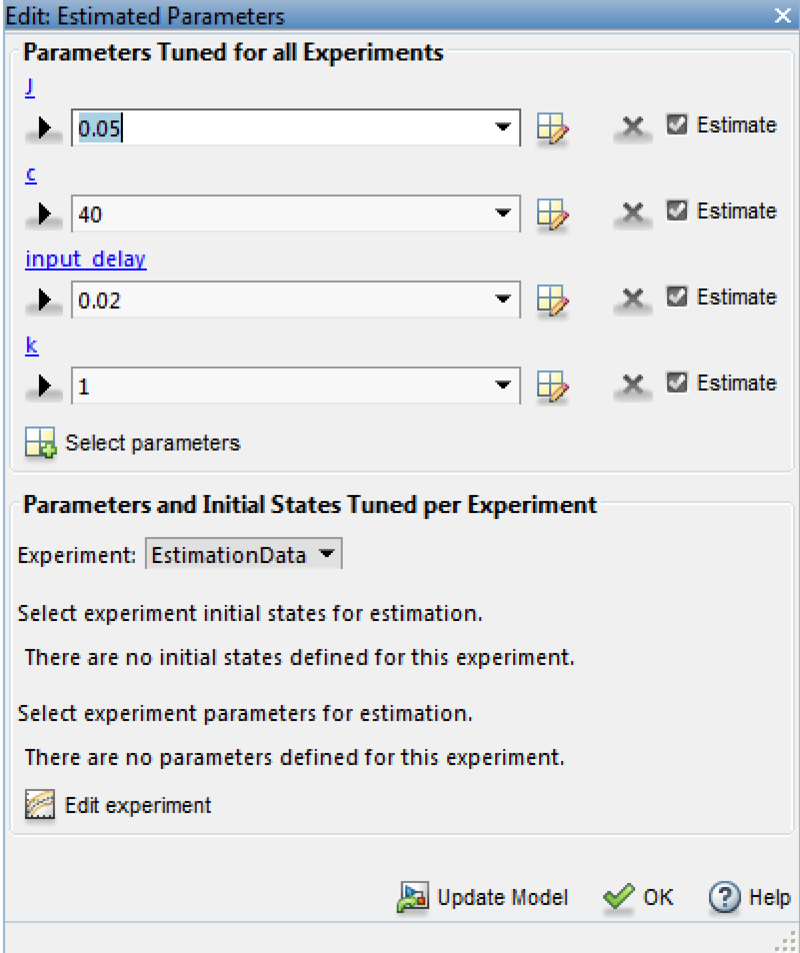
The experiment plot is also used to see how well the measured data matches the current model. Click **Plot Model Response** to display simulated signal data on the experiment plots.



The simulation results show that the model does not match the measured data and that model parameters need to be estimated.

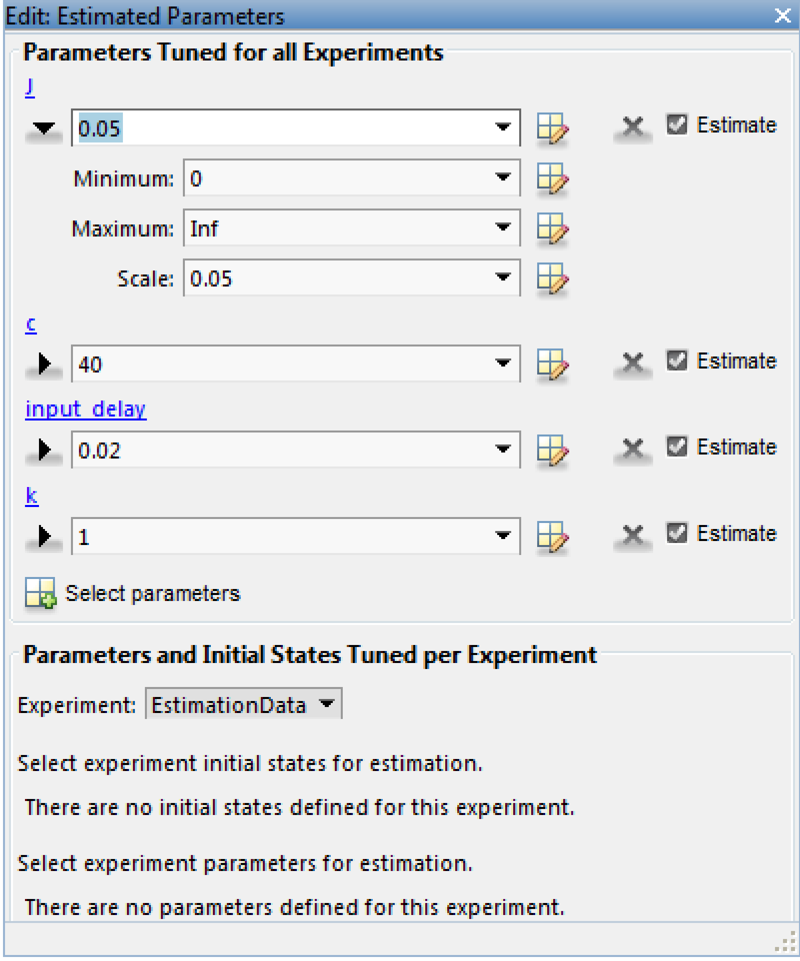
Estimated Parameters

The next step is to define the parameter to estimate. Click **Select Parameters** to open a dialog to select model parameters to estimate. This example contains four unknown parameters; the butterfly valve inertia, `J`; the damping coefficient, `c`; the return spring constant, `k`; the time lag in motor response, `input_delay`.



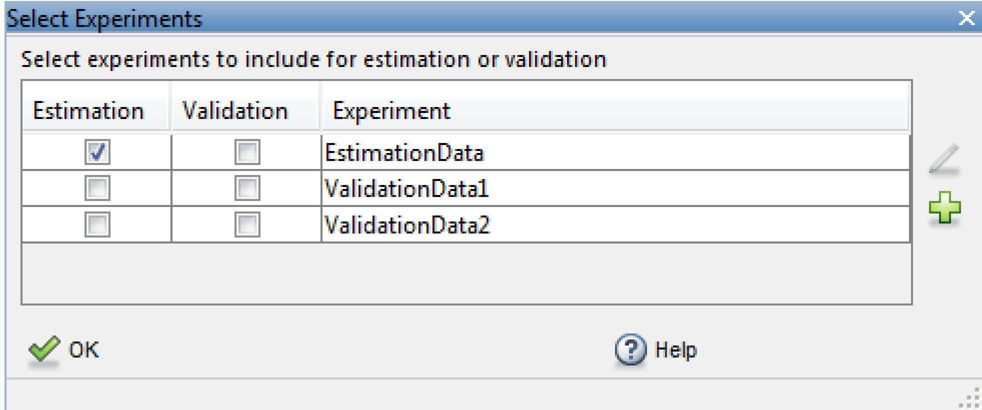
Since it is known from physical insight that all of these parameters have positive values, set their lower limits to zero. Also, put an upper bound of 0.1 sec on the `input_delay` parameter. You can also select an initial value for the parameters. These can come from some quick calculations of some formulas that determine the parameters.

Click the right arrow toggle button to modify the parameter minimum and maximum bounds.



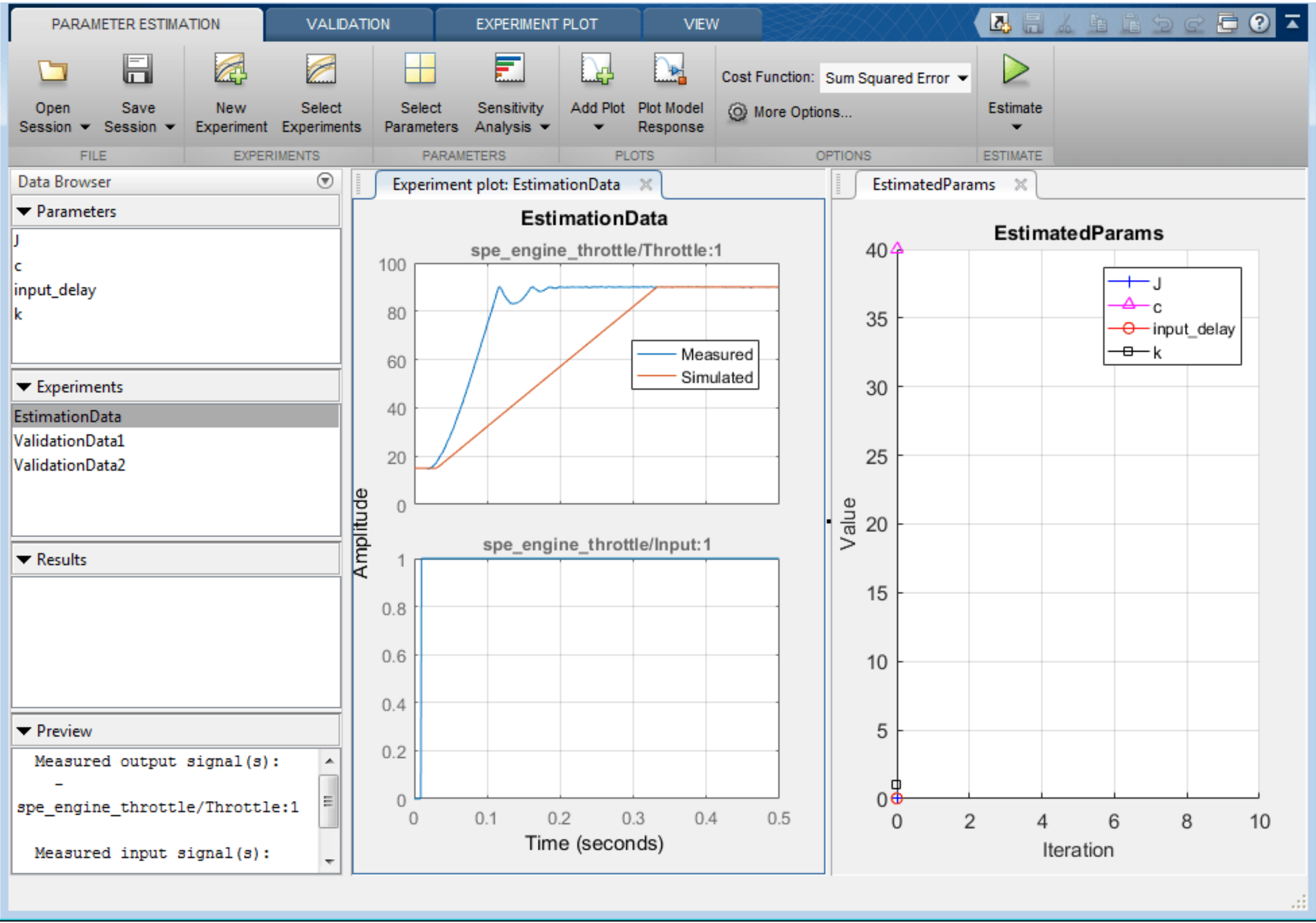
The Estimation Task

After selecting the parameters for estimation, select the experiments to use for estimation. Click **Select Experiments** and select `EstimationData` for estimation.



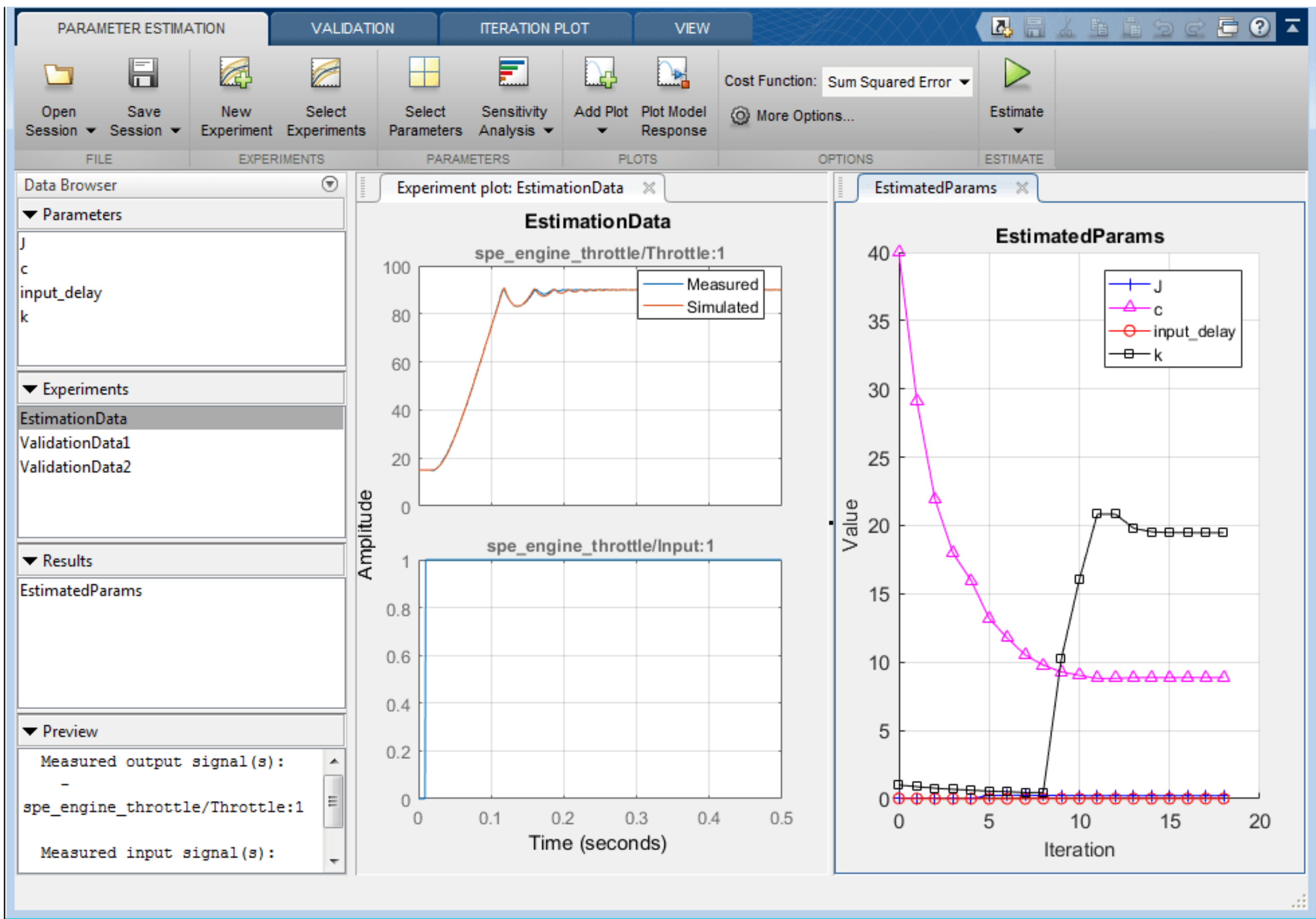
You can now start the estimation but first create plots to monitor the estimation progress. Click **Add Plot** and select **Parameter Trajectory**. This creates a plot that shows how the estimated parameter

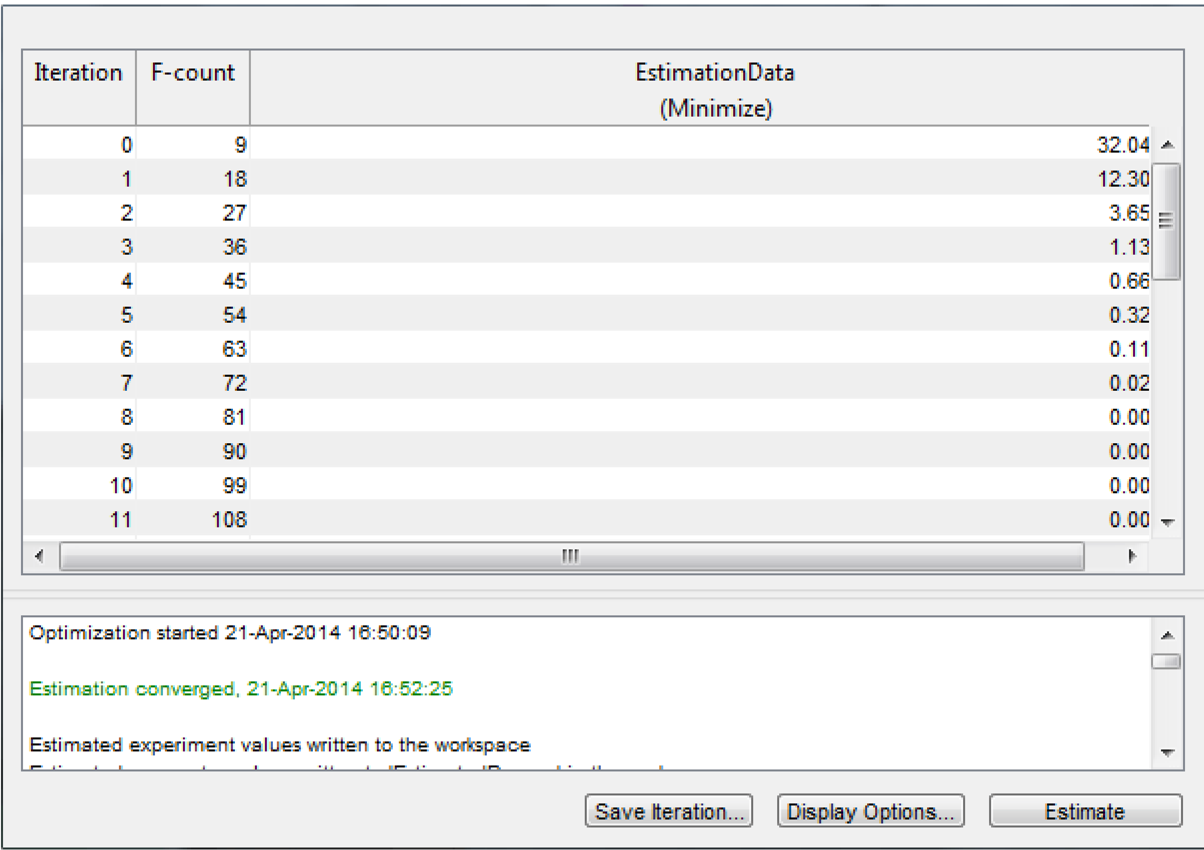
values change during estimation. Click the **View** tab to layout the plots so that **Experiment plot:EstimationData** and **EstimatedParams** are both visible.



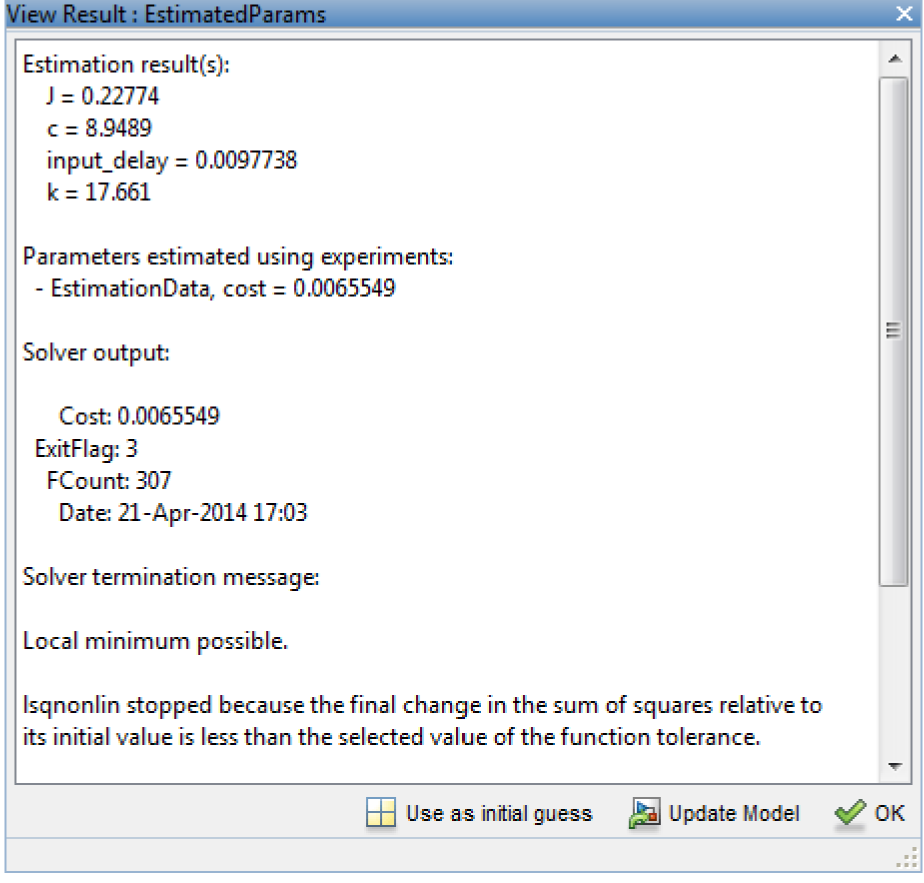
Click the **Estimate** button to start the estimation. You can modify estimation options by setting the **Cost Function** combobox and clicking **More Options**.

While the estimation is running, the plots update and a dialog showing estimation progress appears. The progress dialog shows the estimation iterations, the number of times the model has been evaluated (F-count), and the estimation cost at each iteration.


PARAMETER ESTIMATION
VALIDATION
ITERATION PLOT
VIEW
Open Session
Save Session
New Experiment
Select Experiments
Select Parameters
Sensitivity Analysis
Add Plot
Plot Model Response
Cost Function: Sum Squared Error
More Options...
Estimate
FILE
EXPERIMENTS
PARAMETERS
PLOTS
OPTIONS
ESTIMATE
Data Browser
Parameters
J
c
input_delay
k
Experiments
EstimationData
ValidationData1
ValidationData2
Results
EstimatedParams
Preview
Measured output signal(s):
-
spe_engine_throttle/Throttle:1
Measured input signal(s):
Experiment plot: EstimationData
EstimationData
spe_engine_throttle/Throttle:1
Measured
Simulated
spe_engine_throttle/Input:1
Amplitude
Time (seconds)
EstimatedParams
J
c
input_delay
k
Value
Iteration



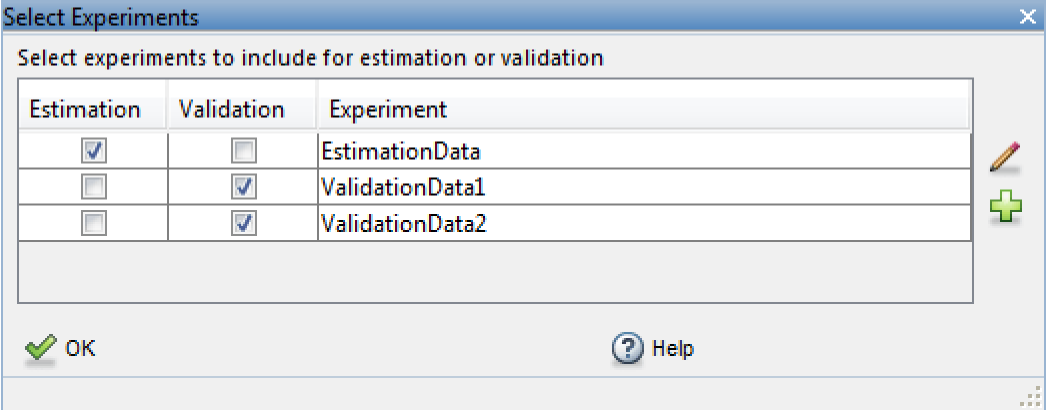
After a number of iterations the estimation converges and terminates. The model is updated with the estimated parameters and the estimation results are saved in the data browser. To see the details of the estimation result, right-click `EstimatedParams` and select **Open**.



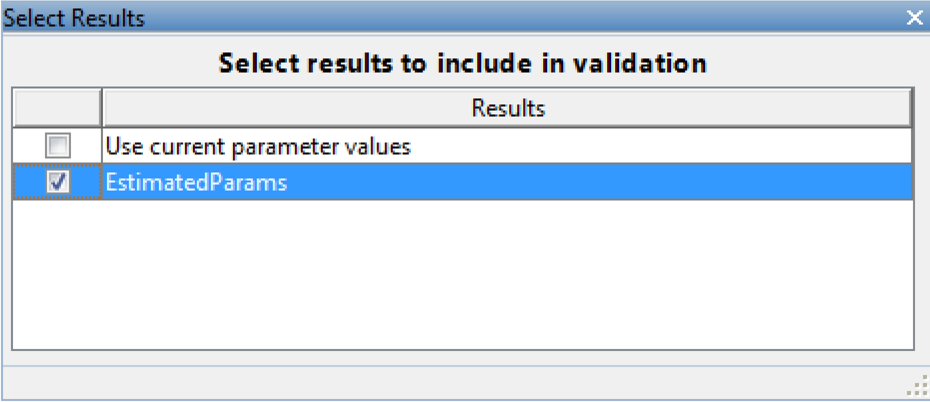
Validation

It is important to validate the estimation results against other experiments. A successful estimation will not only match the experimental data that was used for estimation but also other independent measured data that were collected in experiments.

To select experiments for validation, click the **Validation** tab and click **Select Experiments**. Select both `ValidationData1` and `ValidationData2` for validation.



Click **Select Results** to select the estimation result(s) to use for validation. Select `EstimatedParams` and deselect `Use current parameter values`.



Click **Validate** to validate the estimation result against the validation experiments. Validation simulates the model using the estimated parameters and selected experiments and creates plots showing the measured and simulation data. Use the **View** tab to layout the plots so that the **Experiment plot:ValidationData1** and **Experiment plot:ValidationData2** are both visible.

The validation plots confirm that the estimation was successful. The plots also show that the estimated parameters are robust enough to handle a variety of inputs.

Related Examples

To learn how to estimate model parameters using the `sdo.optimize` command, see “Estimate Model Parameter Values (Code)” on page 2-58.

Close the model.

```
bdclose('spe_engine_throttle')
```

Estimate Model Parameters Per Experiment (GUI)

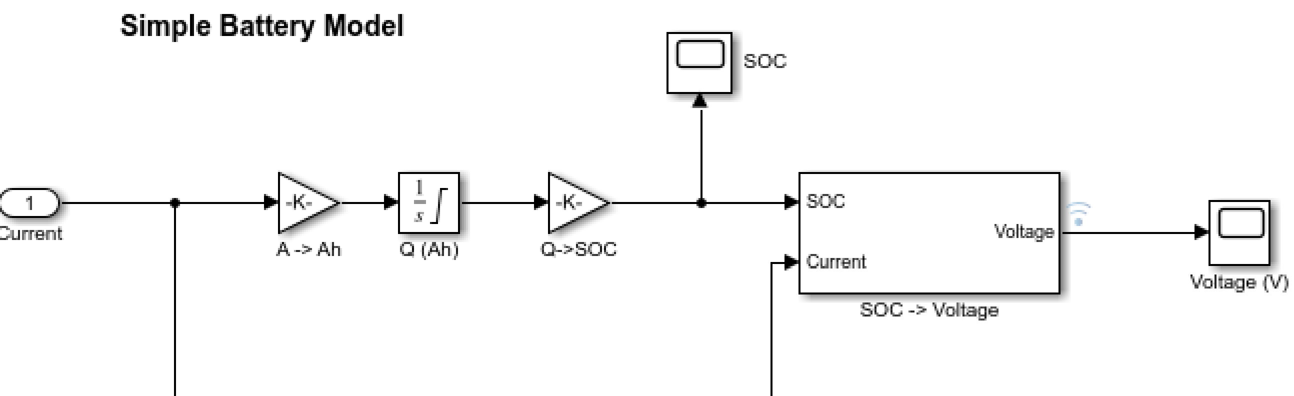
This example shows how to use multiple experiments to estimate a mix of model parameter values; some that are estimated using all the experiments and others that are estimated using individual experiments. The example also shows how to configure estimation experiments with experiment dependent parameter values.

You estimate the parameters of a rechargeable battery based on data collected in experiments that discharge and charge the battery.

Open the Model and Get Experimental Data

This example estimates parameters of a simple, rechargeable battery model, `sdoBattery`. The model input is the battery current and the model output, the battery terminal voltage, is computed from the battery state-of-charge.

```
open_system('sdoBattery')
```



The model is based on the equation

$$E = (1 - \mathrm{Loss})V - KQ_{\max}\frac{1 - s}{s}$$

In the equation:

E is the battery terminal voltage in Volts.

V is the battery constant voltage in Volts.

K is the battery polarization resistance in Ohms.

$Q_{\max}$ is the maximum battery capacity in Ampere-hours.

s is the battery charge state, with 1 being fully charged and 0 discharged. The battery state-of-charge is computed from the integral of the battery current with a positive current indicating discharge and

a negative current indicating charging. The battery initial state-of-charge is specified by Q_0 in Ampere-hours.

Loss is the voltage drop when charging, expressed as a fraction of the battery constant voltage. When the battery is discharging this value is zero.

`V`, `K`, `Qmax`, `Q0`, and `Loss` are variables defined in the model workspace.

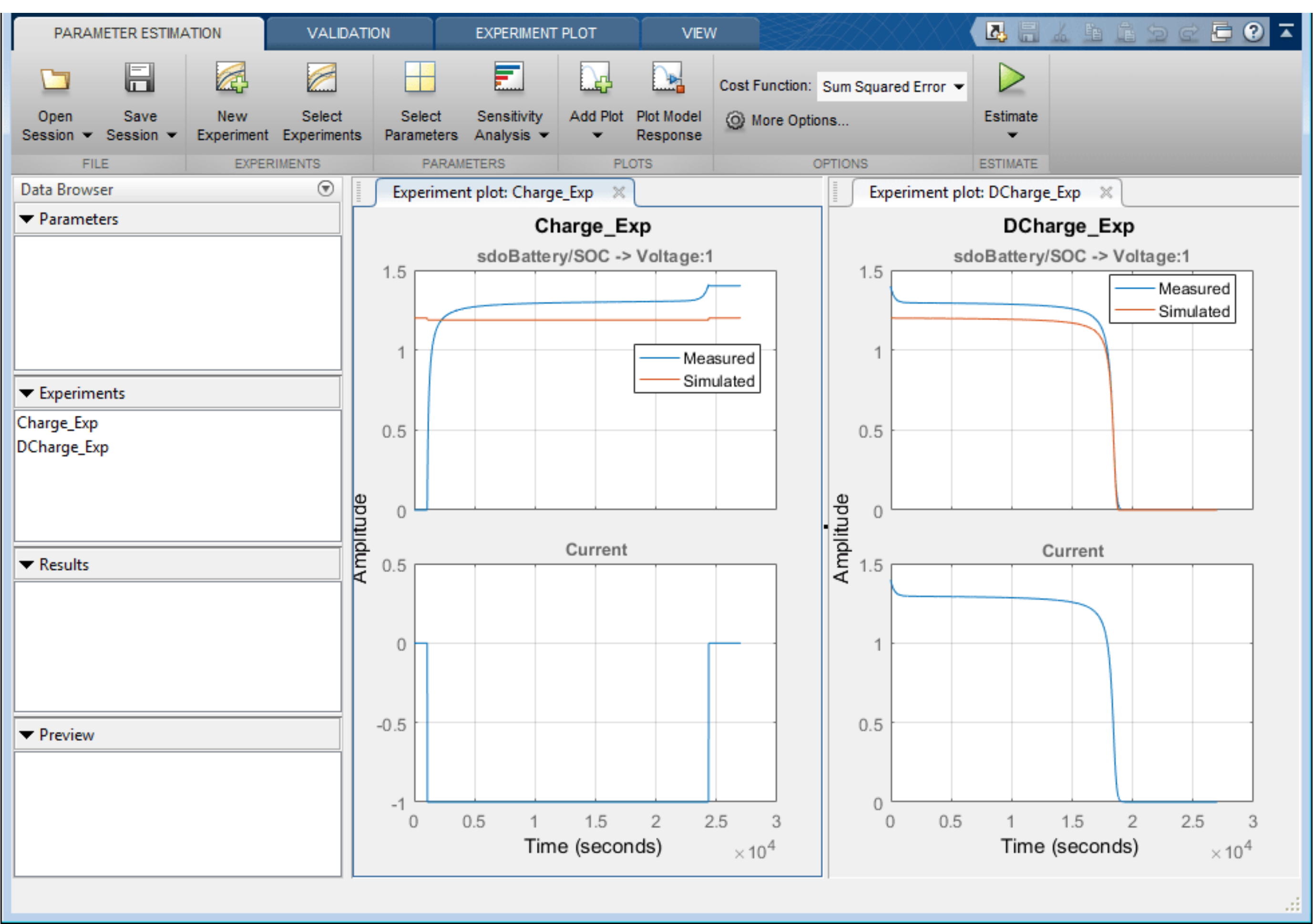
Estimation Experiment Data

A 1.2V (6500mAh) battery was subjected to a discharge and a charging experiment. This experiment data has been loaded into a preconfigured estimation session.

Use the following commands to load the pre-configured estimation session.

```
load sdoBattery_spesession
spetool(SDOSessionData)
```

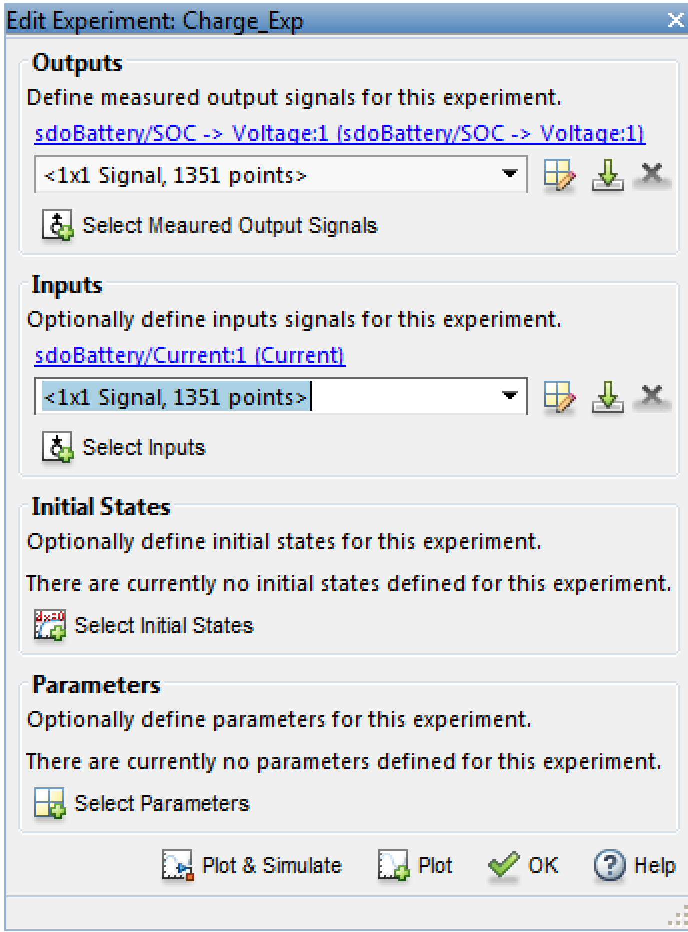
The measured charge and discharge experiment data are loaded and plotted. Click the **View** tab to layout the plots so that the `Experiment plot:Charge_Exp` and `Experiment plot:DCharge_Exp` are both visible. Click **Plot Model Response** to see how well the model simulation matches the measured experiment data.



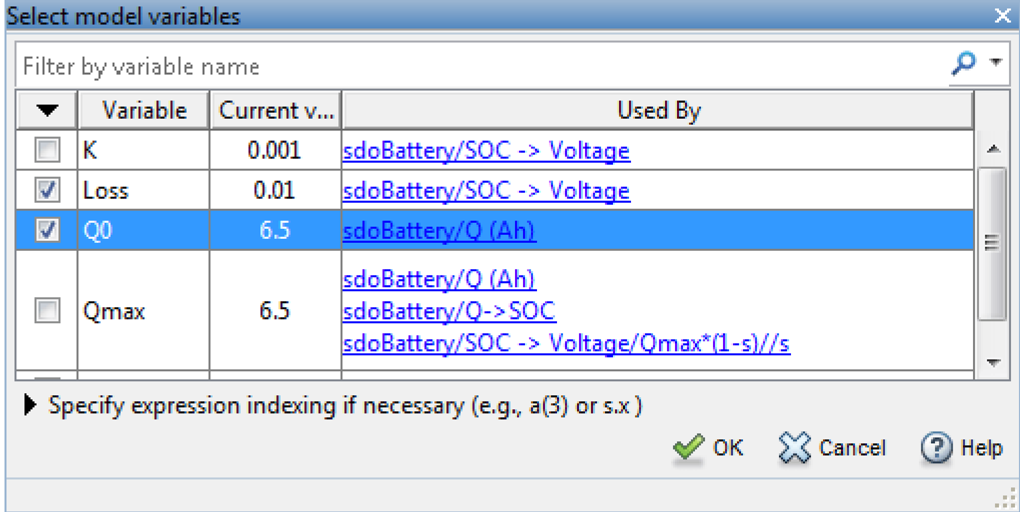
The plots show that the battery initial charge Q0 is not set correctly for the Charge_Exp experiment and that the model V, K, and Loss parameters need to be estimated.

Setting Experiment Parameter Values

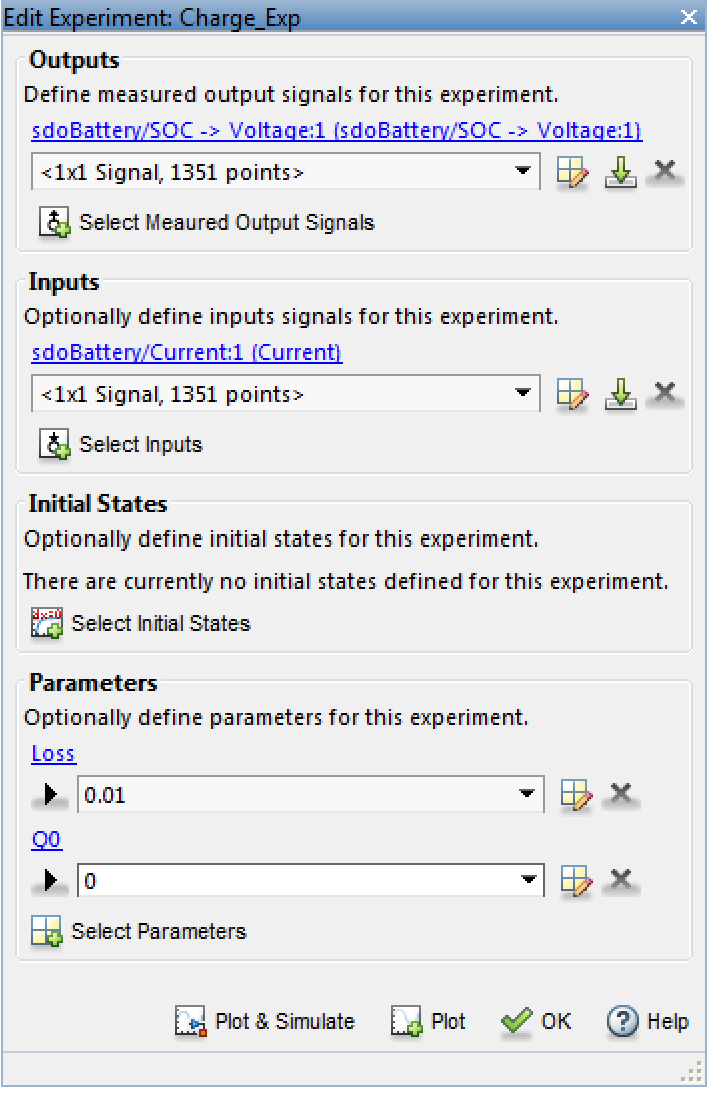
The previous plot indicates that the Charge_Exp battery initial charge, Q0, is not set correctly. Add the initial charge to both experiments. Right click Charge_Exp and select **Edit**. A dialog to edit the experiment opens.



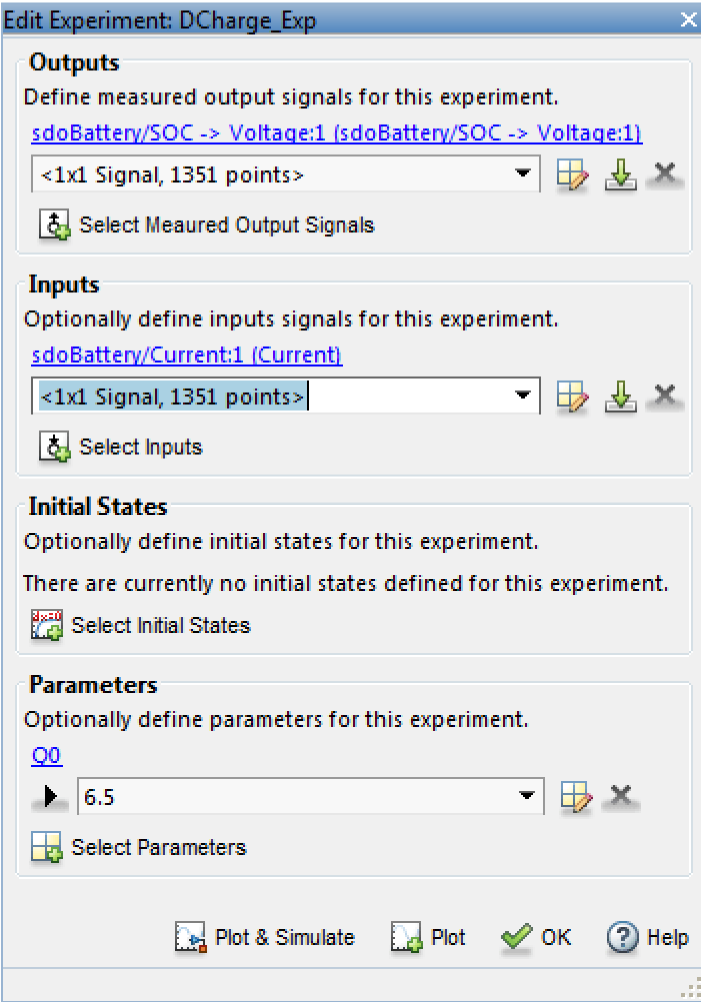
Click **Select Parameters** to open a dialog to add model parameters to the experiment. Select Loss and Q0 to add to the experiment. Select Loss as we need to estimate this parameter using only the Charge_Exp experiment. Click **Ok** to add the Q0 and Loss parameters to the experiment.



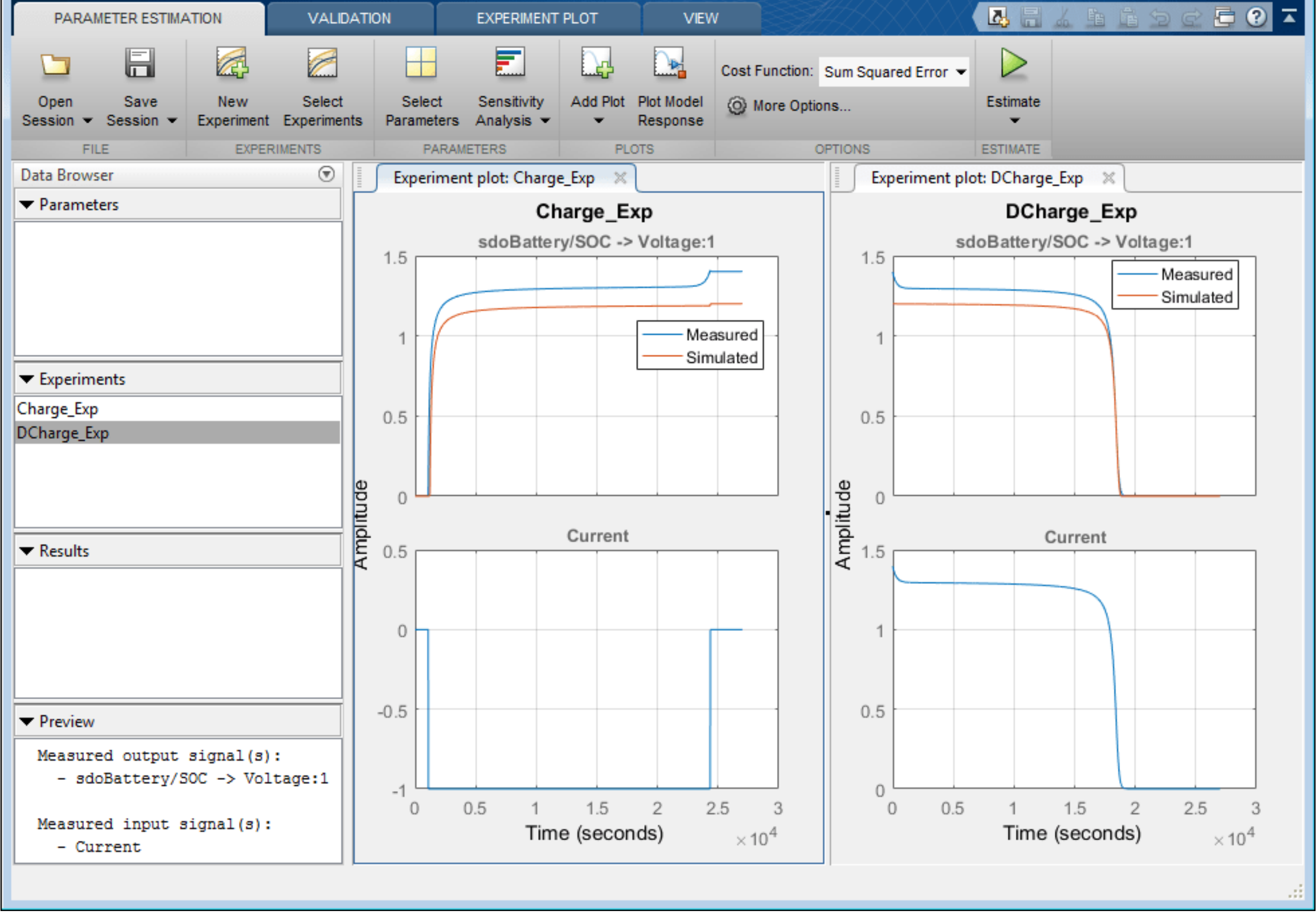
Set the battery initial charge `Q0` in the `Charge_Exp` to 0, i.e. there is no initial charge.



Similarly add the battery initial charge `Q0` to the `DCharge_Exp` experiment and set the initial charge to 6.5., i.e. for this experiment there is an initial charge.



Now that the experiments are updated with the correct initial battery charge click **Plot Model Response** to simulate the model and compare measured and simulated data.

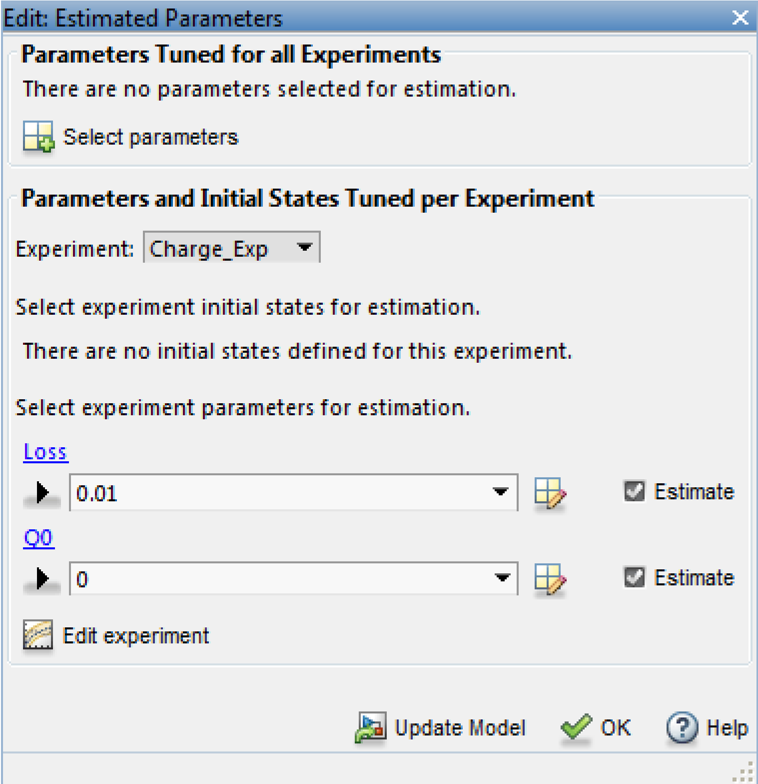


The experiment plots show that the experiment initial conditions match but the battery response does not. The next step is to estimate the K and V model parameters.

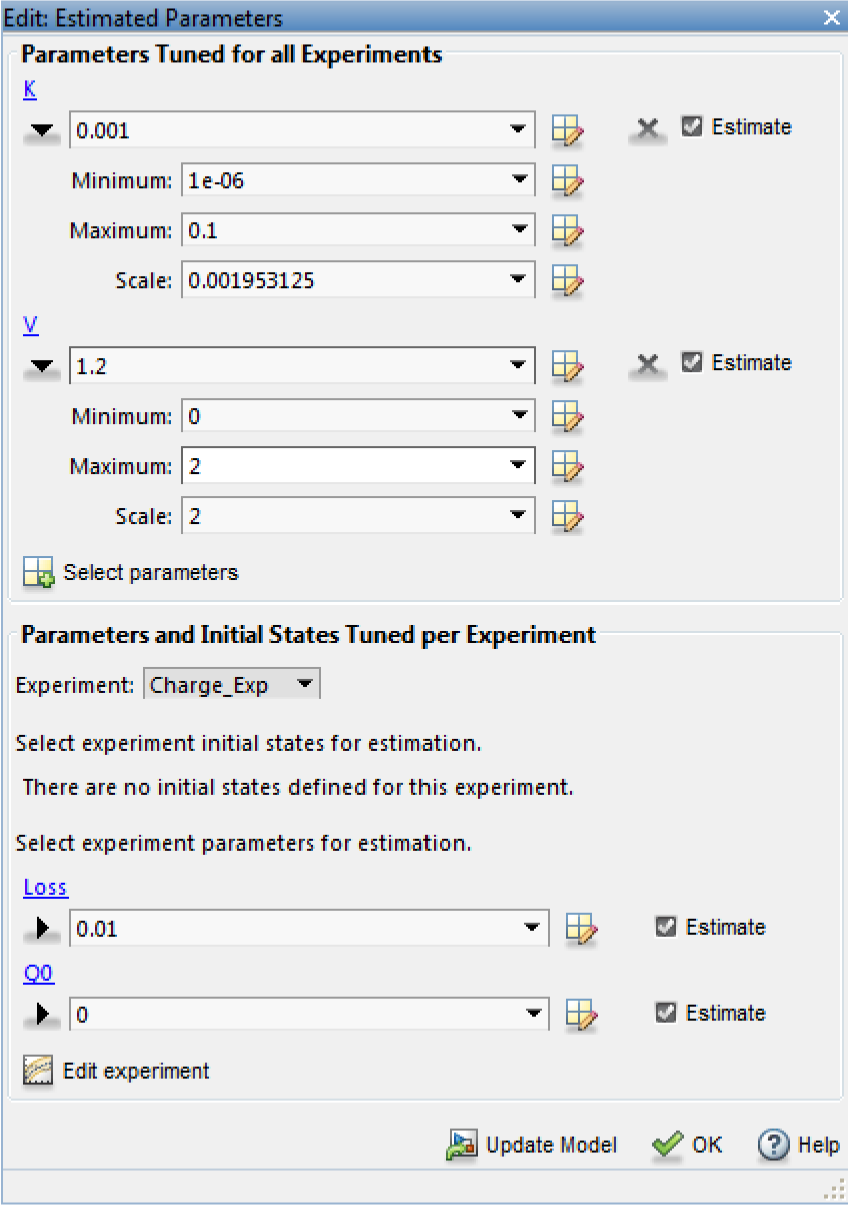
Select Estimation Parameters

The previous plot showed that the model response does not match the measured data and we need to estimate the model V and K parameters.

Click **Select Parameters** to open a dialog to select model parameters.

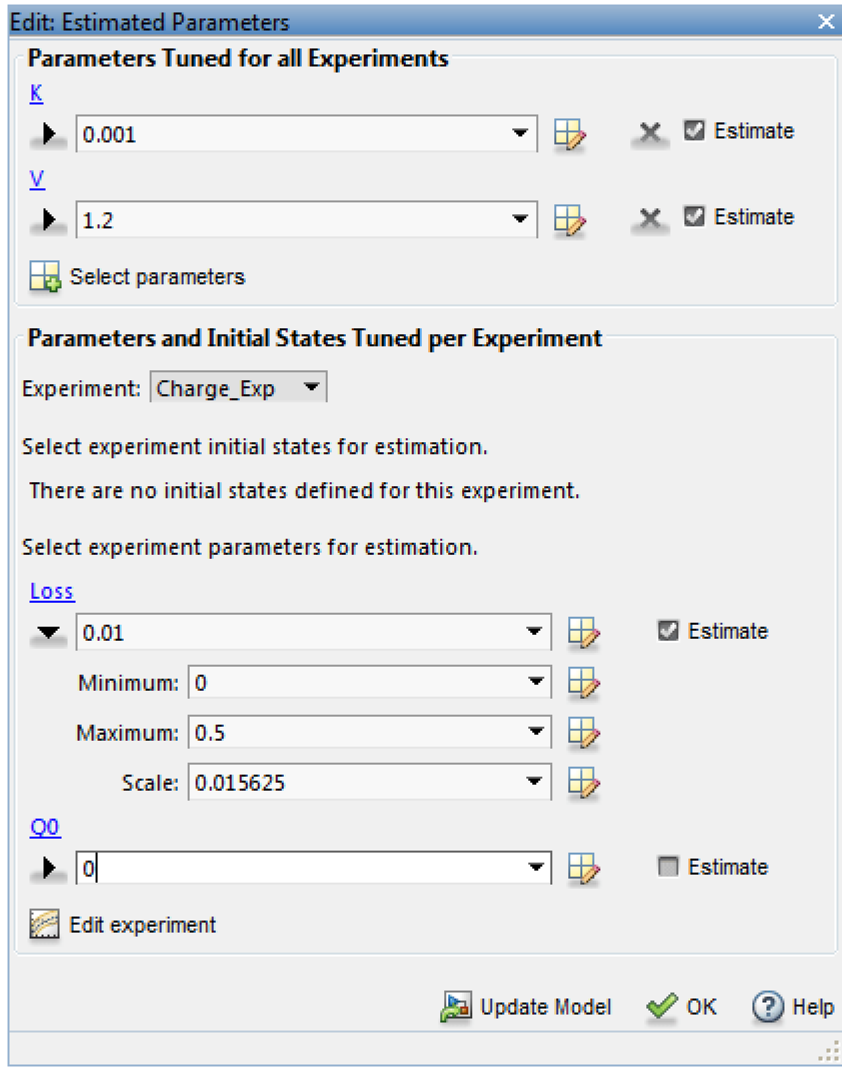


The upper portion of the select parameters dialog has a section for parameters that are tuned using all experiments. Click **Select Parameters** and add the V and K model parameters to the estimated parameters. Set the V minimum to 0 and the maximum to 2, similarly set the K minimum to 1e-6 and maximum to 0.1.

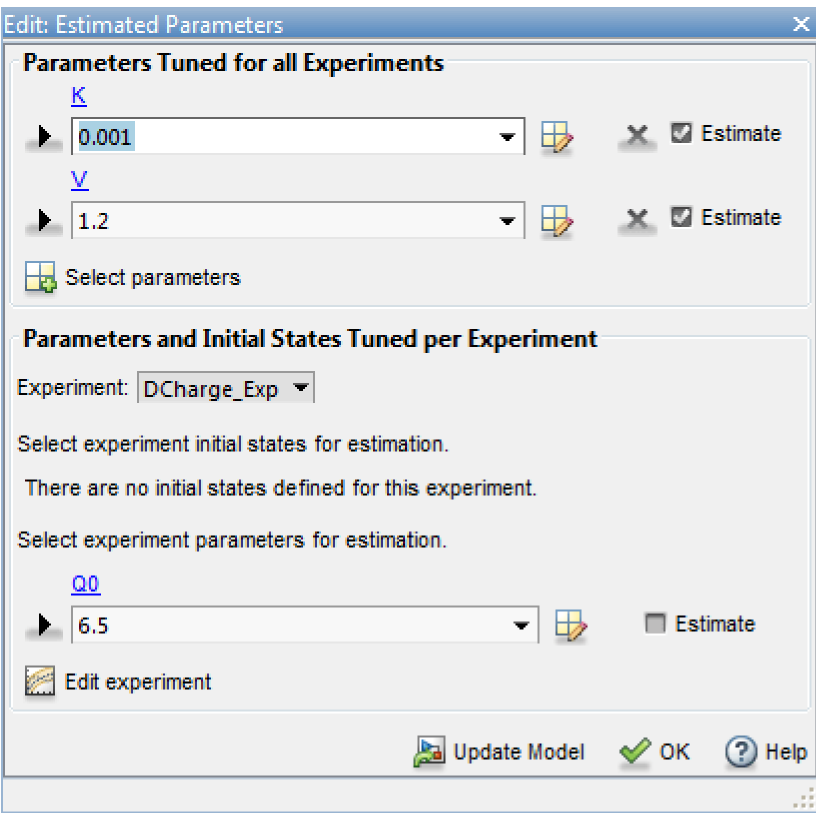


The lower section of the dialog has a section for initial states and parameters that are tuned using individual experiments.

For the `Charge_Exp` we tune the `Loss` parameter and set its minimum to 0 maximum to 0.5. The battery initial charge `Q0` is fixed to 0 and should not be estimated; uncheck **Estimate**.

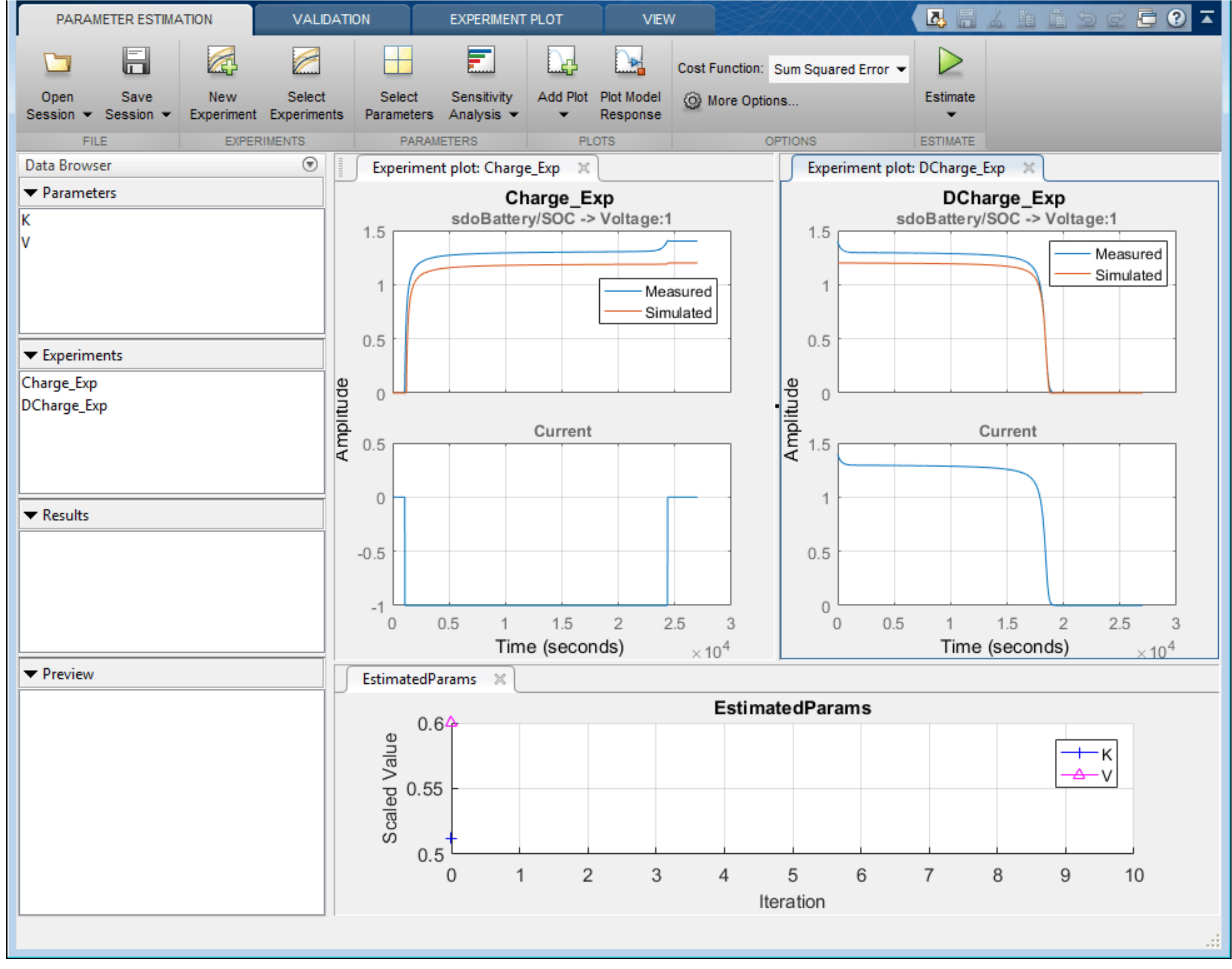


Select `DCharge_Exp` from the **Experiment** combobox to view the parameter settings for the `DCharge_Exp` experiment. The battery initial charge `Q0` is fixed to 6.5 and should not be estimated; uncheck **Estimate**.



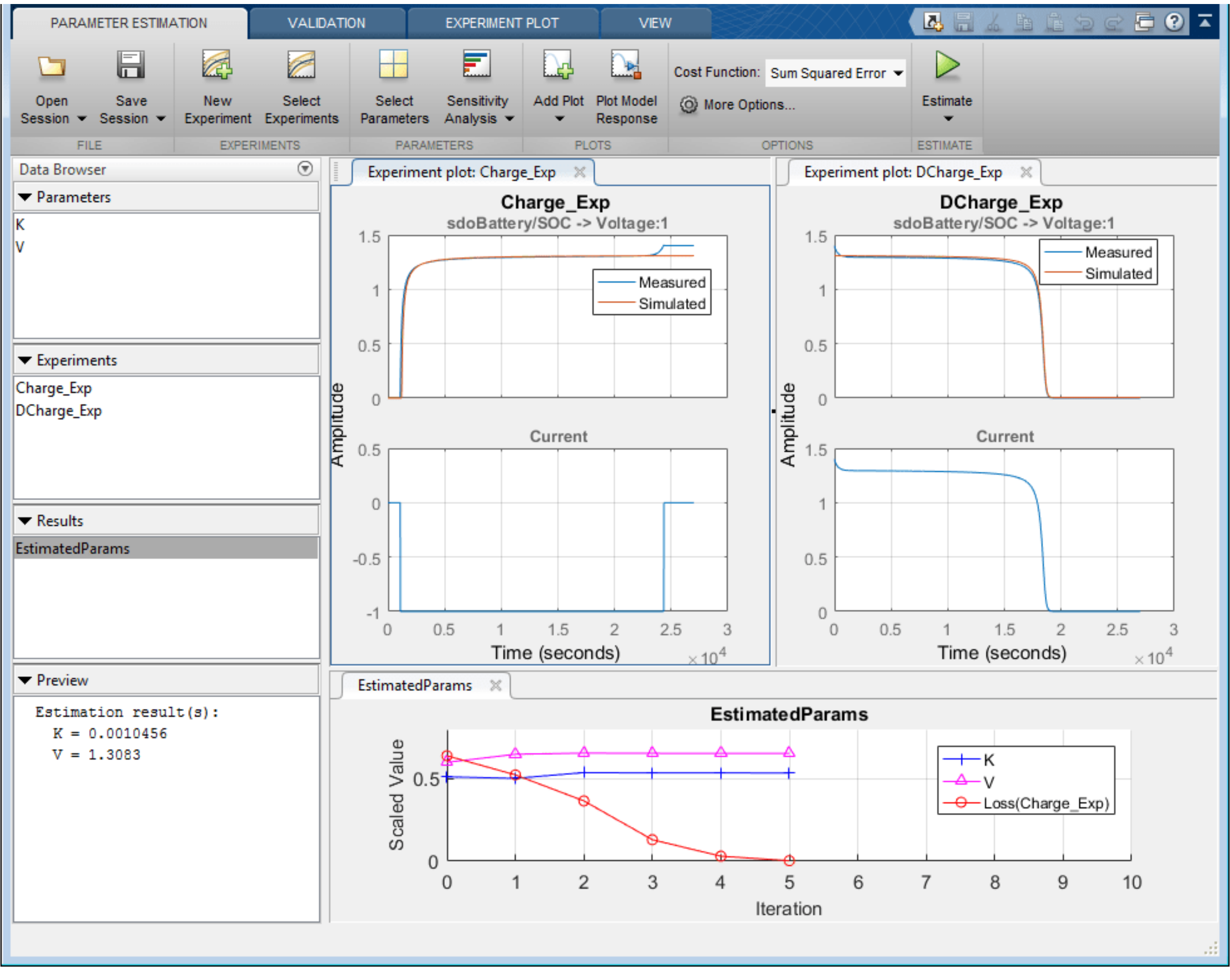
Estimate Parameter Values

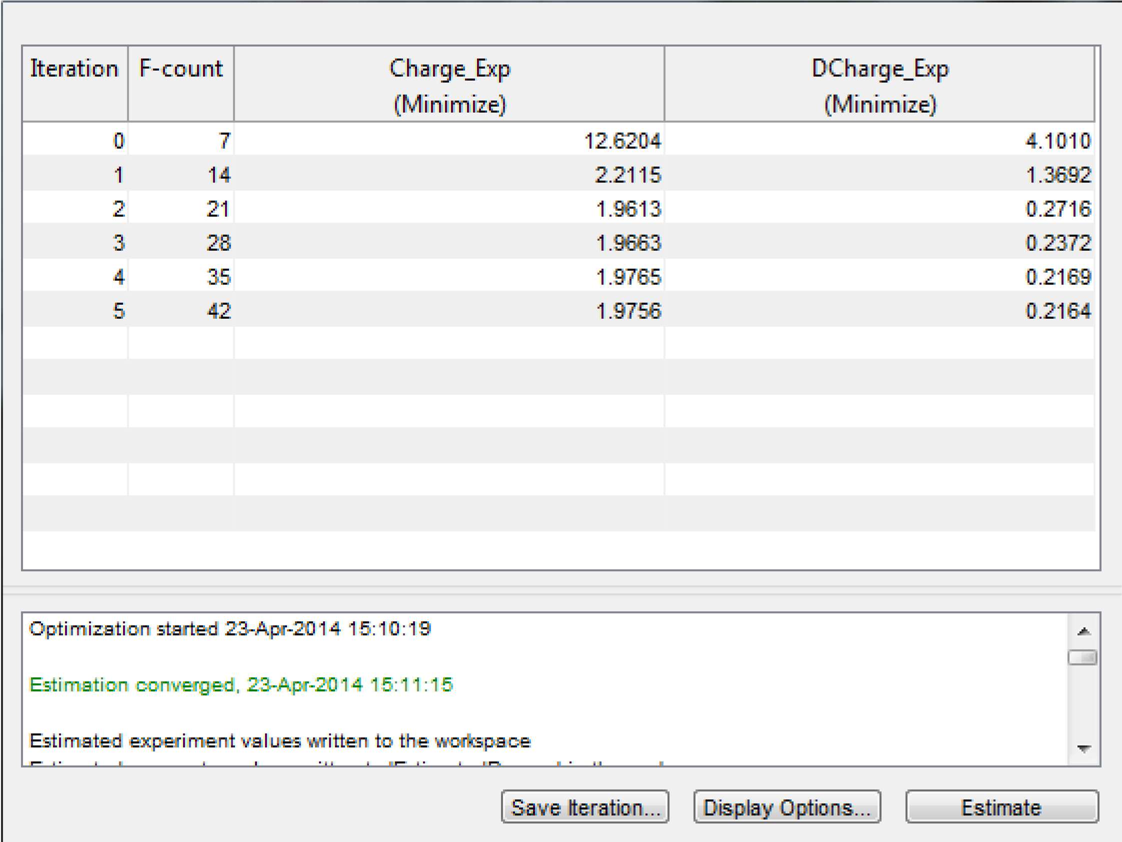
The experiments and estimated parameters are configured and we a ready to run the estimation. First create a plot to monitor the estimation progress. Click **Add Plot** and select **Parameter Trajectory**. This creates a plot that shows how the estimated parameter values change during estimation. Click the **View** tab to layout the plots so that the experiment and parameter trajectory plots are all visible.



Click the **Estimate** button to start the estimation. You can modify estimation options by setting the **Cost Function** combobox and clicking **More Options**.

While the estimation is running the plots update and a dialog showing estimation progress appears. The progress dialog shows the estimation iterations, the number of times the model has been evaluated (**F-count**), and the estimation cost at each iteration.


PARAMETER ESTIMATION
VALIDATION
EXPERIMENT PLOT
VIEW
Open Session
Save Session
New Experiment
Select Experiments
Select Parameters
Sensitivity Analysis
Add Plot
Plot Model Response
Cost Function:
Sum Squared Error
More Options...
Estimate
FILE
EXPERIMENTS
PARAMETERS
PLOTS
OPTIONS
ESTIMATE
Data Browser
Parameters
K
V
Experiments
Charge_Exp
DCharge_Exp
Results
EstimatedParams
Preview
Estimation result(s):
K = 0.0010456
V = 1.3083
Experiment plot: Charge_Exp
Charge_Exp
sdoBattery/SOC -> Voltage:1
Measured
Simulated
Current
Amplitude
Time (seconds)
Experiment plot: DCharge_Exp
DCharge_Exp
EstimatedParams
Scaled Value
Loss(Charge_Exp)
Iteration



Iteration	F-count	Charge_Exp (Minimize)	DCharge_Exp (Minimize)
0	7	12.6204	4.1010
1	14	2.2115	1.3692
2	21	1.9613	0.2716
3	28	1.9663	0.2372
4	35	1.9765	0.2169
5	42	1.9756	0.2164

After a number of iterations the estimation converges and terminates. The experiment plots show the measured and simulation data matching well. The `EstimatedParams` plot shows the `V`, `K`, and `Loss` parameters changing during the estimation; the scale of `V`, `K`, and `Loss` are different, right click on the plot and select **Show scaled values** to see how all the parameters changed from their original values.

Related Examples

To learn how to estimate parameters per experiment using the `sdo.optimize` command, see “Estimate Model Parameters Per Experiment (Code)” on page 2-86.

Close the model

```
bdclose('sdoBattery')
```

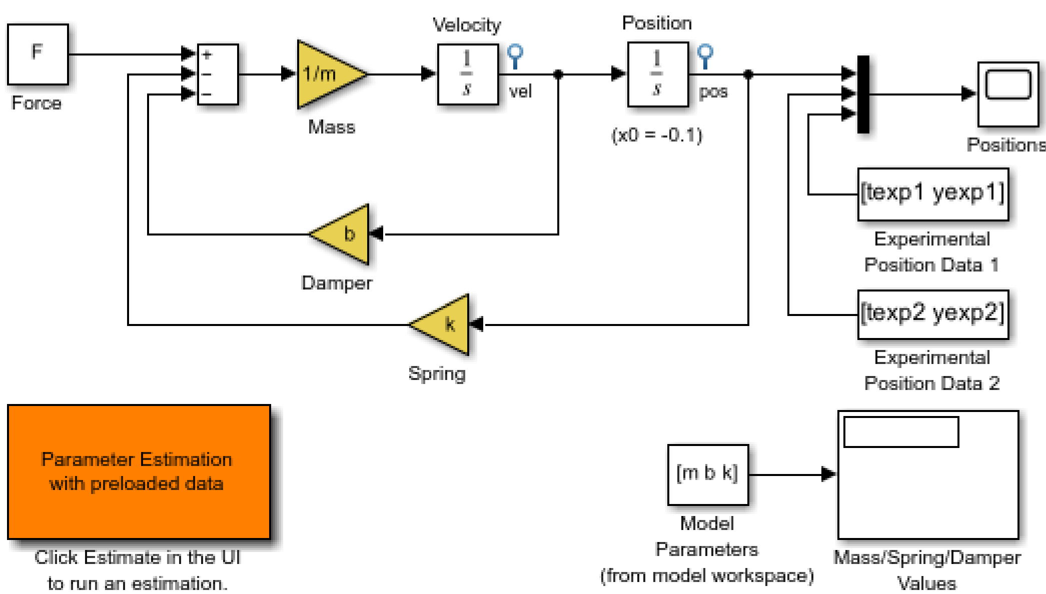
Estimate Model Parameters and Initial States (GUI)

This example shows how to estimate the physical parameters - mass (m), spring constant (k) and damping (b) of a simple mass-spring-damper model. This example illustrates the significance of initial state estimation.

Mass Spring Damper System Model

Open the Simulink® model.

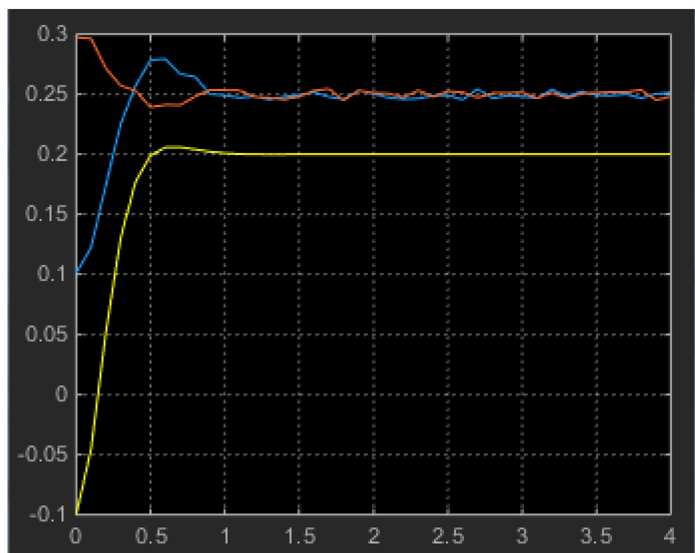
```
open_system('msd_system')
```



The model's output is the displacement response (position) of the mass in a mass-spring-damper system, subject to a constant force (F), and an initial displacement (x0). x0 is the initial condition of the Position integrator block. Run the simulation once to observe the response of the model to a nominal set of parameter values.

Experimental Data Sets

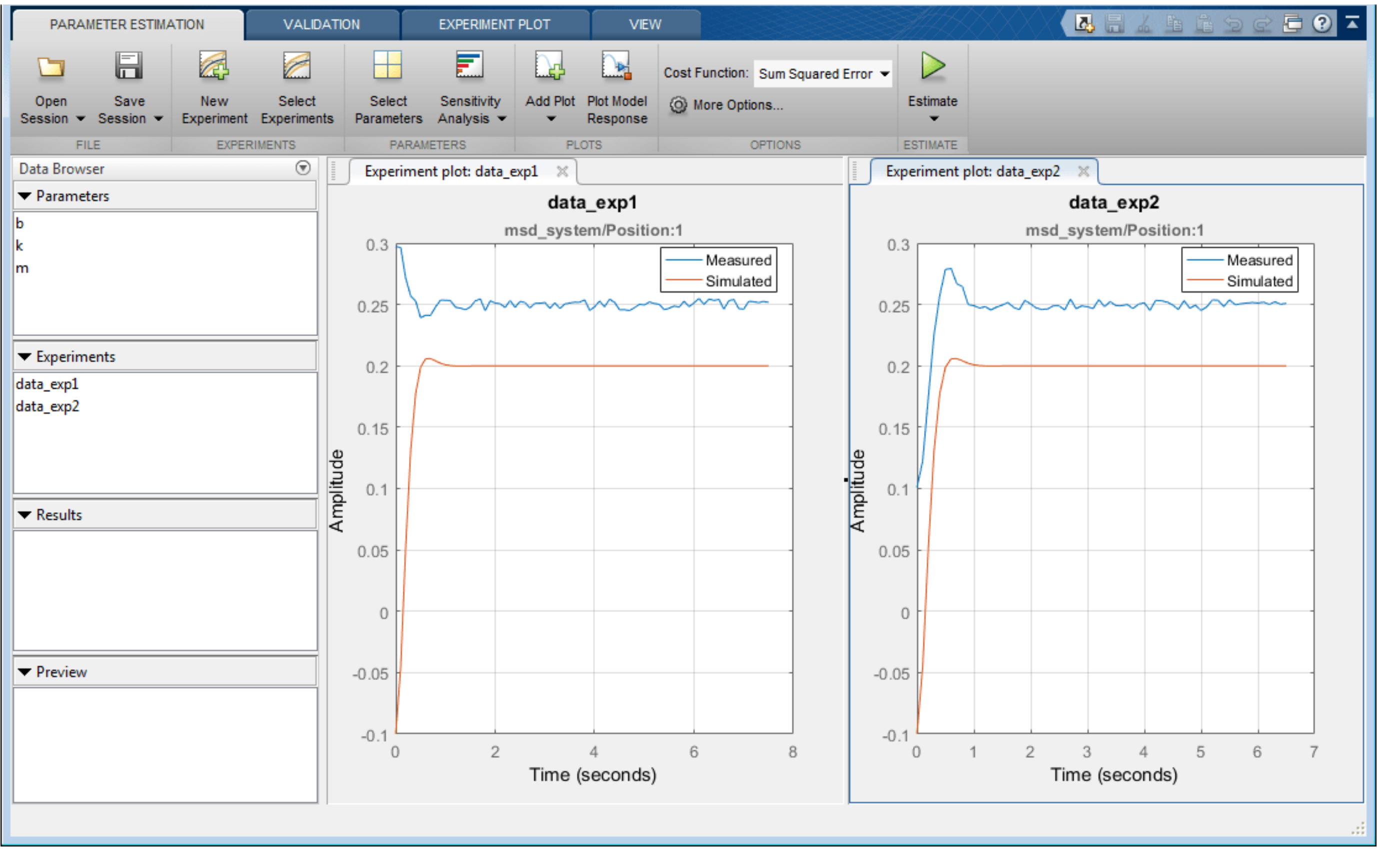
For estimation of the model parameters (m, b, and k), two sets of experimental data are used. These data sets were obtained using two different initial positions (0.1 and 0.3), and contain additive noise. Following is the plot of these data sets (orange and cyan curves), along with the simulated response (yellow curve) of the Simulink model for x0=–0.1 and a nominal set of parameter values (m=8, k=500, b=100).



Estimation of Model Parameters

The model has three parameters (`k`, `b`, `m`) that appear in the Gain blocks of the Simulink model `msd_system`. We estimate these parameters using Parameter Estimation.

Double-click the Parameter Estimation GUI with preloaded data block in the model to open a pre-configured estimation GUI session. The experimental data sets are already loaded in the project (`data_exp1` and `data_exp2`). Click the **View** tab to lay out the plots so that the **Experiment plot:data_exp1** and **Experiment plot:data_exp2** are both visible. Click **Plot Model Response** to simulate the model for the two experiments. The plots show that the model simulation does not match the experiment data.

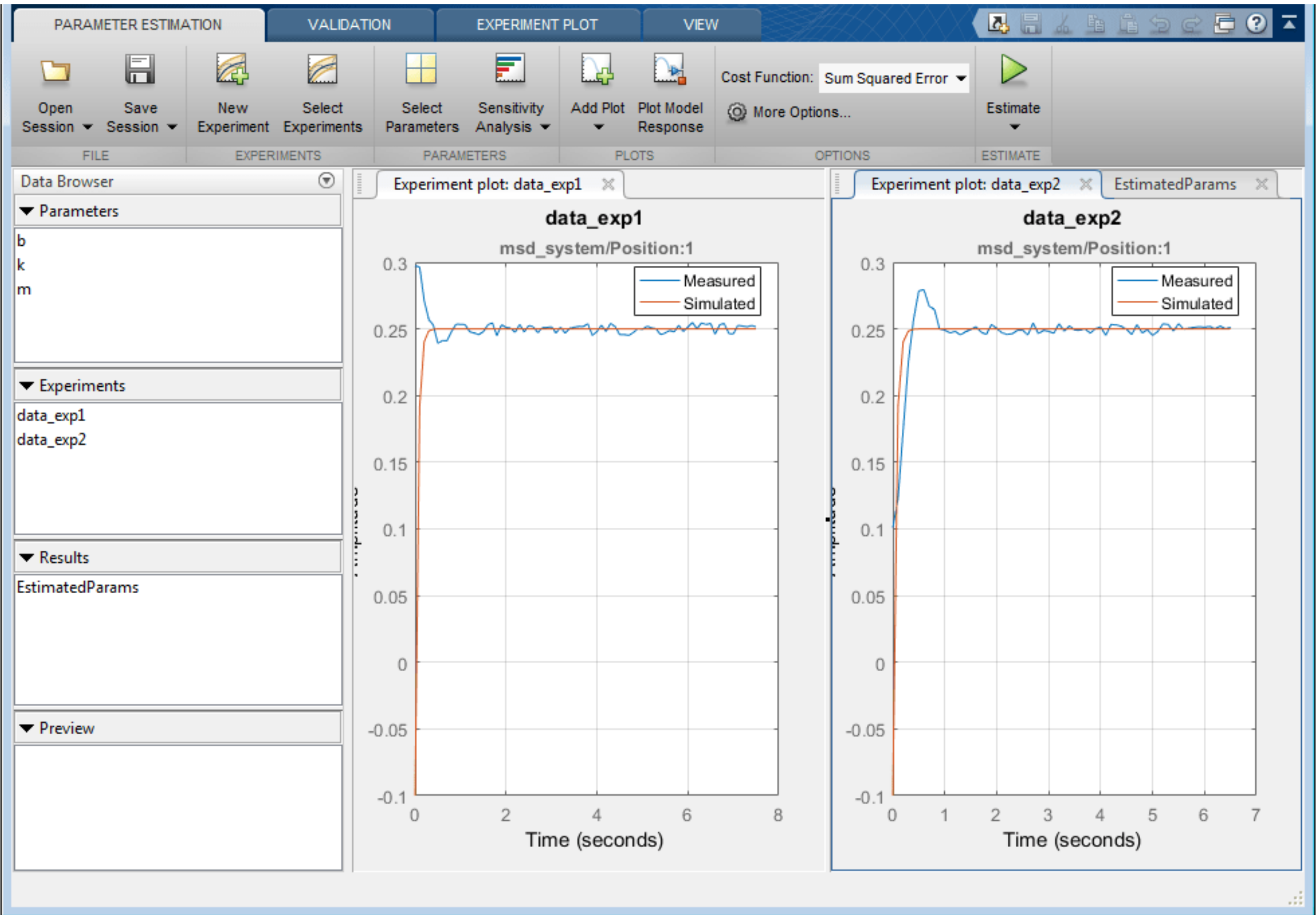


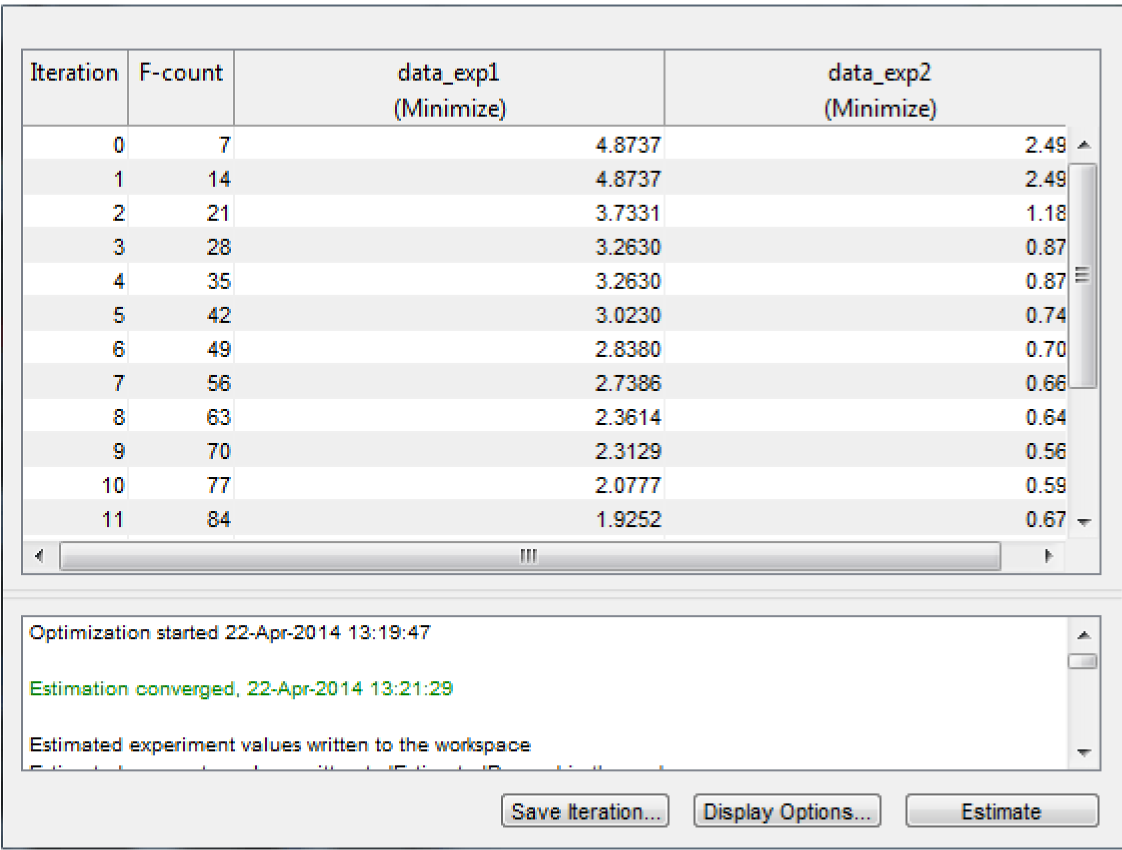
Parameter Estimation with No State Estimation

The app is configured to estimate the model parameters using both `data_exp1` and `data_exp2` experiments; click **Select Parameters** to see the selected parameters and **Select Experiments** to see the experiments selected for estimation.

Click **Estimate** to start the estimation. You can modify estimation options by setting the **Cost Function** combobox and clicking **More Options**.

While the estimation is running, the plots update and a dialog showing estimation progress appears. The progress dialog shows the estimation iterations, the number of times the model has been evaluated (F-count), and the estimation cost at each iteration.


PARAMETER ESTIMATION
VALIDATION
EXPERIMENT PLOT
VIEW
Open Session
Save Session
New Experiment
Select Experiments
Select Parameters
Sensitivity Analysis
Add Plot
Plot Model Response
Cost Function: Sum Squared Error
More Options...
Estimate
FILE
EXPERIMENTS
PARAMETERS
PLOTS
OPTIONS
ESTIMATE
Data Browser
Parameters
b
k
m
Experiments
data_exp1
data_exp2
Results
EstimatedParams
Preview
Experiment plot: data_exp1
Experiment plot: data_exp2
EstimatedParams
data_exp1
msd_system/Position:1
Measured
Simulated
Time (seconds)
data_exp2
msd_system/Position:1
Measured
Simulated
Time (seconds)



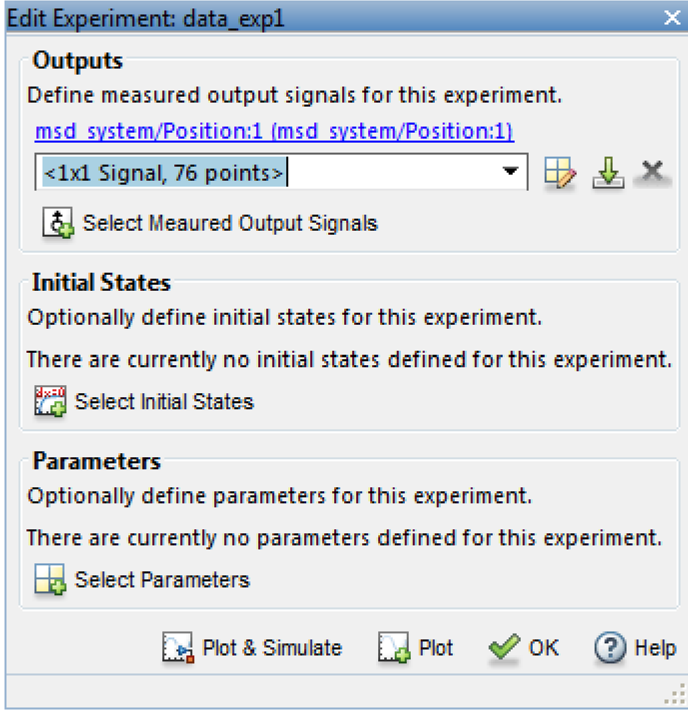
After a number of iterations the estimation converges and terminates. The model is updated with the estimated parameters and the estimation results are saved in the data browser.

The `data_exp1` and `data_exp2` experiment plots show that the model parameters have been tuned to match the measured experiment data as closely as possible. The simulated measured signals match well from the 2 second mark onward but don't match well before 2 seconds. The simulation results for both experiments start at -0.1. This is the initial condition of the model which was not estimated; these plots show that the initial condition should also be estimated.

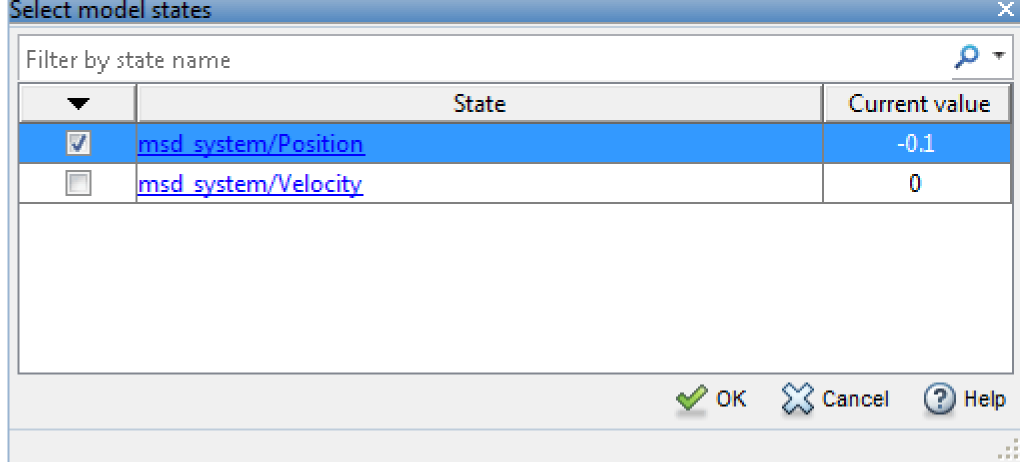
Parameter Estimation with Initial State Estimation

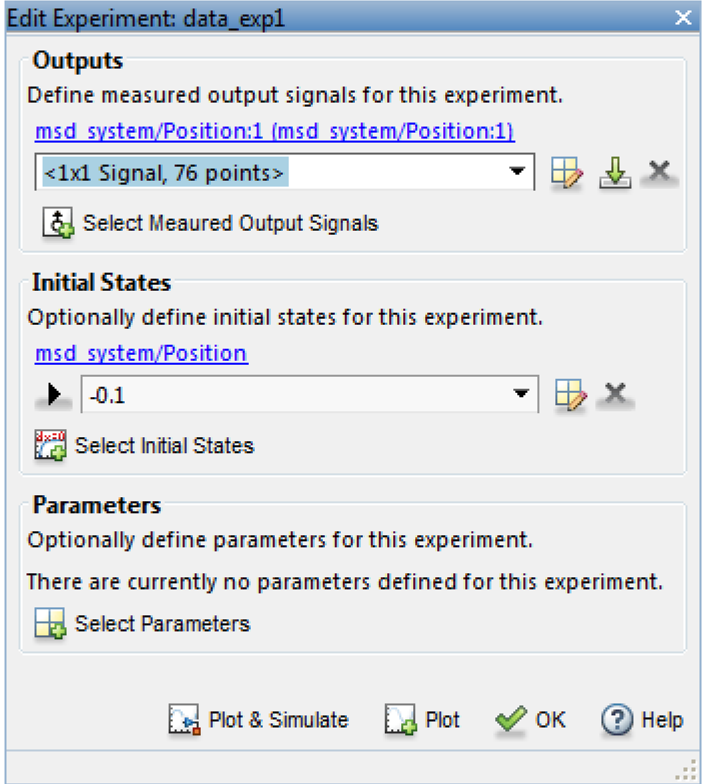
The `data_exp1` and `data_exp2` experiments specify the measured output data but as seen above must also specify the model initial state. Add the initial states to the experiments and estimate them.

Right-click `data_exp1` and select **Edit** to open a dialog to configure the experiment.



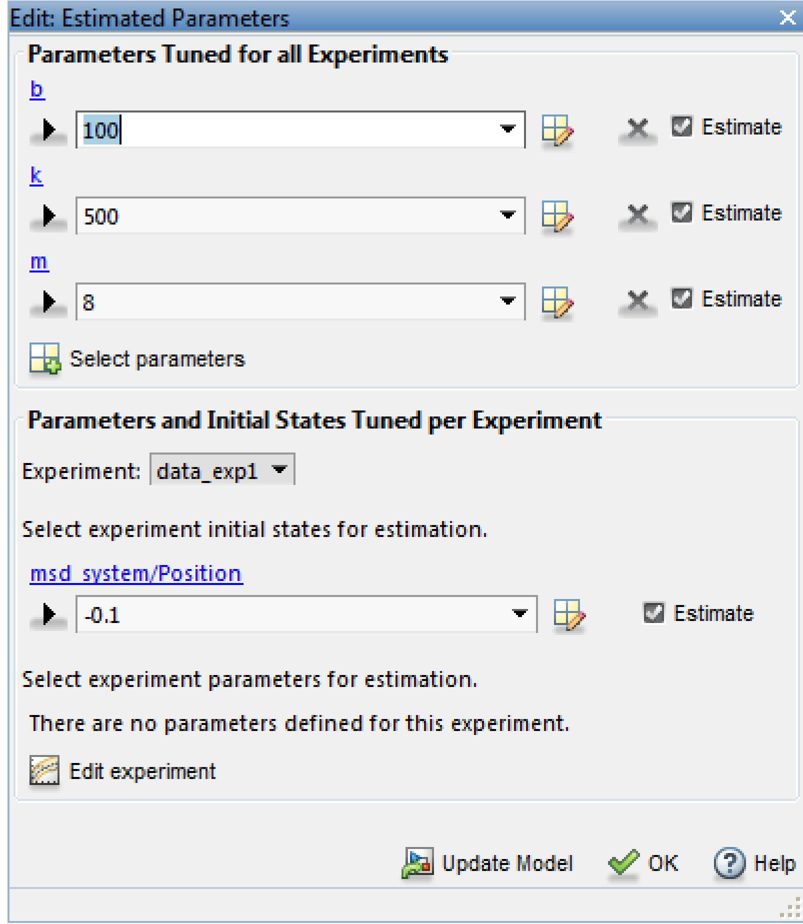
Click **Select Initial States** and select the position state. Click **OK** to close the state selector and add the selected state to the experiment.





Right-click `data_exp2` and select **Edit** and add the position state to the experiment.

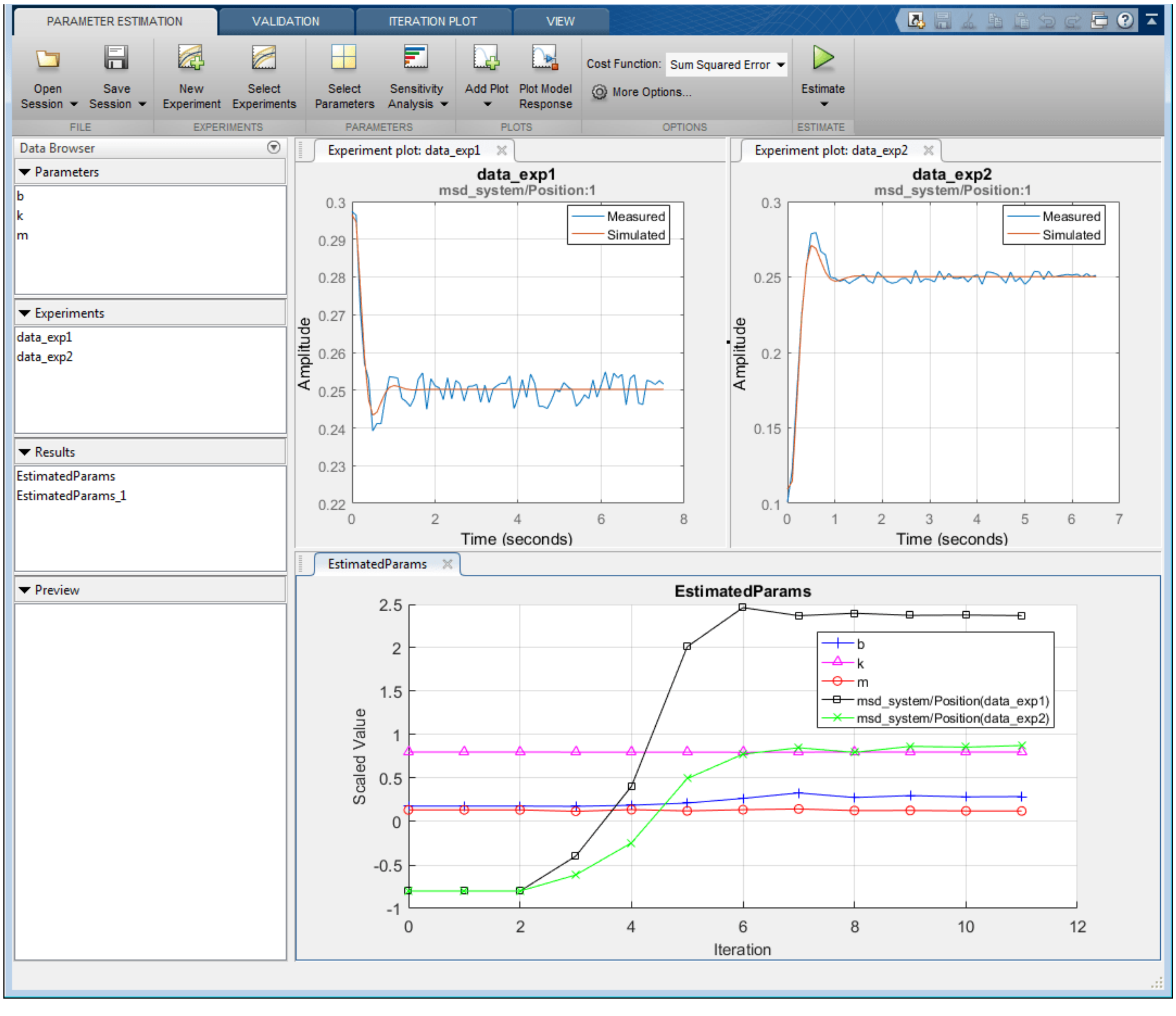
The experiments are now configured to include initial states that can be estimated. Click **Select Parameters**.



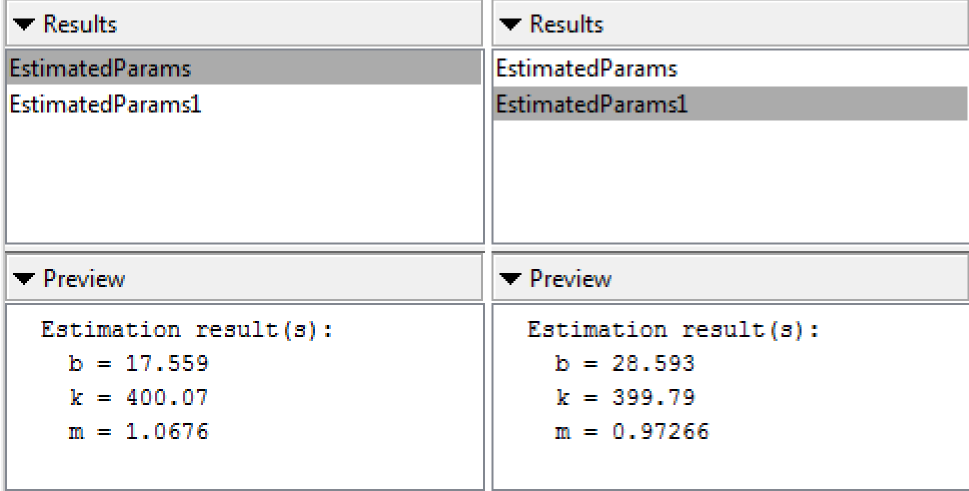
The upper portion of the select parameters dialog has a section for parameters that are tuned using all experiments selected for estimation. The lower section of the dialog has a combo-box to select an experiment and widgets to specify initial states and parameters that are tuned using only the selected experiment. For this problem, the `data_exp1` and `data_exp2` experiments estimate the model initial state for each experiment.

You can now start the estimation, but first create plots to monitor the estimation progress. Click **Add Plot** and select **Parameter Trajectory**, right click the plot and select **Show scaled values**. This creates a plot that shows how the estimated parameter values change during estimation. Click the **View** tab to lay out the plots so that the **Experiment plot:data_exp1**, **Experiment plot:data_exp2**, and **Iteration plot 1** are both visible.

Click the **Estimate** button to start the estimation.



After a number of iterations the estimation converges and terminates. The `data_exp1` and `data_exp2` experiment plots show how estimating the initial value improves the estimation fit. The `EstimatedParams` plot shows the estimated initial state for the two experiments, the plot also shows that the estimated `k` value did not change while `b` and `m` changed slightly. You can confirm this by clicking `EstimatedParams` and examining the preview pane and then clicking `EstimatedParams1` and examining the preview pane. Alternatively right click `EstimatedParams` and select **Open** to open a dialog to view the results.



This example shows that it is important to independently estimate initial states for each experiment in order to obtain the correct estimates of the model parameters.

Related Examples

To learn how to estimate model parameters and initial states using the `sdo.optimize` command, see “Estimate Model Parameters and Initial States (Code)” on page 2-67.

Close the model

```
bdclose('msd_system')
```

Generate MATLAB Code for Parameter Estimation Problems (GUI)

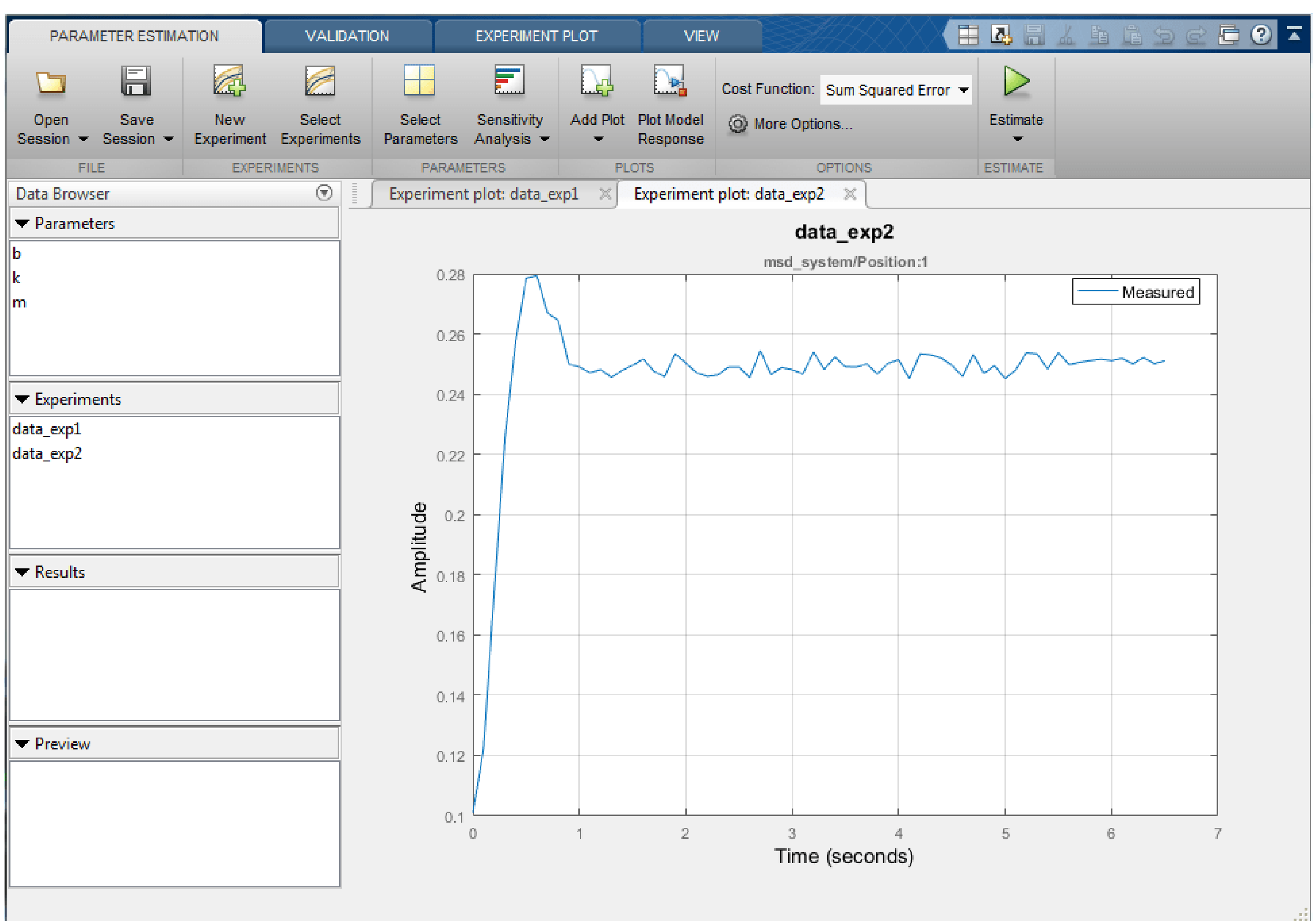
This example shows how to automatically generate a MATLAB® function to solve a parameter estimation problem. You use the **Parameter Estimator** to define an estimation problem for a mass-spring-damper and generate MATLAB code to solve this estimation problem.

Mass-Spring-Damper Estimation Problem

The “Estimate Model Parameters and Initial States (GUI)” on page 2-169 example shows how to use the **Parameter Estimator** to estimate parameters of a mass-spring-damper model. In this example, you load a pre-configured **Parameter Estimator** session based on that example.

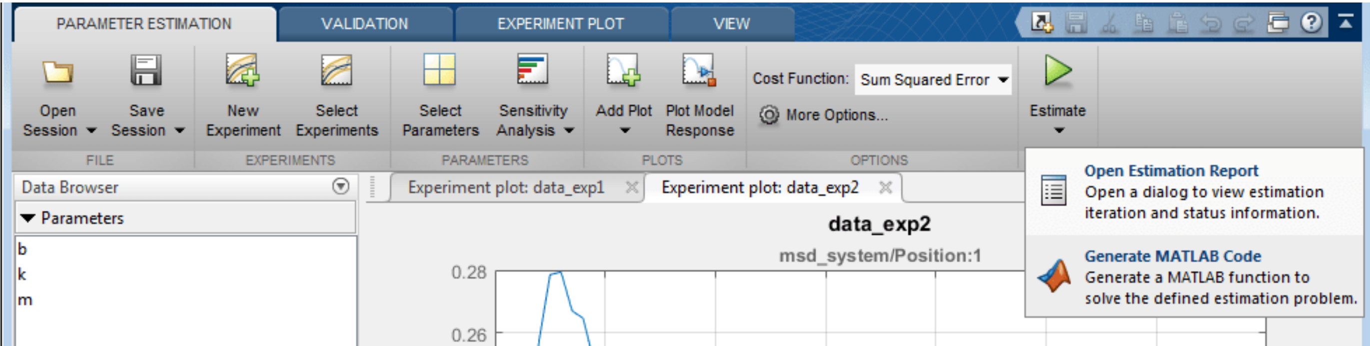
Use the following commands to load the pre-configured estimation session.

```
load sdoMassSpringDamper_sdosession
spetool(SDOSessionData)
```



Generate MATLAB Code

From the **Estimate** list, select **Generate MATLAB Code**.



The generated code is added to the MATLAB editor as an unsaved MATLAB function.

Editor - Untitled3*

```
function [pOpt, Info] = spe_msd_system(p)
%SPE_MSD_SYSTEM
%
% Solve a parameter estimation problem for the msd_system model.
%
% The function returns estimated parameter values, pOpt,
% and estimation termination information, Info.
%
% The, p, input argument defines the model parameters to estimate,
% if omitted the parameters specified in the function body are estimated.
%
% Modify the function to include or exclude new experiments or
% change the estimation options.
%
% Auto-generated by SPETOOL on 22-Oct-2014 07:39:23.
%

%% Open the model.
open_system('msd_system')

%% Specify Model Parameters to Estimate
%
if nargin < 1 || isempty(p)
    p = sdo.getParameterFromModel('msd_system',{'b','k','m'});
    p(1).Minimum = 0;
    p(1).Scale = 100;
    p(2).Minimum = 0;
    p(2).Scale = 500;
    p(3).Minimum = 0;
```

Untitled3*

Examine the generated code. Significant code portions are:

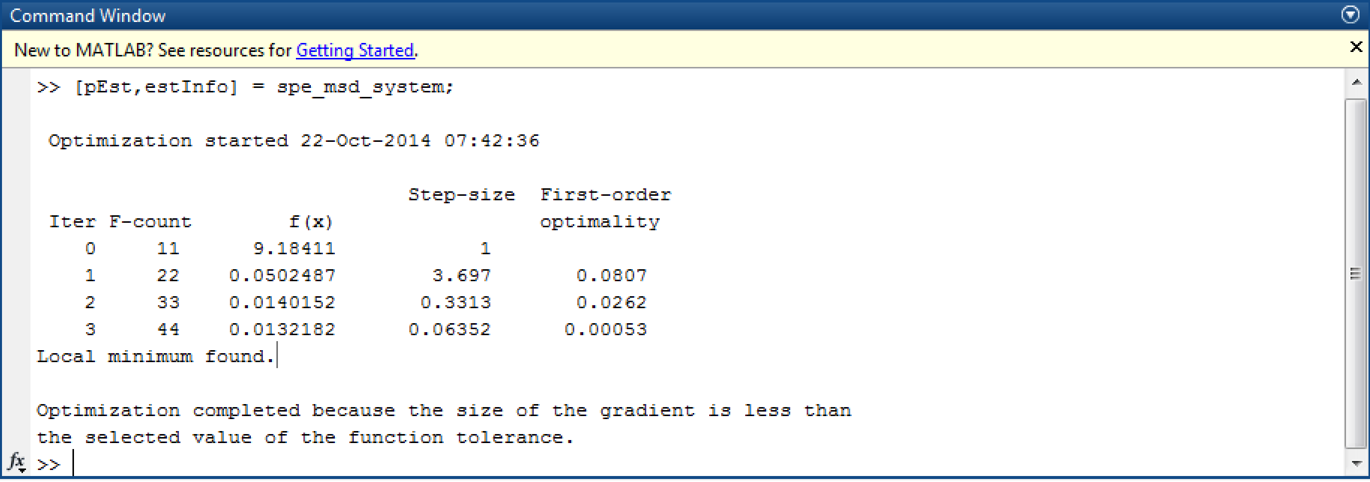
- **Specify Model Parameters to Estimate** - Definition of the model parameters being estimated.
- **Define the Estimation Experiments** - Definition of the measured and expected signal data to use for estimation.
- **Create Estimation Objective Function** - Creation of an anonymous function that calls the subfunction `msd_system_optFcn`, which evaluates the model using each experiment and compares simulation and measured experiment outputs. This anonymous function is called by `sdo.optimize` at each iteration of the optimization problem to solve the estimation problem.

- **Estimate the Parameters** - Solve the estimation problem using the `sdo.optimize` command.

Select **Save** from the MATLAB editor to save the generated function.

Run Generated Code

Run the generated function.



The first output argument, `pOpt`, contains the optimized parameter values and the second output argument, `optInfo`, contains optimization information.

Modify the Generated Code

You can:

- Modify the generated `spe_msd_system` function to include or exclude new experiments or change estimation options.
- Call the generated `spe_msd_system` function with a different set of parameters to estimate.

For details on how to write an objective/constraint function to use with the `sdo.optimize` command, type `help sdoExampleCostFunction` at the MATLAB command prompt.

Close the model.

Improving Optimization Performance Using Fast Restart (GUI)

This example shows how to use the **Fast Restart** feature of Simulink® to speed up optimization of a model. You use fast restart to estimate the parameters of an engine throttle model.

How Fast Restart Speeds up the Optimization

Simulation of Simulink models requires that the model be compiled before it is simulated. In this context compilation of a model means analyzing and formatting the model so that it can be simulated. The idea of fast restart is to perform the model compilation once and reuse the compiled information for subsequent simulations. For more information about when to use fast restart, see “How Fast Restart Improves Iterative Simulations”.

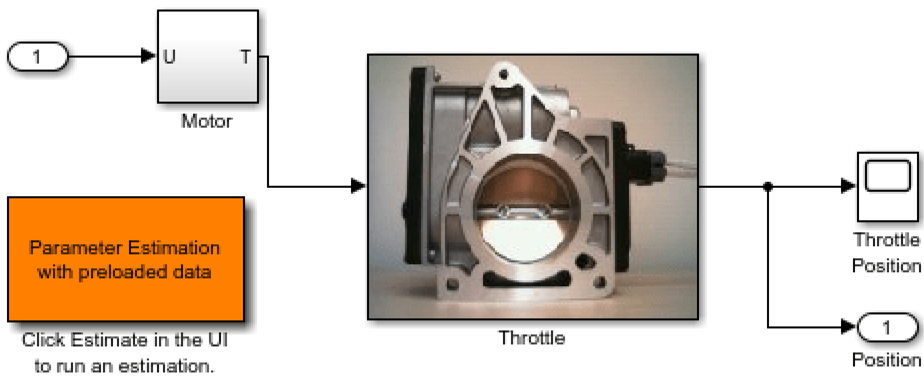
During optimization the model is repeatedly simulated (often tens or hundreds of times) Fast Restart means that the model is only compiled once for these simulation in comparison to non-fast restart where the model is recompiled each time.

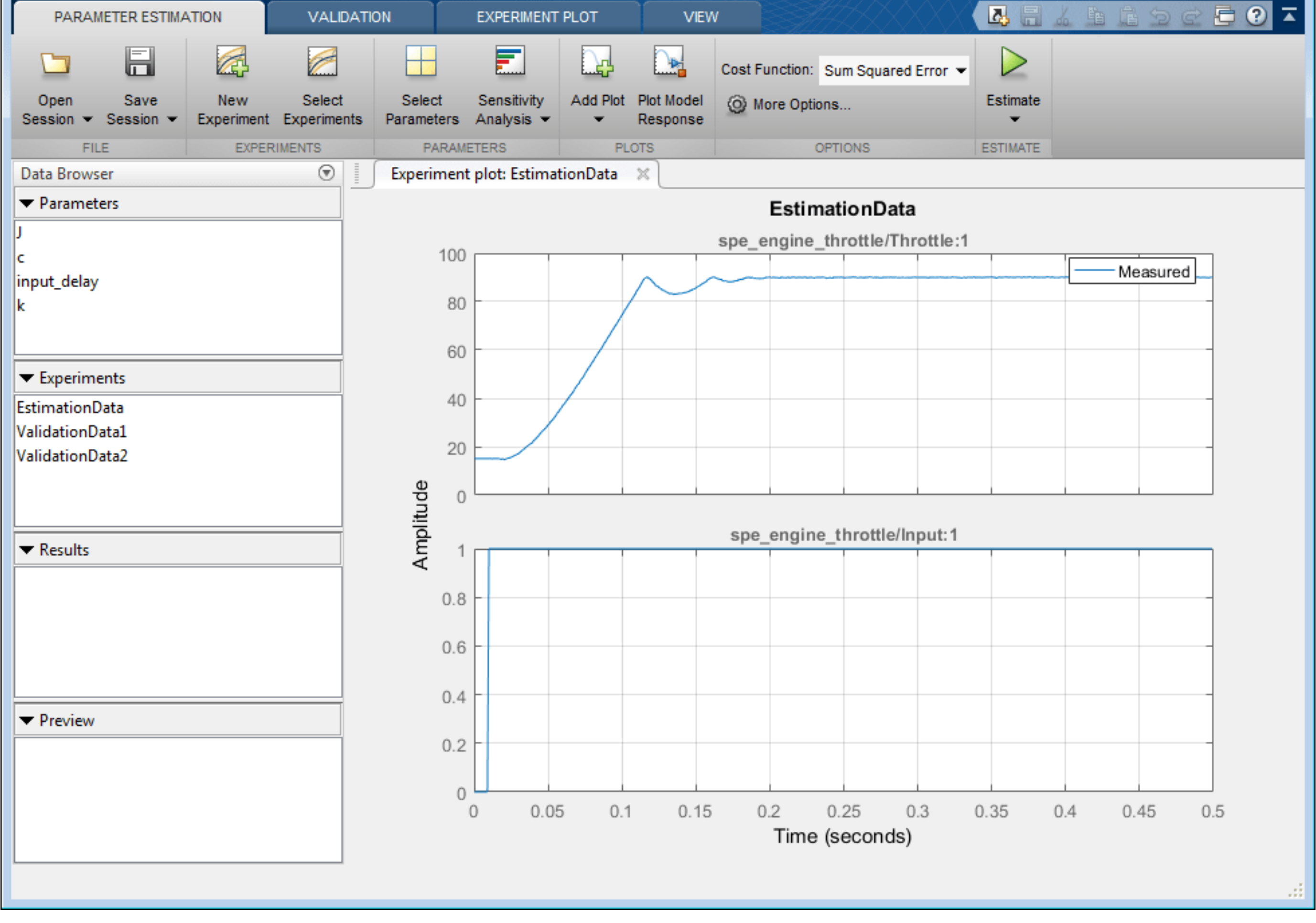
Models where compilation is a significant portion of overall simulation time benefit the most from Fast Restart. Further once a model is compiled not all model parameters can be changed, specifically only tunable parameters can be changed. For more information, see “Get Started with Fast Restart”.

Open Model and Parameter Estimator

Load the model and click the "Parameter Estimation with preloaded data" block to load a preconfigured parameter estimation problem. The goal is to tune the parameters of an engine throttle model to match measured data. For details on the problem setup see the “Estimate Model Parameter Values (GUI)” on page 2-144 example.

```
open_system('spe_engine_throttle')
```

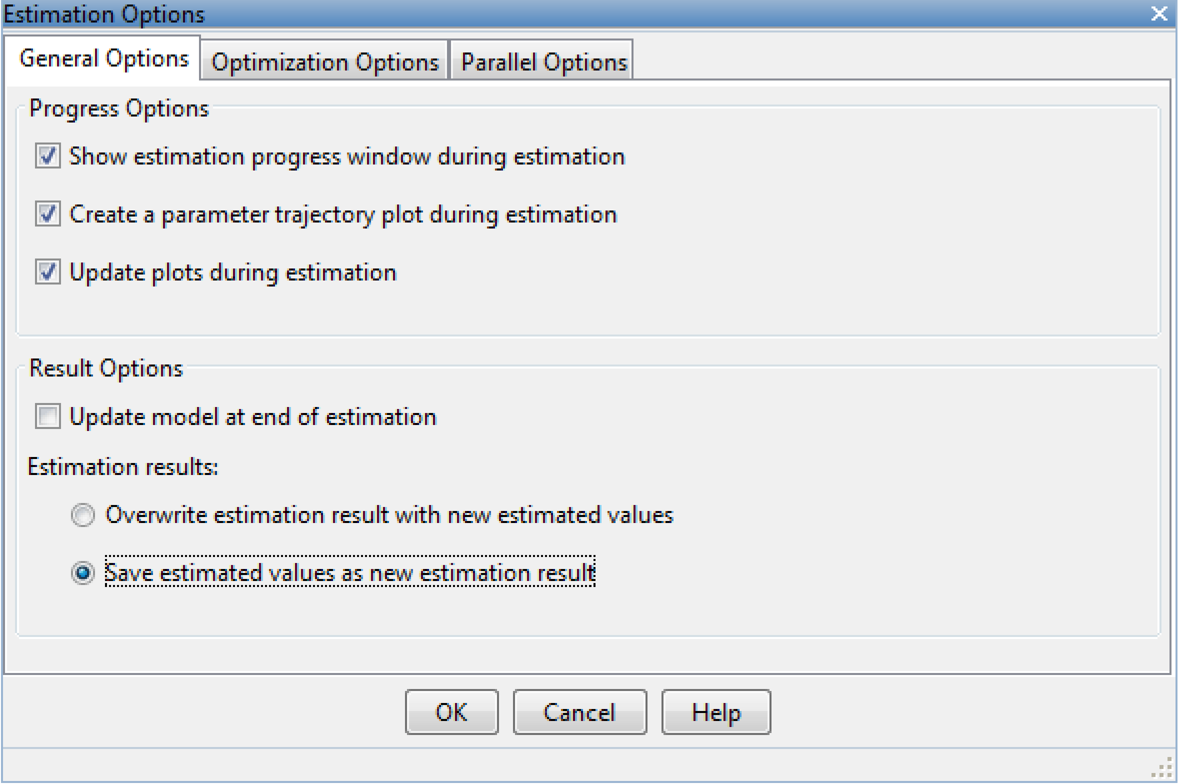




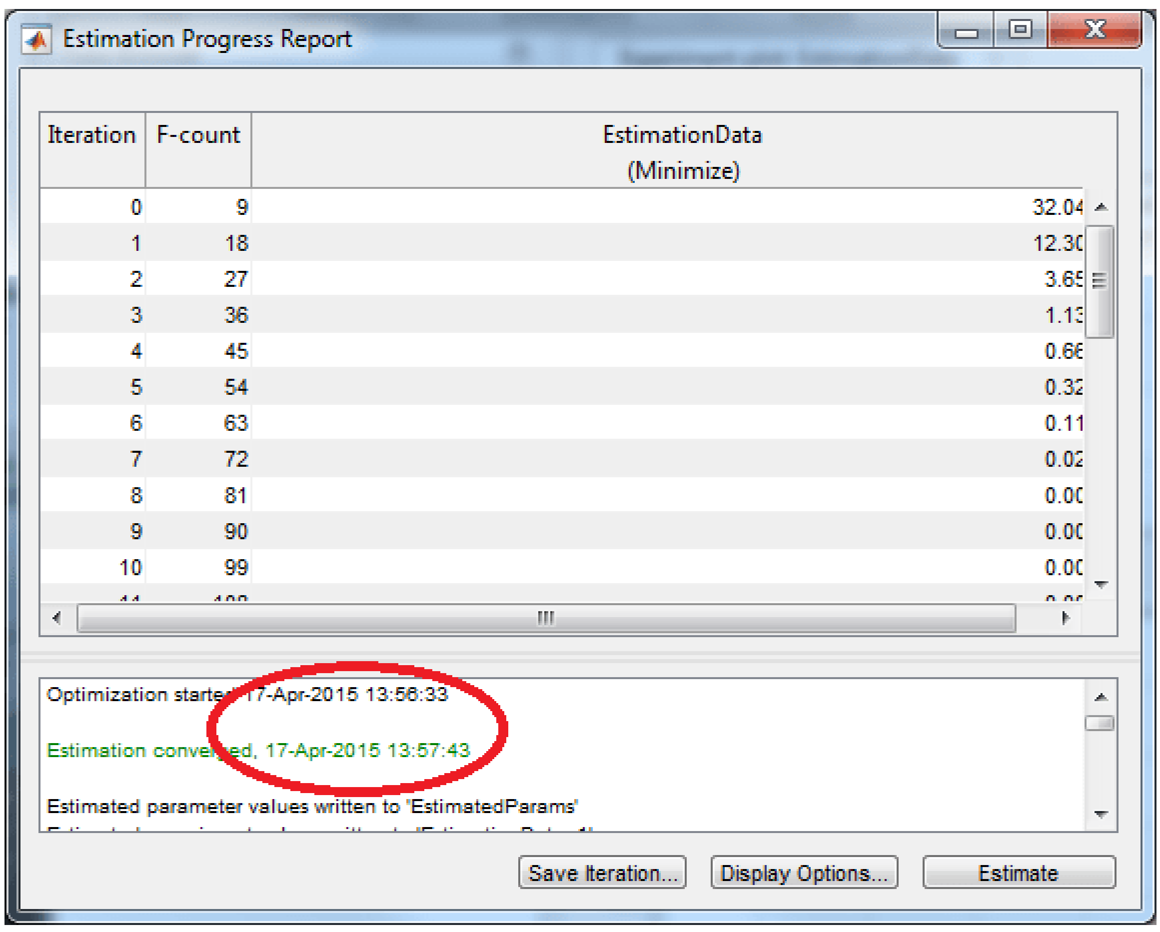
Estimate Without Using Fast Restart

To compare the estimation with and without fast restart, change the estimation options in the app to not update the model with estimated values.

Click **More Options** in the **Parameter Estimator** and click General Options. Clear **Update model at end of estimation**, and select **Save estimated values as new estimation result**.

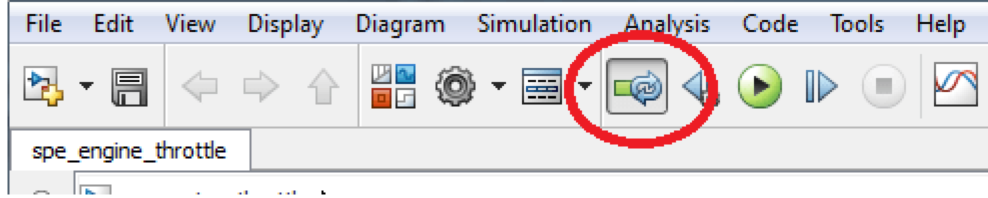


Click **Estimate** to estimate the model parameter values. The estimation progress report shows the estimation start and end time.

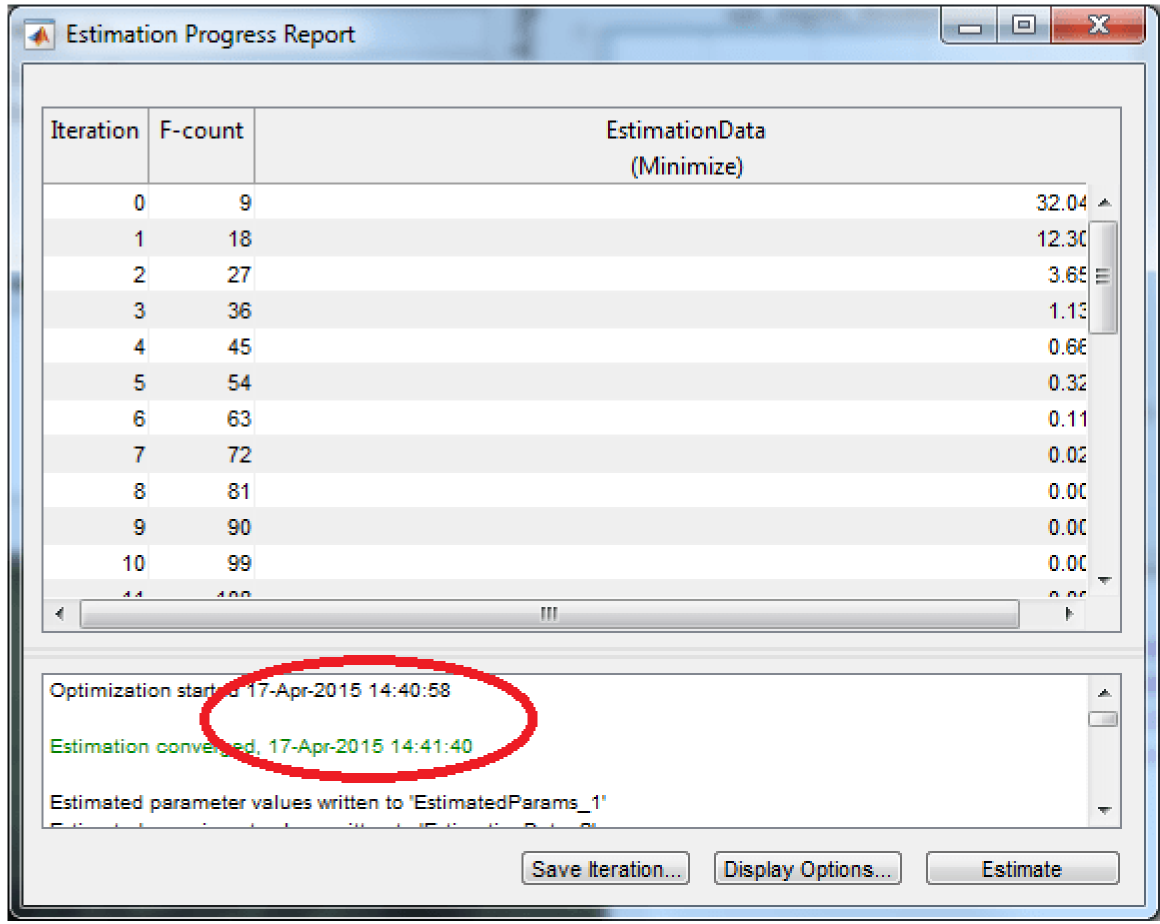


Estimate Using Fast Restart

To configure the model to use Fast Restart during simulation, click **Enable Fast Restart** in the Simulink model.



Click **Estimate** in the **Parameter Estimator**. The estimation progress report shows the estimation start and end time. Note the reduction in total estimation time compared to the estimation without using fast restart, in this case around 28 seconds or 45% of the original estimation time.



Related Examples

The `Generate MATLAB Code` feature of the **Parameter Estimator** and **Response Optimizer** will generate the MATLAB® code to configure the model for fast restart if the app is configured to use fast restart.

To learn how to use Fast Restart at the command line see “Improving Optimization Performance Using Fast Restart (Code)” on page 2-188.

Close the model.

```
bdclose('spe_engine_throttle')
```

See Also

Related Examples

- “Improving Optimization Performance Using Fast Restart (Code)” on page 2-188
- “Use Fast Restart Mode During Response Optimization” on page 3-196
- “Use Fast Restart Mode During Sensitivity Analysis” on page 4-109

More About

- “Ways to Speed Up Design Optimization Tasks”

Improving Optimization Performance Using Fast Restart (Code)

This example shows how to use the **Fast Restart** feature of Simulink® to speed up optimization of a model. You use fast restart to estimate the parameters of an engine throttle model.

How Fast Restart Speeds up the Optimization

Simulation of Simulink models requires that the model be compiled before it is simulated. In this context compilation of a model means analyzing and formatting the model so that it can be simulated. The idea of fast restart is to perform the model compilation once and reuse the compiled information for subsequent simulations. For more information about when to use fast restart, see “How Fast Restart Improves Iterative Simulations”.

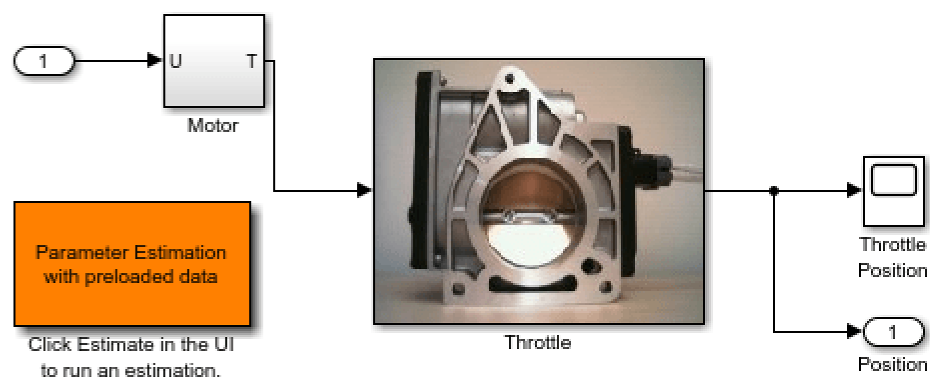
During optimization the model is repeatedly simulated (often tens or hundreds of times) Fast Restart means that the model is only compiled once for these simulation in comparison to non-fast restart where the model is recompiled each time.

Models where compilation is a significant portion of overall simulation time benefit the most from fast restart. Further once a model is compiled not all model parameters can be changed, specifically only tunable parameters can be changed. For more information, see “Get Started with Fast Restart”.

Open Model

Load the engine throttle model. The goal is to tune the parameters of the model to match measured data. For details on the problem setup see the “Estimate Model Parameter Values (GUI)” on page 2-144 example.

```
open_system('spe_engine_throttle')
```



Define the Estimation Problem Data

This examples focuses on the command line interface for using Fast Restart during estimation. For a detailed description of the estimation command line interface see “Estimate Model Parameter Values (Code)” on page 2-58.

Specify the model parameter values to estimate and any parameter bounds.

```
p = sdo.getParameterFromModel('spe_engine_throttle',{'J','c','input_delay','k'});
p(1).Minimum = 0;
p(2).Minimum = 0;
p(3).Minimum = 0;
p(3).Maximum = 0.1;
p(4).Minimum = 0;
```

Define the estimation experiment. The measured experiment data is loaded from the `spe_engine_throttle_ExperimentData` MATLAB file. The MATLAB file contains a `Input_SignalData` and `Output_SignalData` variable specifying the experiment input and output signal data.

```
load spe_engine_throttle_ExperimentData

Exp = sdo.Experiment('spe_engine_throttle');
Input = Simulink.SimulationData.Signal;
Input.Values    = Input_SignalData;
Input.BlockPath = 'spe_engine_throttle/Input';
Input.PortType  = 'inport';
Input.PortIndex = 1;
Input.Name      = 'spe_engine_throttle/Input:1';
Exp.InputData = Input;
Output = Simulink.SimulationData.Signal;
Output.Values    = Output_SignalData;
Output.BlockPath = 'spe_engine_throttle/Throttle';
Output.PortType  = 'outport';
Output.PortIndex = 1;
Output.Name      = 'spe_engine_throttle/Throttle:1';
Exp.OutputData = Output;
```

Create a model simulator from the experiment

```
Simulator = createSimulator(Exp);
```

Configure the Simulator for Fast Restart

The simulator controls whether the model is simulated using fast restart or not. The `fastRestart` command is used to configure the simulator to use Fast Restart.

The `spe_engine_throttle` model uses a variable-step solver, and may not output values at the times in the measured experiment data. To output values at the times of the measured data, use the `set_param` command to specify the model logging output times as a workspace variable. In the estimation objective function, the variable is then used to specify output times to be the same as the measured experiment data. The model `OutputTimes` is set before configuring the simulator for fast restart, as once the model is configured for fast restart, the model logging configuration can not change.

```
set_param('spe_engine_throttle','OutputOption','SpecifiedOutputTimes','OutputTimes','OutputTimes\
Simulator = fastRestart(Simulator,'on');
```

The simulator can now be used during estimation, and the model will be simulated using fast restart.

Run the Estimation

Create an estimation objective function to evaluate how closely the simulation output, generated using the estimated parameter values, matches the measured data. Use an anonymous function with

one argument that calls the `spe_engine_throttle_Objective` function. The `spe_engine_throttle_Objective` function includes the `Simulator` argument that has been configured to use fast restart.

```
optimfcn = @(P) spe_engine_throttle_Objective(P,Simulator,Exp);
```

Set the optimization options, and run the optimization.

```
Options = sdo.OptimizeOptions;
Options.Method = 'lsqnonlin';
[pOpt,Info] = sdo.optimize(optimfcn,p,Options);
```

```
 Optimization started 01-Sep-2022 14:41:02

                                                First-order
 Iter F-count        f(x)      Step-size  optimality
    0      9       32.048           1
    1     18        12.24       0.6495           18
    2     27       3.5944       0.3919         8.65
    3     36      1.11908       0.1881         3.11
    4     45     0.648845        0.197         1.25
    5     54     0.288719        1.218         1.15
    6     63     0.147572       0.2943         0.42
    7     72    0.0874598       0.5345        0.102
    8     81    0.0668259       0.4315        0.169
    9     90    0.0668259        9.907        0.169
   10     99    0.0662283         2.33         0.27
   11    108    0.0491157        0.209       0.0989
   12    117    0.0491157       0.2997       0.0989
   13    126    0.0490206      0.07492       0.0663
Local minimum possible.

lsqnonlin stopped because the final change in the sum of squares relative to
its initial value is less than the value of the function tolerance.
```

Restore the Model

Restore the simulator fast restart settings. This clears the logging and other settings used for the optimization problem.

```
Simulator = fastRestart(Simulator,'off');
set_param('spe_engine_throttle','OutputOption','RefineOutputTimes','OutputTimes','[]');
```

Related Examples

You can also generate code to configure you model for fast restart in the **Parameter Estimator** and the **Response Optimizer**. Configure the model for fast restart as described in "Improving Optimization Performance Using Fast Restart (GUI)" on page 2-182. Then use the `Generate MATLAB Code` feature of the app.

Close the model.

```
bdclose('spe_engine_throttle')
```

See Also

`sdo.SimulationTest` | `fastRestart`

Related Examples

- “Improving Optimization Performance Using Fast Restart (GUI)” on page 2-182
- “Use Fast Restart Mode During Response Optimization” on page 3-196
- “Use Fast Restart Mode During Sensitivity Analysis” on page 4-109

More About

- “Ways to Speed Up Design Optimization Tasks”

Parameter Tuning for Digital Twins

This example shows how to monitor the condition of an electric vehicle battery in the field, with a deployed version of parameter estimation in Simulink® Design Optimization™, together with Simulink Compiler™.

Battery Monitoring

Batteries in electric vehicles are expensive to replace and need to be monitored and maintained carefully, to ensure they function well for their intended lifetime. In this example, an electric car is driven to work and back on a daily commute. At home, the car is plugged in to a smart charger that monitors both the current and the battery voltage. The charger analyzes the battery data to estimate the battery parameters, using a deployed version of parameter estimation in Simulink Design Optimization, together with Simulink Compiler. The charger relays these parameters to the car manufacturer through an Internet of Things (IoT) connection, so that the manufacturer can monitor the battery health over time.

Battery Model

This example estimates parameters of a simple, rechargeable battery model, `sdoBattery`. The input to `sdoBattery` is the battery current, and the model output is the battery terminal voltage which is computed from the battery state of charge.

The battery model is based on the equation:

$$E = (1 - \text{Loss})V - KQ_{\text{max}}\frac{1 - s}{s}$$

where:

- E is the battery terminal voltage in Volts.
- V is the battery constant voltage in Volts.
- K is the battery polarization resistance in Ohms.
- Q_{max} is the maximum battery capacity in Ampere-hours. Q_0 is the battery initial state of charge in Ampere-hours.
- s is the battery charge state, with 1 being fully charged and 0 discharged. The battery state of charge is computed from the integral of the battery current with a positive current indicating discharge and a negative current indicating charging.
- Loss is the voltage drop when charging, expressed as a fraction of the battery constant voltage.

Use the following command to open the model.

```
open_system('sdoBattery')
```

Battery Characteristics

The following battery characteristics are known:

- Voltage, V = 400V
- Loss factor, Loss = 0.012
- Resistance, K = 0.32 Ohms.

Q_{max} is known to be 250 Ampere-hours (100 kWh) when the battery is new. As the battery ages, Q_{max} is expected to decrease, and this is monitored to track the health of the battery. The initial state of charge Q_0 and the new battery capacity Q_{max} need to be estimated.

Steps for Deployed Parameter Estimation

There are two main steps to run parameter estimation in deployed mode:

1. Make a *setup* file, to set up parameter estimation objects for use in deployed mode
2. Make a *run* file, which is a MATLAB function for parameter estimation that can be compiled and run in deployed mode

It is recommended to create the *setup* and *run* files by starting with MATLAB code generated from the **Parameter Estimator**. Copy, split, and modify the generated code to make the *setup* and *run* files as demonstrated in the following section.

Parameter Estimation in Non-Deployed Mode

First generate MATLAB code to estimate Q_0 and Q_{max} in non-deployed mode. Use the following commands to load the pre-configured estimation session:

```
load sdoBattery_spesession_forDeployment
spetool(SDOSessionData)
```

This step loads and plots the experiment with measured voltage and current data and configures the **Parameter Estimator** to estimate Q_0 and Q_{max}.

Navigate to the **Estimate** button in the toolstrip and from the dropdown list, select **Generate MATLAB Function** (see “Generate MATLAB Code for Parameter Estimation Problems (GUI)” on page 2-179). This step generates a MATLAB function which is added to the MATLAB editor, and a MAT-file `parameterEstimation_sdoBattery_Data.mat`. The generated code is available for you in file `parameterEstimationSdoBattery.m`. You can use the generated code to estimate parameters in non-deployed mode.

It is recommended to start with this generated code and copy, split and modify the code to create the *setup* and *run* files described in the following sections.

Setup-File for Deployed Parameter Estimation

To estimate parameters in deployed mode, the code for non-deployed parameter estimation can be split into a *setup* file to use in non-deployed mode, and a *run* file to use in deployed mode. The setup file is available as `parameterEstimationSdoBattery_setup.m` and the main parts are:

1. Define parameters
2. Define experiments
3. Prepare for deployment and save

Define Parameters

Parameters are defined in `parameterEstimationSdoBattery_setup.m` in the same way as the generated MATLAB code, `parameterEstimationSdoBattery.m`. Use the `sdo.getParameterFromModel` command to create a parameter object, containing fields for parameter value, minimum and maximum, and a field ("Free") indicating whether the parameter will be tuned during estimation.

In this example, parameter information is also stored in a database in which cars are identified by a code akin to a pseudo vehicle identification number (VIN). The car manufacturer can use this to monitor the health of the battery over time. The `parameterEstimationSdoBattery_setup.m` file uses the VIN database to update battery parameter values. See the `parameterEstimationSdoBattery_setup.m` file for more details.

The initial database is loaded from the MATLAB file `sdoBatteryVinDatabase.mat` which has the VIN database stored in variable `vinDatabase`. This is a `containers.Map` object, and the VIN key `4DEF` is used to look up parameters for the battery in this example.

Run

```
vinDatabase("4DEF")
```

to display the following table:

	K	Loss	Qmax	Q0	V
CurrentValue	0.32	0.012	250	150	400
PreviousValue	0.32	0.012	250	150	400

Define Experiments

Experiments are defined in `parameterEstimationSdoBattery_setup.m` in the same way as the generated MATLAB code, `parameterEstimationSdoBattery.m`. Experiments have measured data and information about specific ports or signals in the model that are associated with the data.

Prepare for Deployment and Save

At the end of the `parameterEstimationSdoBattery_setup.m` file, define a simulator which can run the model and compare model output to measured data. Use the `prepareToDeploy` command to configure the experiments and simulator so they can be used in deployed mode. Save these prepared objects to a MAT-file.

```
84      %% Configure objects for deployment and save to a MATLAB file
85      %
86 -    Exper = prepareToDeploy(Exper);
87      %
88 -    Simulator = createSimulator(Exper);
89 -    Simulator = prepareToDeploy(Simulator,p);
90 -    save sdoBatteryObjectsToDeploy Exper Simulator p vinDatabase
```

When running these steps on another model and preparing for deployment, you may be prompted to save the model to continue after running the *setup* function. Save the model to preserve logging settings that need to be in place for deployed mode.

The *run* file `parameterEstimationSdoBattery_run.m` uses the objects saved in `sdoBatteryObjectsToDeploy.mat` for parameter estimation in deployed mode.

Run-File for Deployed Parameter Estimation

The *run* file is available as `parameterEstimationSdoBattery_run.m` and the main parts are:

1. Load preconfigured deployment objects
2. Update experiments and parameters
3. Run optimization
4. Update Parameter Database

Load Preconfigured Deployment Objects

The `parameterEstimationSdoBattery_run.m` needs a pragma so that the Simulink Compiler includes the model in the compiled code as follows:

```
20      %% Ensure model is compiled
21      %#function sdoBattery.slx
```

Load the preconfigured objects that were saved at the end of `parameterEstimationSdoBattery_setup.m` file as follows:

```
24      %% Load configured experiment and simulator objects
25  -   load sdoBatteryObjectsToDeploy Exper Simulator p vinDatabase
```

Update Experiments and Parameters

The `parameterEstimationSdoBattery_run.m` file takes two input arguments:

- `dataFilename` — a data file name for experiment data
- `vin` — a vehicle identification number for parameter values

Read the data from the comma-separated-values (CSV) text file specified by `dataFilename`. Use the *updateIOData* command to update the deployed experiments with new input and output data (current and voltage data for this model). Since the data is from a CSV file, you do not need the `getData` function that is present in the generated MATLAB code, `parameterEstimationSdoBattery.m`.

```
31  -   data = readtable(dataFilename);
32      %Update experiment with input current data
33  -   current = timeseries(data.Current,data.Time);
34  -   Exper = updateIOData(Exper,'sdoBattery/Current',current);
35      %Update experiment with output voltage data
36  -   voltage = timeseries(data.Voltage,data.Time);
37  -   Exper = updateIOData(Exper,'sdoBattery/SOC -> Voltage',voltage);
```

Use the VIN as a key to look up this car's battery parameters in the parameter database. Use the current value from the database to update the initial parameter values prior to running the new estimation. See the `parameterEstimationSdoBattery_run.m` file for more details.

Run Optimization

The next several steps in `parameterEstimationSdoBattery_run.m` are very similar to the code in `parameterEstimationSdoBattery.m` (for non-deployed estimation). Define a handle to the estimation objective function, specify optimization options, and use the `sdo.optimize` function. This step runs the model and compares model output to experiment data. Parameters are tuned to achieve a close match between the model and data.

The objective function is defined in the subfunction `sdoBattery_optFcn` which is also like the objective function in `parameterEstimationSdoBattery.m`. However, the name of the signal logging variable needs to be specified since it cannot be queried from the model in deployed mode.

```
117 -   SimLog = find(Simulator.LoggedData,'logsout');
```

To determine the name of the variable ('`logsout`' in this case), query the model from MATLAB in non-deployed mode:

```
get_param('sdoBattery','SignalLoggingName')
```

Alternatively, in Simulink use the **Modeling** tab in the toolstrip and click **Model Settings**. In the configuration dialog, select **Data Import/Export** and find the variable name in the `Signal logging` box.

Update Parameter Database

After calling `sdo.optimize` in the main function of `parameterEstimationSdoBattery_run.m`, update the VIN database. For each parameter that is estimated, copy the `CurrentValue` to the `PreviousValue` and then use the new parameter estimate to update the `CurrentValue`. See `parameterEstimationSdoBattery_run.m` for more details.

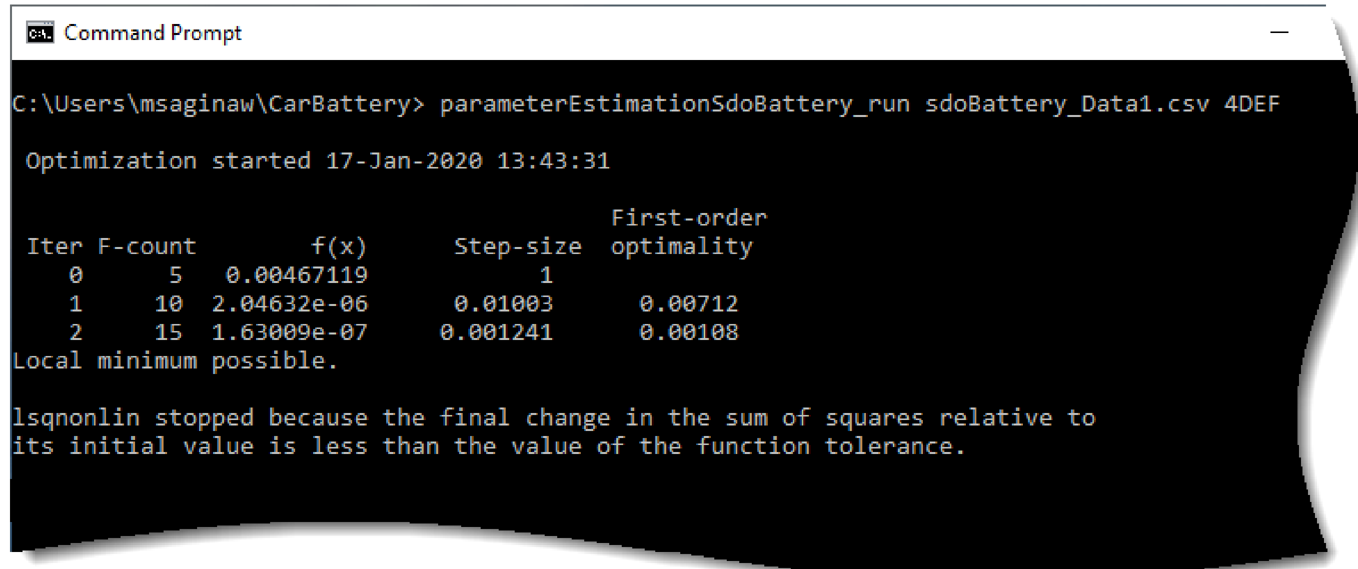
```
40      %% Update Parameters for this Vehicle from the Database
41 -    if nargin < 2
42 -        vin = "4DEF";
43 -    end
44 -    carData =  vinDatabase(vin);
45 -    for ct = 1:width(carData)
46 -        variableName = carData.Properties.VariableNames{ct};
47 -        bIdx = strcmp(variableName,{p.Name});
48 -        p(bIdx).Value = carData{'CurrentValue',variableName};
49 -    end
```

Running Parameter Estimation in Deployed Mode

Use the `mcc` command to compile the `parameterEstimationSdoBattery_run.m` function from either the MATLAB command window or the DOS or UNIX command prompt. You need to have MATLAB Runtime installed to complete the following steps. For more information, see “Install and Configure MATLAB Runtime” (MATLAB Compiler).

```
Command Window
>> mcc -m parameterEstimationSdoBattery_run
### Building the rapid accelerator target for model: sdoBattery
### Successfully built the rapid accelerator target for model: sdoBattery
```

Run parameter estimation in deployed mode.



In MATLAB, run

```
vinDatabase("4DEF")
```

to display the following result:

```
                     K      Loss     Qmax       Q0       V
                    ____    _____    ______    ______    ___

    CurrentValue    0.32    0.012    250.35    152.81    400
    PreviousValue   0.32    0.012       250       150    400
```

Tracking Battery Parameters over Time

The table below shows estimates of battery parameters Q_0 and Q_{max} over time. The file `sdoBattery_Data1.csv` contains data for the battery when it was new, `sdoBattery_Data2.csv` contains data for the battery when it was 1 year old and `sdoBattery_Data3.csv` contains data for the battery when it was 2 years old.

Data File	Q_0	Q_{max}	Ratio
sdoBattery_Data1.csv	152.81	250.35	61%
sdoBattery_Data2.csv	101.50	199.01	51%
sdoBattery_Data3.csv	86.91	184.45	47%

Observe that there is degradation in battery capacity over time. There is a high rate of degradation in the first year after which the rate of degradation reduces. When the battery was new, the round-trip commute left the battery state of charge at 61% while after 2 years, the commute left the battery state of charge at 47%. If the state of charge falls below 40%, this condition reduces the number of

times the battery can be recharged. By tracking battery parameters over time, the manufacturer can monitor the battery health, and determine if the car needs a new battery.

See Also

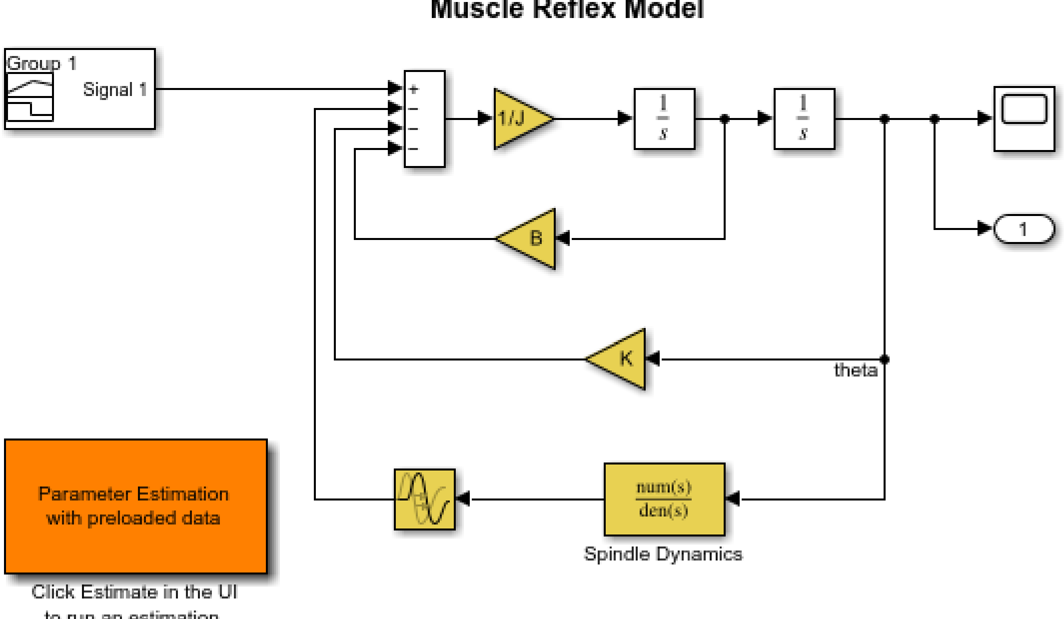
`prepareToDeploy(Experiment)` | `prepareToDeploy(SimulationTest)` | `updateIOData(Experiment)` | `sdo.Experiment` | `sdo.SimulationTest`

Muscle Reflex Parameter Estimation

This example shows how to estimate parameters of a muscle reflex model.

Simulink Model of the Muscle Reflex

The Simulink® model for the muscle reflex system, `spe_muscle`, is shown below.



Muscle Reflex Model Description

For this example a simple knee reflex action of humans is modeled. When the patellar tendon is excited, for example when a doctor strikes it with the nub of a small rubber hammer, the tendon reacts with a small but quick reflex force. This in turn pulls the muscle and we observe that the leg jerks forward slightly at the knee.

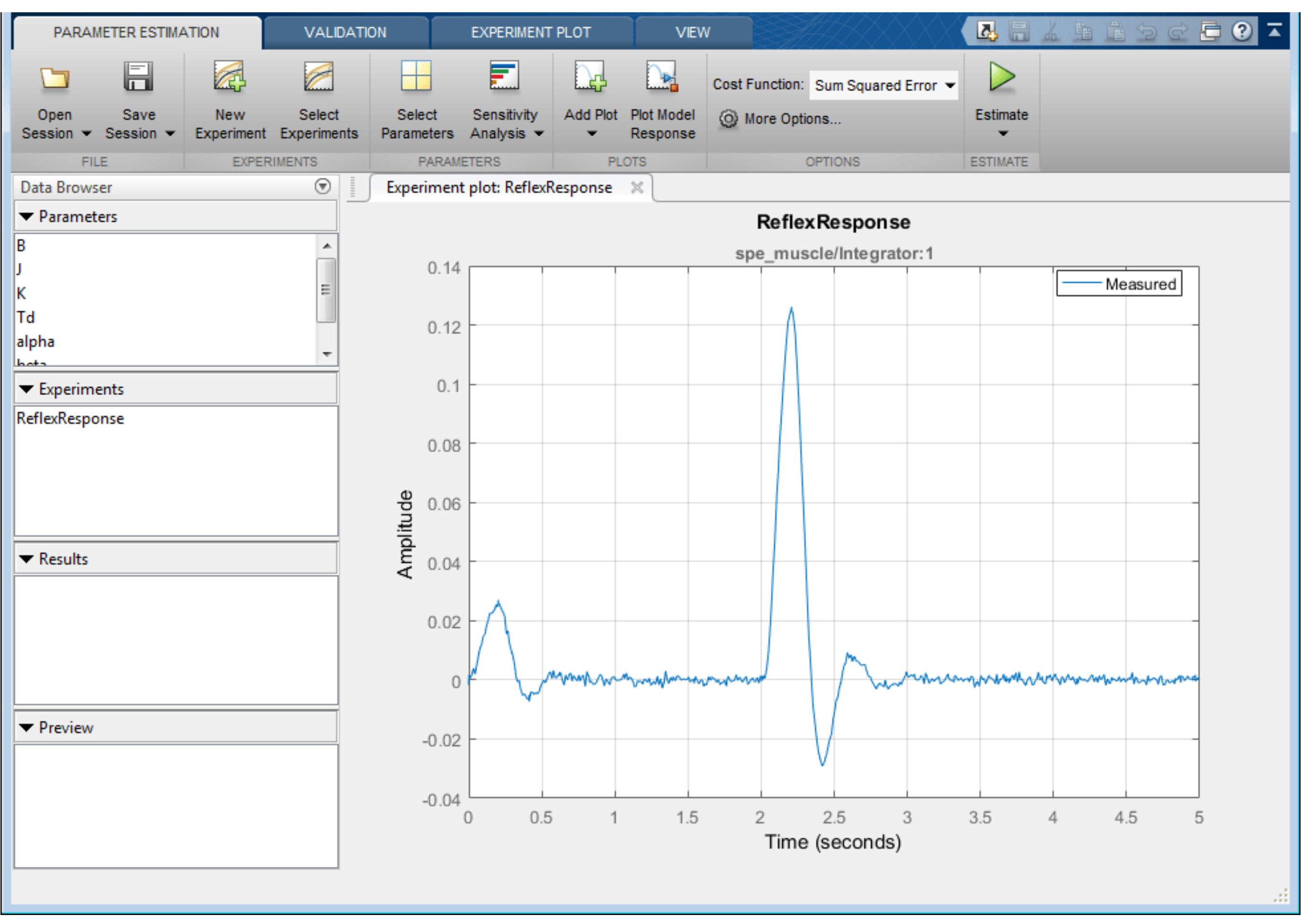
For this model we treat the tendon itself as a small torsional spring damper with inertia (J), stiffness (K) and damping (B). When the tendon is excited a signal is sent through the nervous system to the spinal cord reporting a structural change (i.e. tendon length). The nervous system then sends a signal back to the tendon to produce a reflex. There are receptors on the muscle called spindles that have their own dynamics, shown in the model as a transfer function in the feedback path. The spindles are modeled as a spring (Kpe) and damper (Bpe) in parallel, and then with the pair in series with another spring (Kse). The differential equation describing these dynamics is given by

$$T' = (Kse/b) * [Bpe * x' + Kpe * x)] - [(Kse + Kpe)/b] * T$$

For this model we supply two brief pulses, one stronger than the other, as input. This is similar to what one might experience in a doctor's office.

Estimation Data

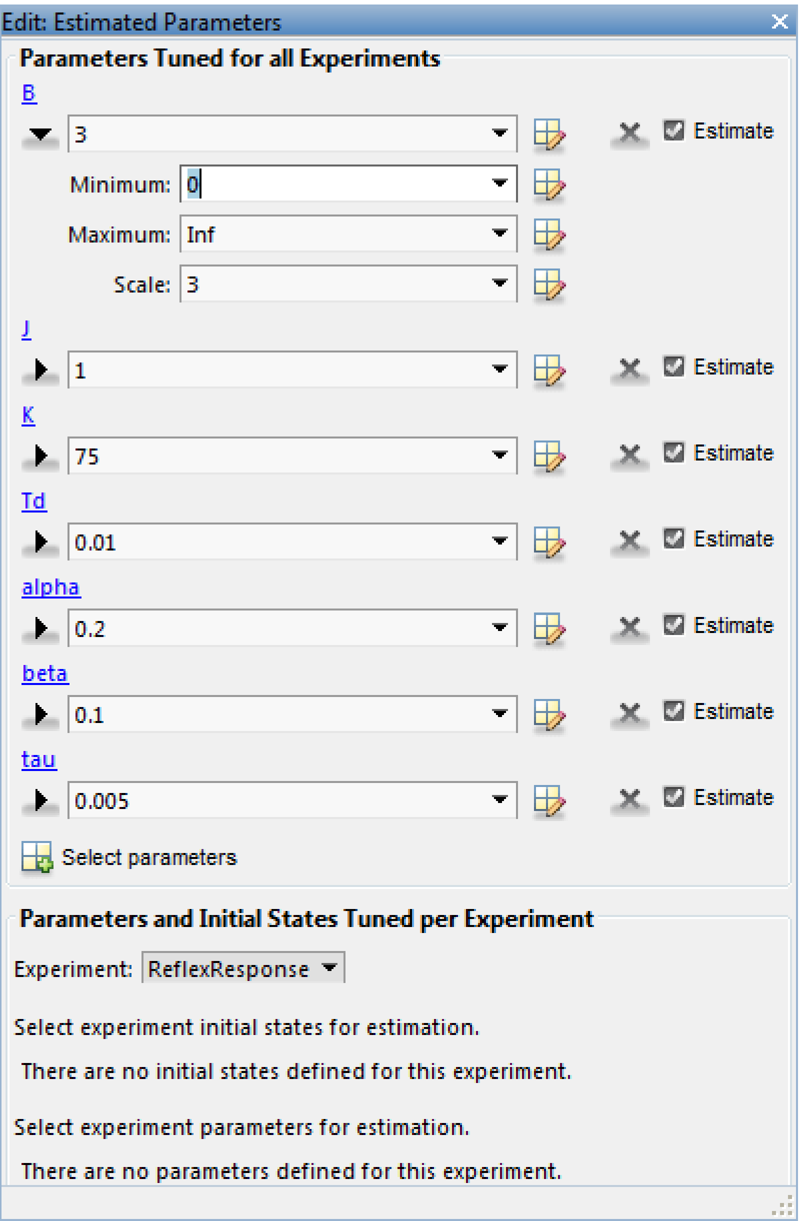
There is a project already associated with this model. You can access it by double-clicking the orange block in the lower left corner of the model. This opens the **Parameter Estimator** configured with measured experiment data `ReflexResponse` and parameters `J`, `B`, `K`, `Td`, `beta`, `alpha`, and `tau` selected for estimation. The measured data in the `ReflexResponse` experiment is shown in the plot. There is only one data set used for this example.



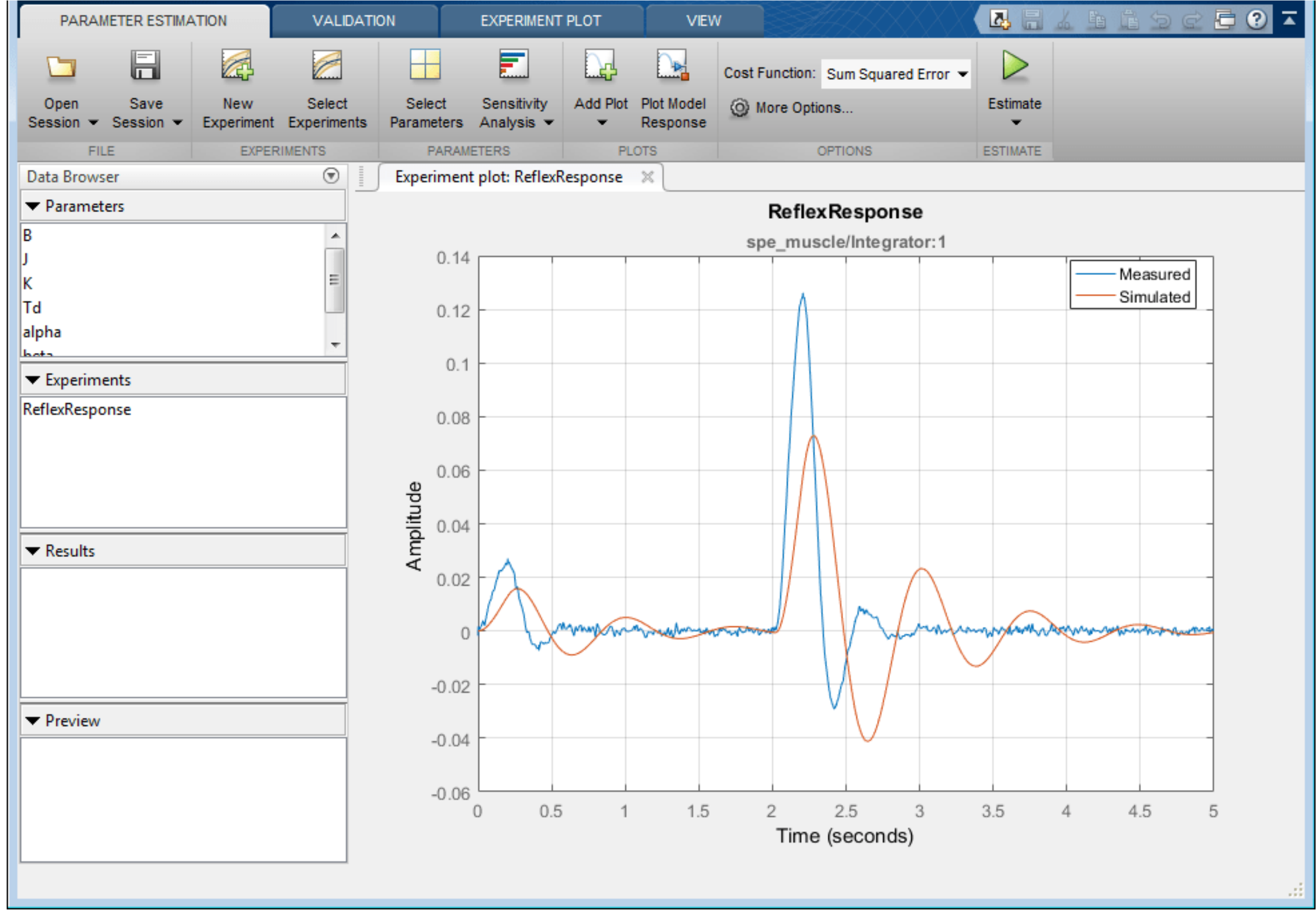
The experiment data can be imported from various sources including MATLAB® variables, MAT files, Excel® files, or comma-separated-value files.

Estimated Parameters

The estimation parameters are selected by clicking on **Select Parameters** in the **Parameter Estimation** tab. We have already loaded the parameters for this model. These parameters are the inertia, `J`; damping coefficient, `B`; the return spring constant, `K`; the neural transmission delay, `Td` as well as the spindle dynamics parameters `beta`, `alpha`, and `tau`. Since we know from our physical insight that none of these parameters can be negative we set their lower limits to zero. Based on known neural transmission times, we set the lower limit of `Td` to 10 microseconds.



The experiment plot is also used to see how well the measured data matches the current model. Click **Plot Model Response** to display simulated signal data on the experiment plots. The simulation results show that the model does not match the measured data and that model parameters need to be estimated.

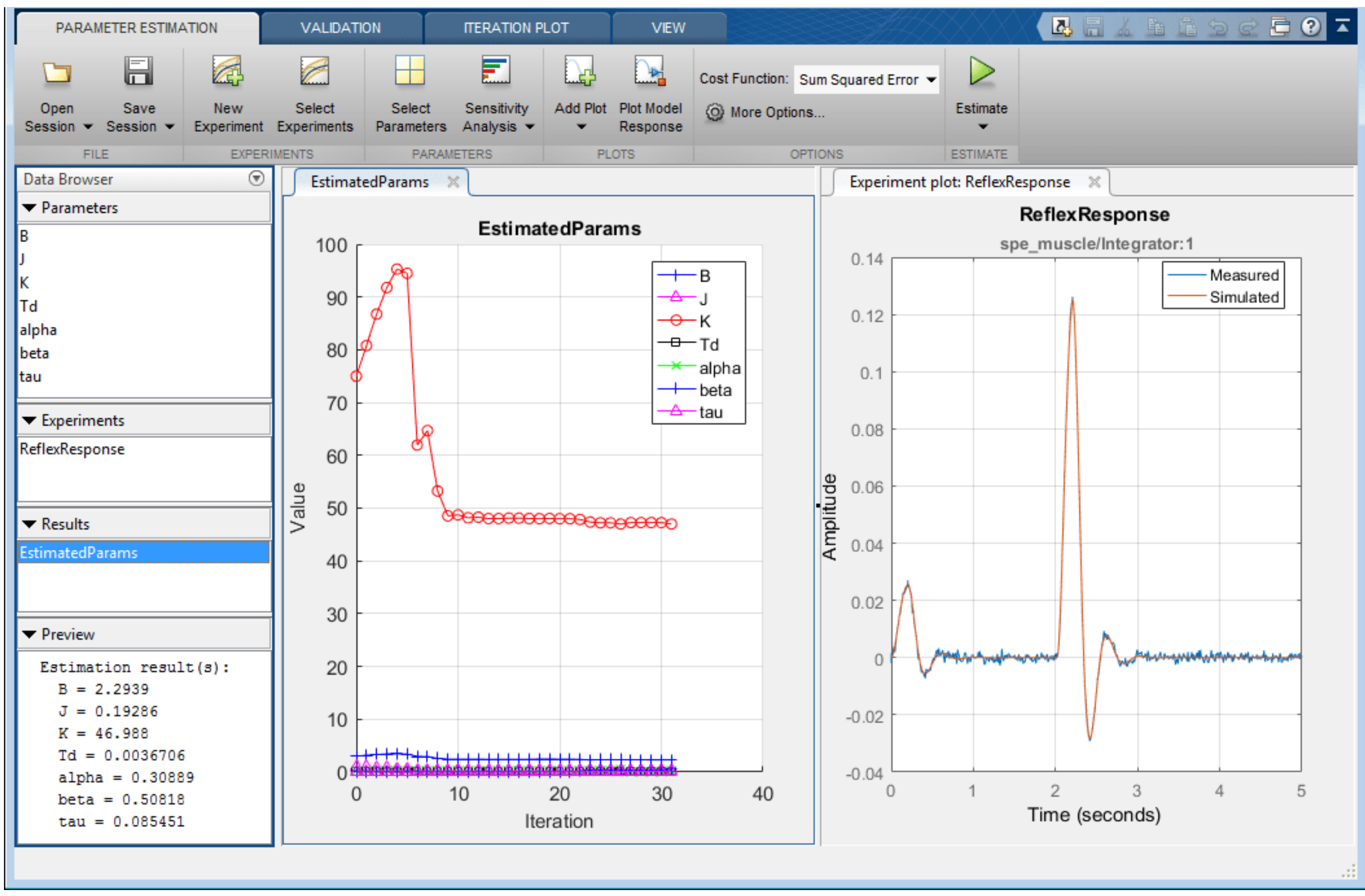


Estimation

With the parameters for estimation specified, we select experiments to use for estimation. Click **Select Experiments** in the **Parameter Estimation** tab and select `ReflexResponse` for estimation.

We are now almost ready to start our estimation but first create another plot to monitor the estimation progress. Click **Add Plot** and select **Parameter Trajectory**. This creates a plot that shows how the parameter values change during estimation. Click the **View** tab to lay out the plots so that the experiment plot and trajectory iteration plot are both visible.

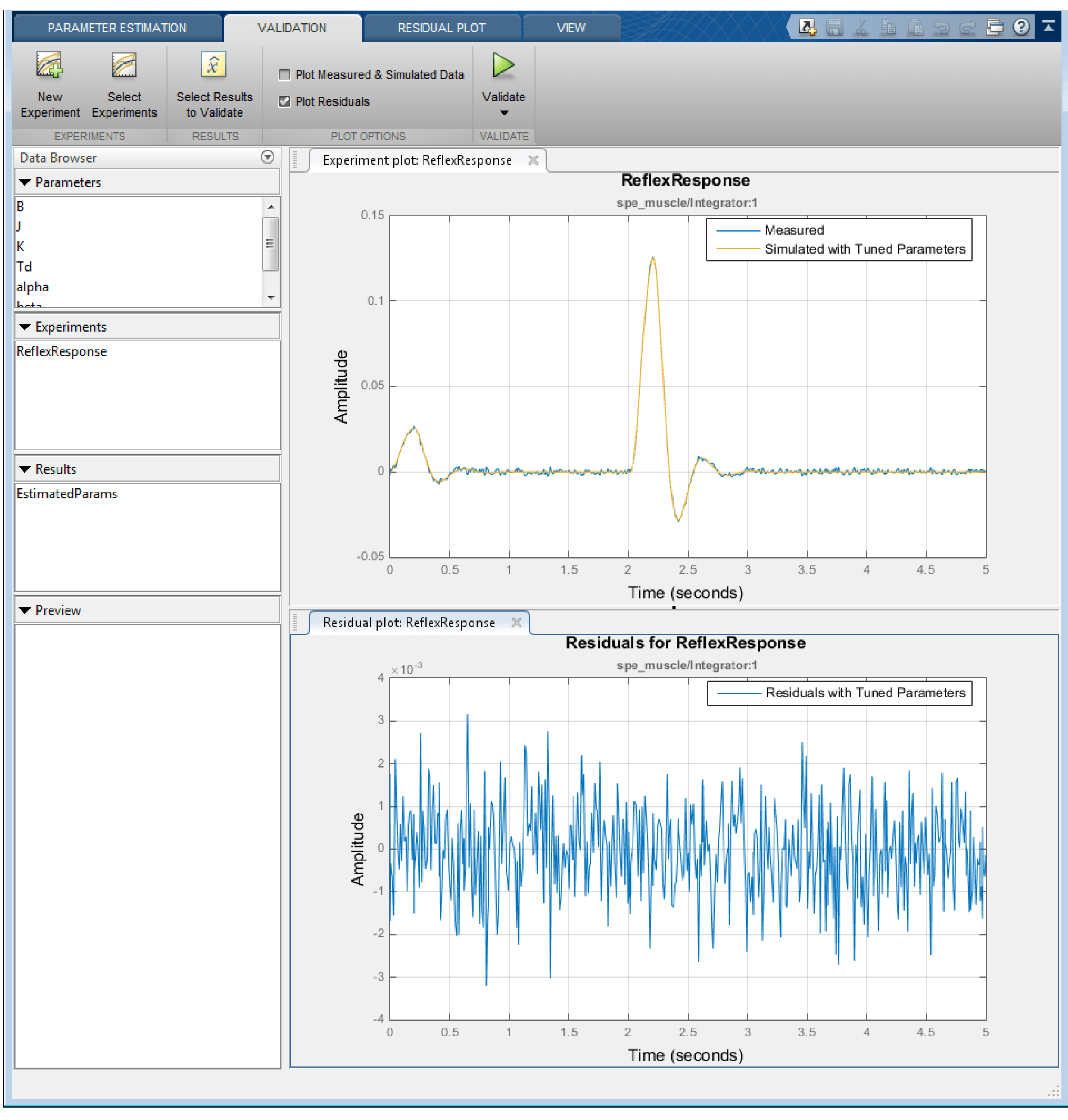
Click the **Estimate** button in the **Parameter Estimation** tab to start the estimation. The estimation will keep iterating the parameter values until the estimation converges and terminates. The plot below shows the measured data overlaid with the simulated data. The simulated data comes from the model with the estimated parameters. The results of the estimation appear satisfactory, the simulated curve closely matches the measured results.



Validation

We can also view residuals of the estimation. Residuals are the error between the measured response and simulated response at each time step.

Click the **Validation** tab and click **Select Experiments**. Select the `ReflexResponse` experiment for validation. In the **Validation** tab, select **Plot Residuals** and click **Validate**. The plot below shows that the residuals do not exhibit a correlation pattern. They are one or two orders of magnitude smaller than the measured data and are essentially the noise from the experimental data, so we are again satisfied that parameters in the model were estimated well.



The parameters of the model have been tuned to match the experimental results very well and our estimation error is only the original noise in the results. We can conclude that the parameters in the model have been successfully estimated.

Close the model.

See Also

More About

- “Specify Parameters for Estimation” on page 2-7
- “Validate Estimation Results” on page 2-25

DC Servo Motor Parameter Estimation

This example shows how to estimate the parameters of a multi-domain DC servo motor model constructed using various physical modeling products.

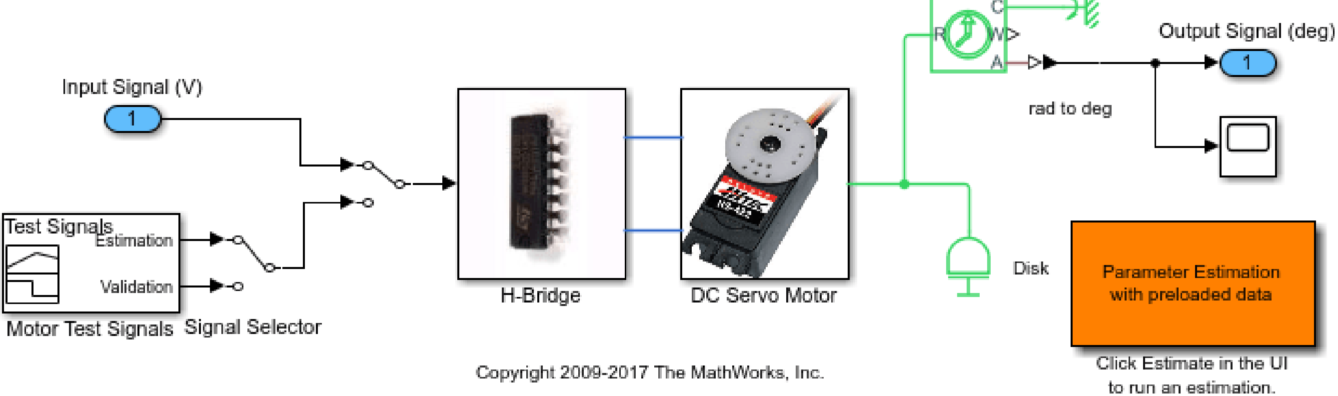
This example requires Simscape™ Driveline™ and Simscape™ Electrical™.

Description of the DC Servo Motor System

A DC servo motor, with its electrical and mechanical components, provides a great example to illustrate multi-domain modeling using first principles.

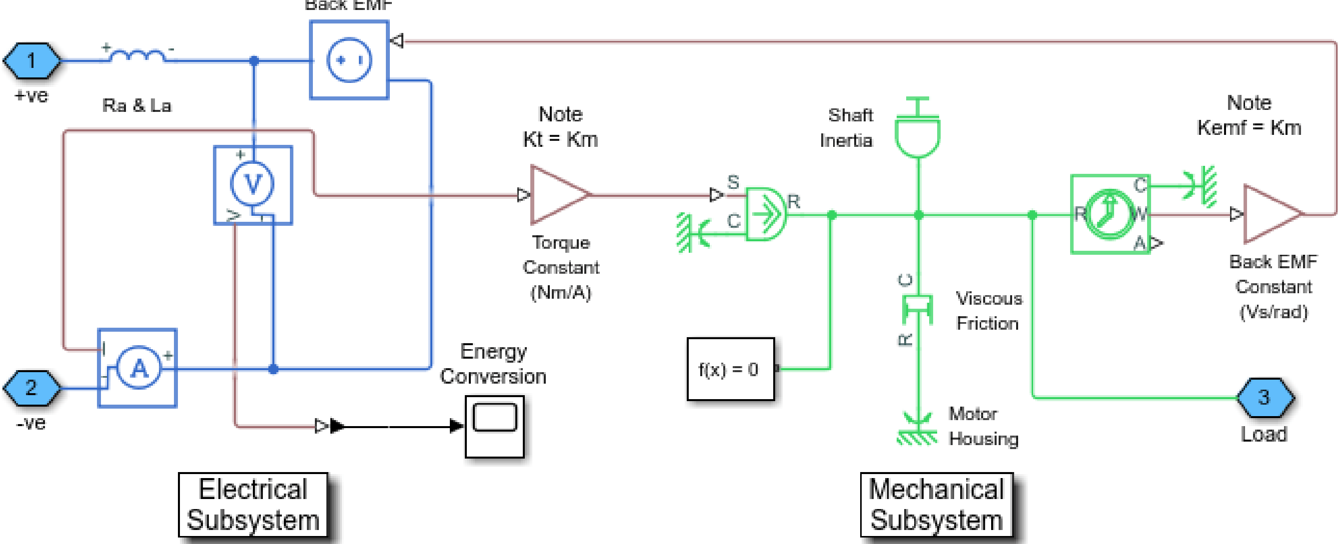
The DC servo motor is part of a larger system that contains the control electronics (H-Bridge) and a disk attached to the motor shaft. The overall model, `spe_servomotor`, is shown below, where the Input Signal (V) is the voltage signal applied to the H-bridge circuit, and the Output Signal (deg) is the angular position of the motor shaft.

```
open_system('spe_servomotor')
```



We developed a first-principles model of the DC motor within the DC servo motor subsystem. We used Simscape Electrical to model the electrical components and Simscape Driveline to model the mechanical components of the motor. The figure below shows the content of the servo motor subsystem.

```
open_system('spe_servomotor/DC Servo Motor')
```



The DC motor model shows a relationship from current to torque (the green line on the left). The torque causes the shaft of the motor to spin and we have a relationship between this spinning to the Back EMF (electromotive force). The rest of the parameters include a shaft inertia, viscous friction (damping), armature resistance, and armature inductance.

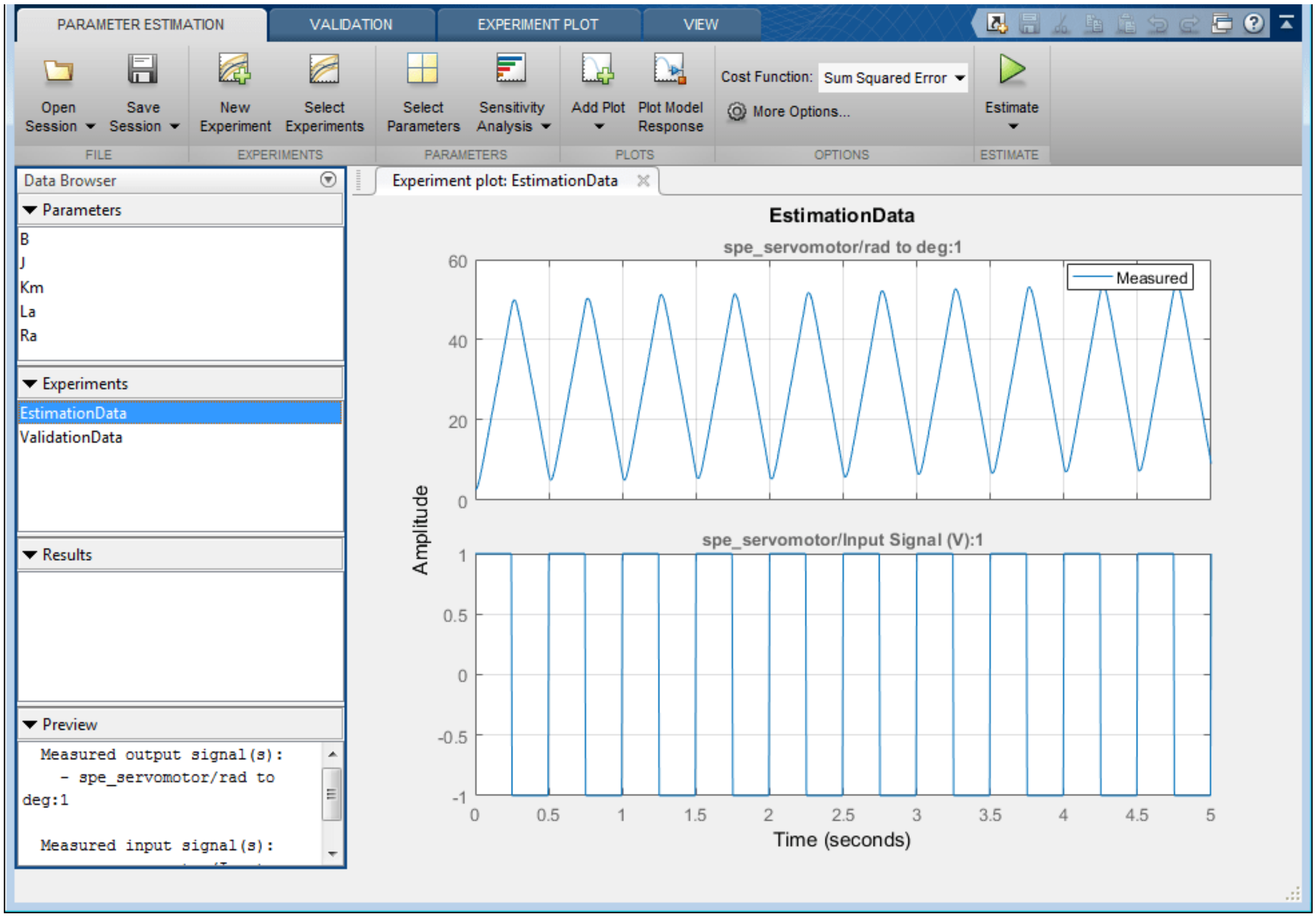
While manufacturers may provide values for some of these quantities, they are only approximate. We want to estimate these parameters as precisely as possible for our model to ascertain whether it is an accurate representation of the actual DC servo motor system.

When we apply a series of voltage pulses to the motor input, the motor shaft turns in response. However, if the model parameters do not match those of the physical system, the model response will not match that of the actual system, either. This is where Simulink® Design Optimization™ plays a pivotal role in estimating parameter values. A parameter estimation process consists of a number of well-defined steps:

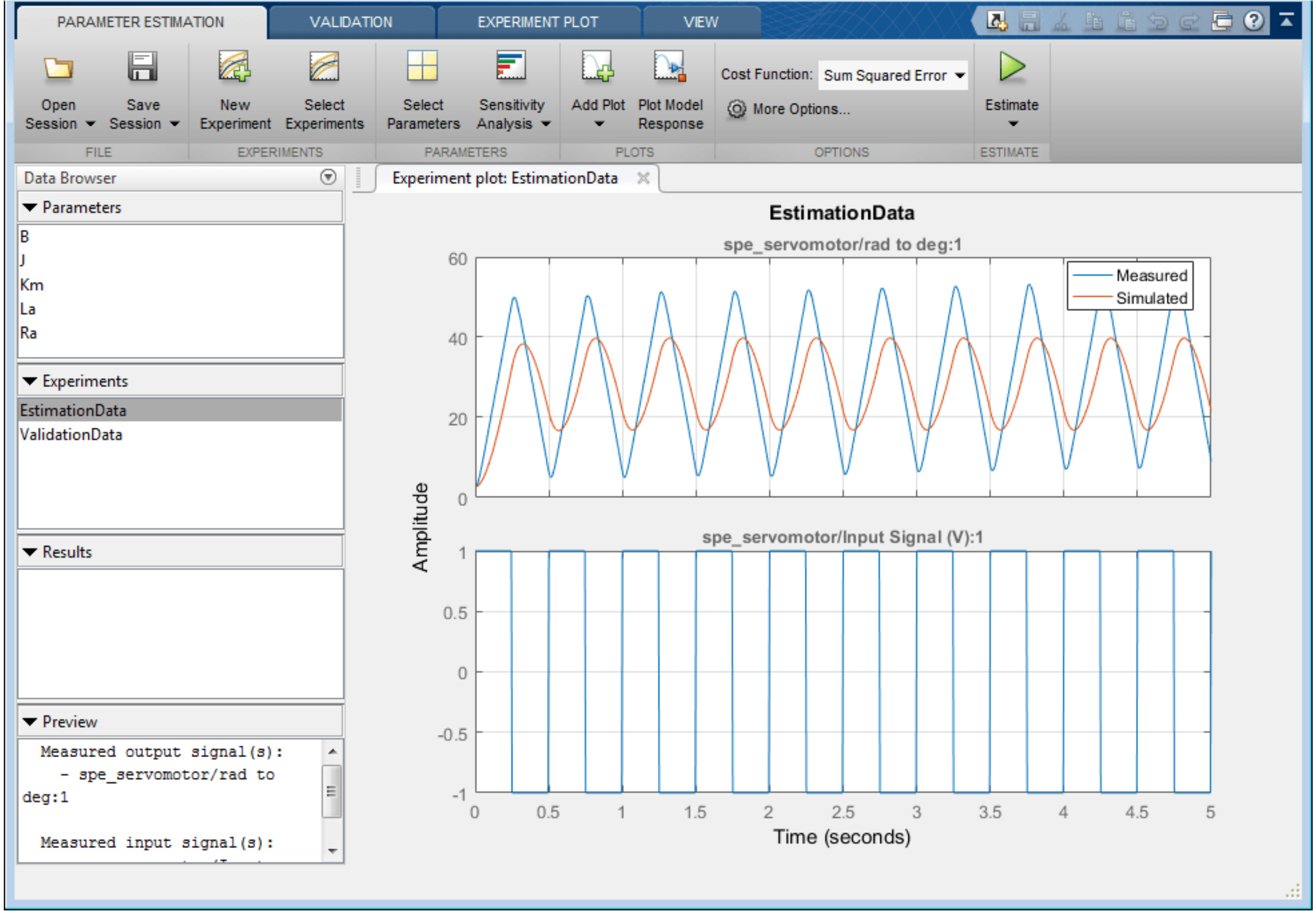
- Collect test data from your system (experiment).
- Specify the parameters to estimate (including initial guesses, parameter bounds, etc.).
- Configure your estimation and run a suitable estimation algorithm.
- Validate the results against other test data sets and repeat above steps if necessary.

Simulink Design Optimization provides the **Parameter Estimator** app which is a user interface to help you perform parameter estimation, organize your estimation project, and save it for future work.

Double-click the orange block in the lower right corner of the servomotor model to launch the **Parameter Estimator**, pre-loaded with data for this project. This is configured with measured experiment data `EstimationData`. For other uses you can import experimental data sets from various sources including MATLAB® variables, MAT files, Excel® files, or comma-separated-value files. The **Parameter Estimator** is also pre-loaded with parameters for the servomotor subsystem selected for estimation: `B`, `J`, `Km`, `La`, and `Ra`. It is also configured with validation data `ValidationData` which we will use later, after estimation. The measured data in `EstimationData` is shown in the experiment plot. There is only one data set used for estimation in this example.

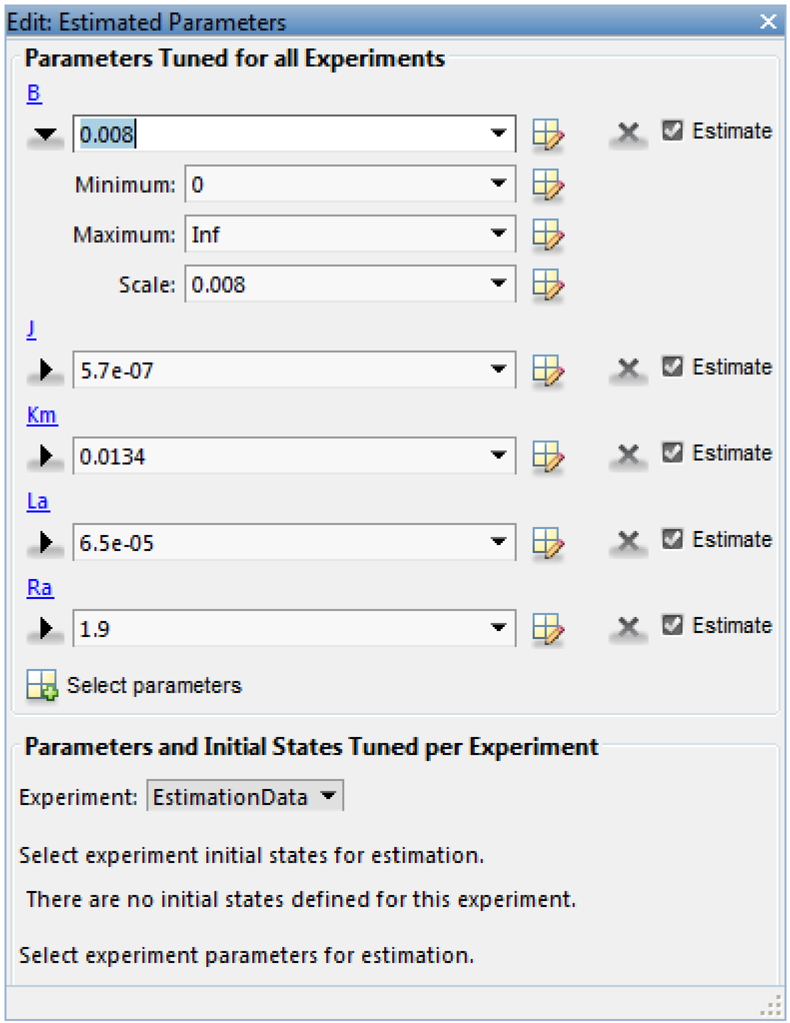


The experiment plot is also used to see how well the measured data matches the current model. Click **Plot Model Response** in the **Parameter Estimation** tab to display simulated signal data on the experiment plots. The simulation does not match the measured data, showing that the model parameters need to be estimated.



Selecting Parameters for Estimation

Simulink Design Optimization lets you estimate some or all of the parameters in your model in a manner that best suits your application. The estimation parameters are selected by clicking **Select Parameters** in the **Parameter Estimation** tab. For our DC motor example, we have already loaded the five parameters of the motor model: `B`, `J`, `Km`, `La`, and `Ra`. Since we know from our physical insight that none of these parameters can be negative we set their lower limits to zero.



Estimating Parameters of the DC Motor Model

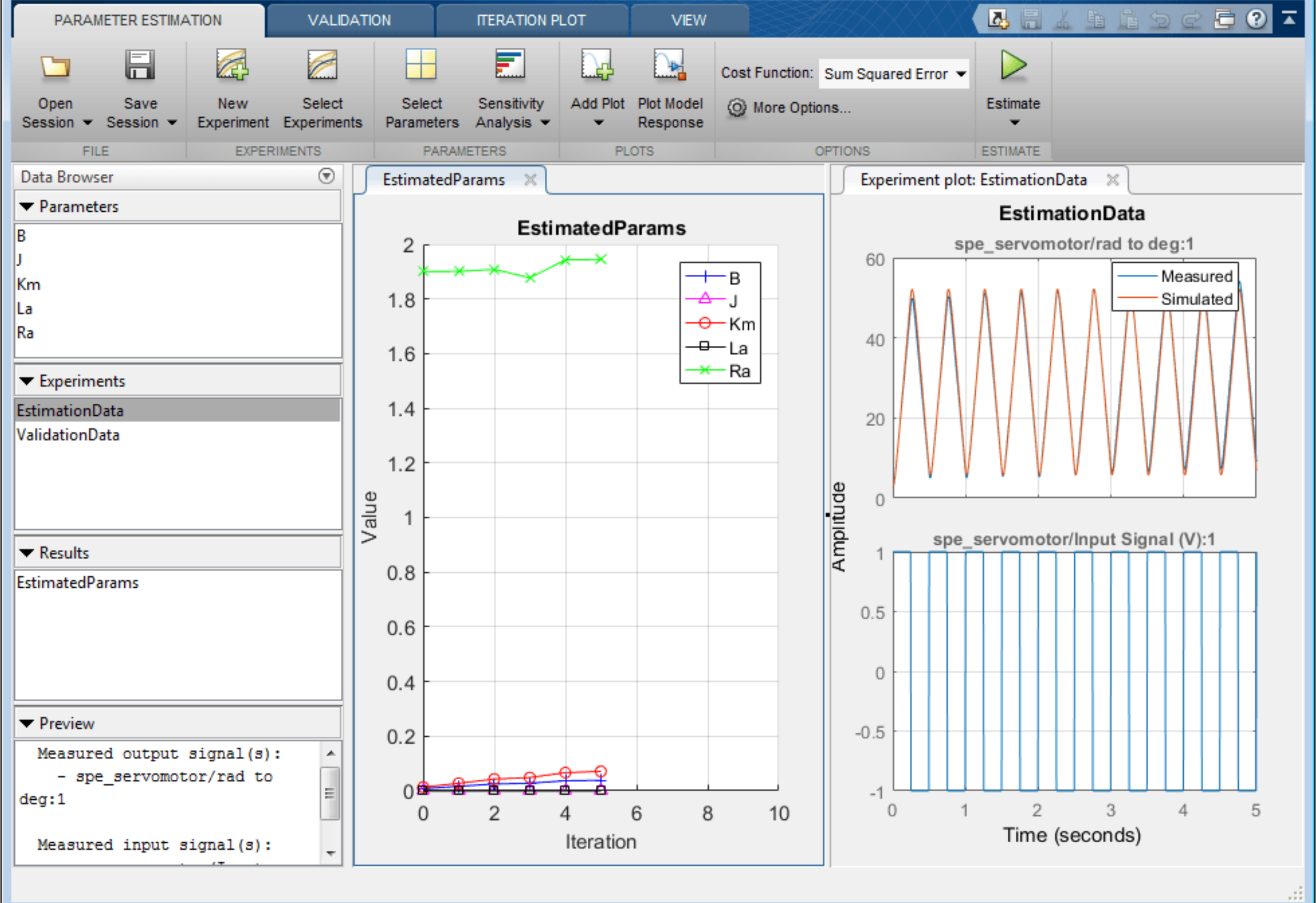
With the parameters for estimation specified, we select experiments to use for estimation. Click **Select Experiments** in the **Parameter Estimation** tab and select `EstimationData` for estimation.

We are now almost ready to start our estimation but first create another plot to monitor the estimation progress. Click **Add Plot** and select **Parameter Trajectory**. This creates a plot that shows how the parameter values change during estimation. Click the **View** tab to lay out the plots so that the experiment plot and trajectory iteration plot are both visible.

Click the **Estimate** button in the **Parameter Estimation** tab to start the estimation. The estimation will keep iterating the parameter values until the estimation converges and terminates. Parameter Estimation provides various state-of-the-art estimation methods. The most common selections include the nonlinear least-squares and Nelder-Mead optimization methods. More information on these methods is available in the Optimization Toolbox™ documentation. You can also use the pattern search method in the Global Optimization Toolbox for parameter estimation.

The plot below shows the measured data overlaid with the simulated data. The simulated data comes from the model with the estimated parameters. Comparing the response of the system before and

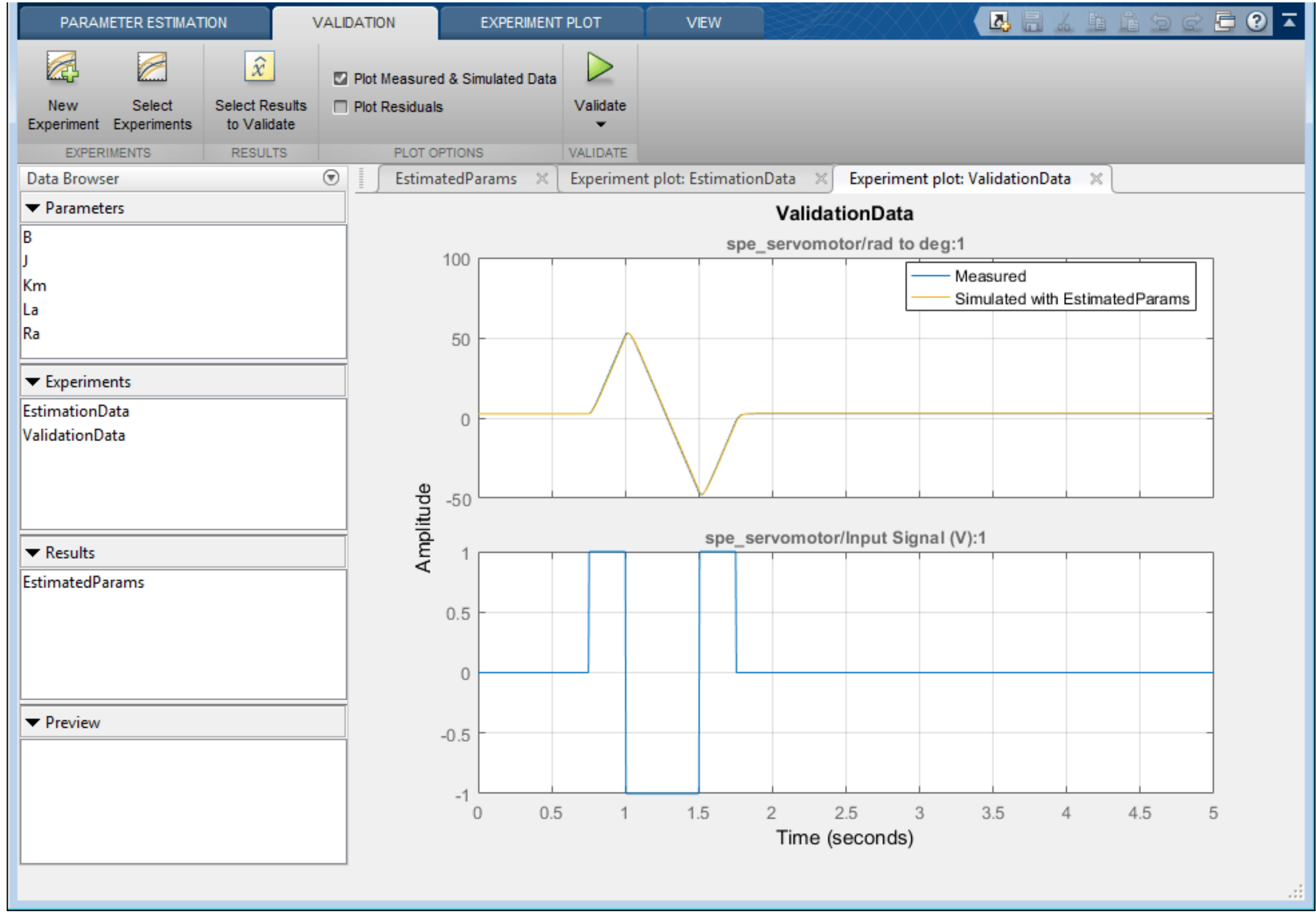
after the estimation process clearly shows that the estimation successfully identified the model parameters and the simulated response accurately matches the experimental data.



Validation

After completing the estimation, it is important to validate the results against other data sets. A successful estimation should match not only the experimental data that we used for estimation, but also the other data sets that we collected in our experiments.

We used our second data set in `ValidationData` for validating the estimation results. As the next figure shows, the match between the model response and the data set is very good. In fact, the two curves are almost identical for this example.



Summary

Engineers and scientists across disciplines and industries are well acquainted with the benefits of modeling dynamic systems. They may use either first-principles mathematics or test-data based methods. First-principles models provide important insight into system behavior, but may lack accuracy. Data-driven models provide accurate results, but tend to offer limited understanding of the physics of the system. This article showed the use of Parameter Estimation to improve the accuracy of a DC Servo Motor model by estimating the model parameters using experimental data.

Close the model

```
bdclose('spe_servomotor')
```

Engine Speed Model Parameter Estimation

This example shows how to estimate the coefficients of a nonlinear (quadratic) function to approximate the dynamic behavior of a system component.

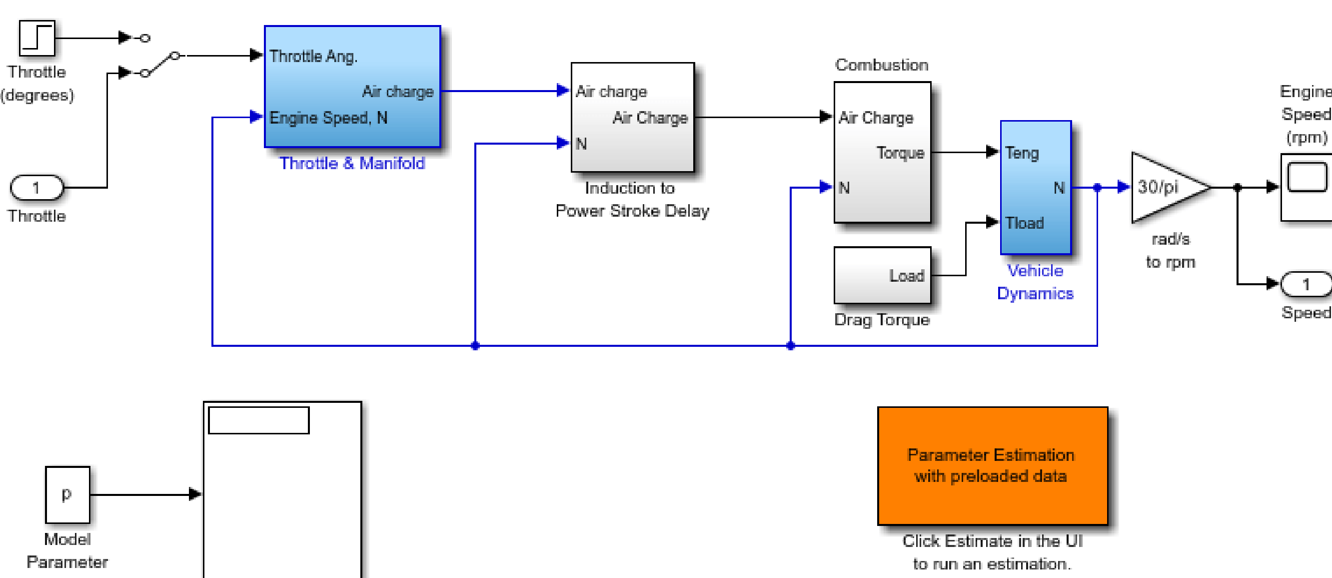
Description of the Engine Speed Model

The Simulink® model for the engine system, `spe_speed`, is shown below.

The throttle angle from the block labeled "Throttle" on the left side of the diagram drives the simulation. The output of interest in the model is the engine speed, which can be monitored by opening the Scope block labeled "Engine Speed (rpm)".

Open the engine speed model.

```
open_system('spe_speed')
```

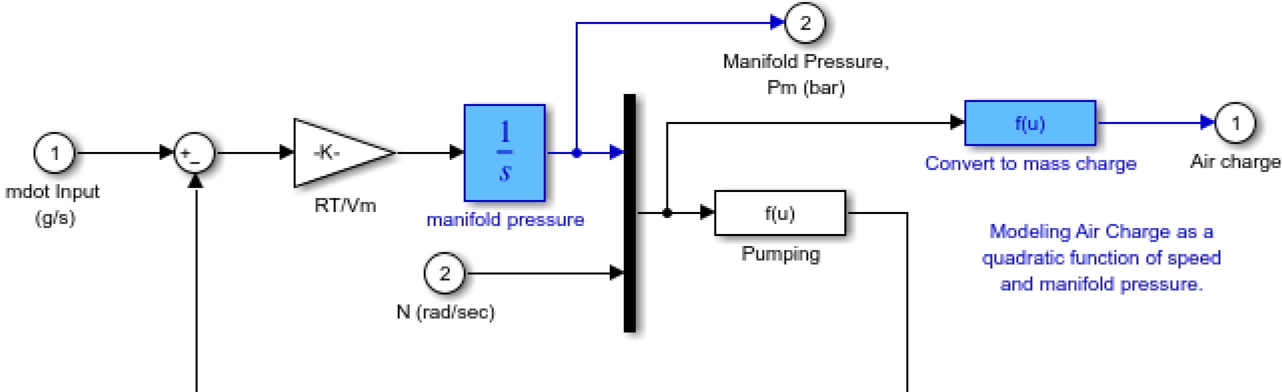


Modeling Air Charge Using a Nonlinear Function

Among other dynamic components in the model, the "Intake Manifold" subsystem is used to model the dynamics of the air intake manifold in the engine.

Open the Intake Manifold subsystem.

```
open_system('spe_speed/Throttle & Manifold/Intake Manifold')
```



In particular, the "Convert to mass charge" block above defines a quadratic multi-variable polynomial to approximate the relationship between the Air Charge, the Manifold Pressure, and the Engine Speed. This approximation has the following form:

$$AirCharge = p(1) \times EngineSpeed + p(2) \times ManifoldPressure$$

$$+p(3) \times (ManifoldPressure)^2 + p(4) \times EngineSpeed \times ManifoldPressure + p(5)$$

The Parameter Estimation Problem

When measured data for various signals in your model are available, you can use Simulink® Design Optimization™ to compute the unknown parameters.

The parameter estimation problem in our case is to compute the coefficients

$$p(1), p(2), p(3), p(4), p(5)$$

using measured data.

You can launch a pre-configured parameter estimation task in the **Parameter Estimator** by first opening the model and by double-clicking on the orange block in the lower corner of the model.

Close the model

```
bdclose('spe_speed')
```

Clutch Friction Coefficient Estimation

This example shows how to use Simulink® Design Optimization™ to estimate parameters of a clutch model created using Simscape™ Driveline™ library blocks.

Requires Simscape Driveline.

Description of Clutch Model

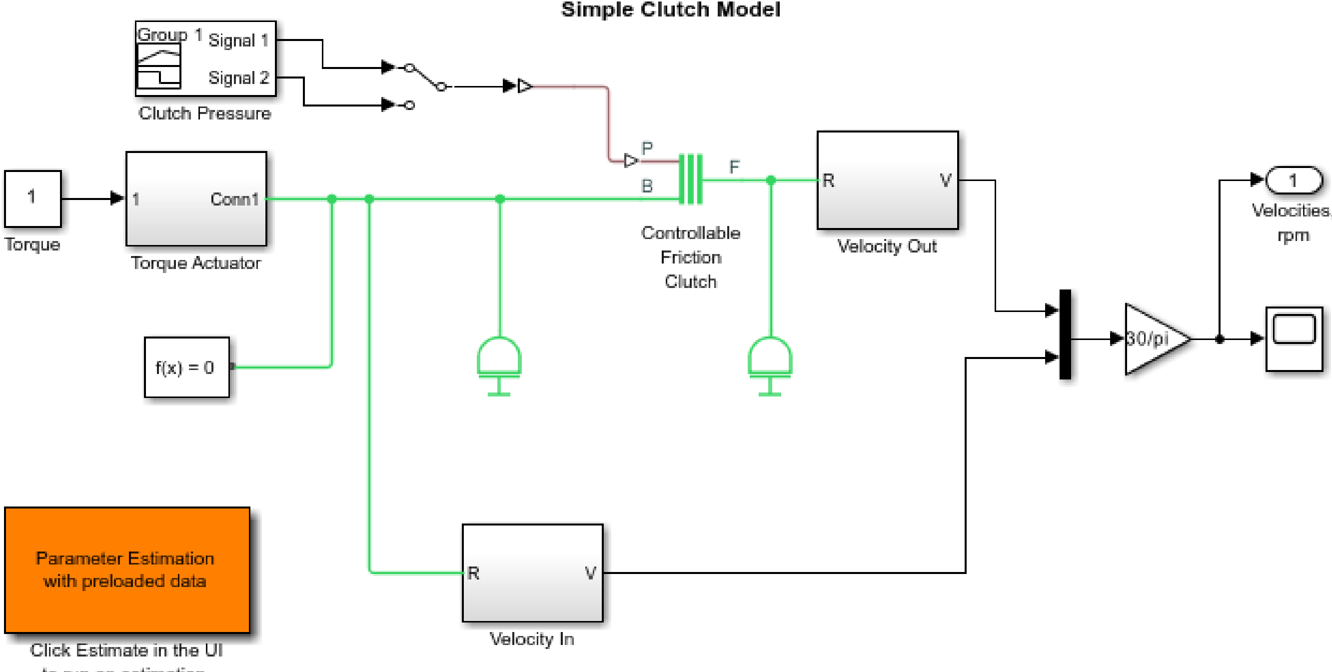
The Simulink® model of the clutch system, `simple_clutch`, is shown below.

This model consists of two inertias coupled by a clutch. Initially, the pressure applied to the clutch plates is zero and Inertia 2 has zero velocity. A constant torque is also applied to Inertia 1. Once the clutch pressure starts increasing, Inertia 2 starts rotating. However, the friction between the clutch plates causes slippage so that the two inertias accelerate at different rates and have different velocities.

The clutch system consists of two rotational inertias and a clutch. Pressure is applied to the clutch plates, which then couples the two inertias. A **Simscape Driveline** block is used to model the clutch, which has a speed-dependent friction coefficient linearly varying from C1 at 0 rad/s to C2 at 10 rad/s.

The coefficients of friction (C1, C2) in the **Controllable Friction Clutch** block are unknown and are estimated using experimental data for the output velocities of Inertia 1 and Inertia 2.

```
open_system('simple_clutch')
set( find_system(gcs, 'FindAll', 'on', 'BlockType', 'Scope'), 'Open', 'off' )
```



Using Simulink Design Optimization

In the **Apps** tab, click **Parameter Estimator** under **Control Systems** to launch the **Parameter Estimator** app.

The launched Parameter Estimation UI consists of projects where we store our experimental data sets and estimation results. These projects can be saved and reused later.

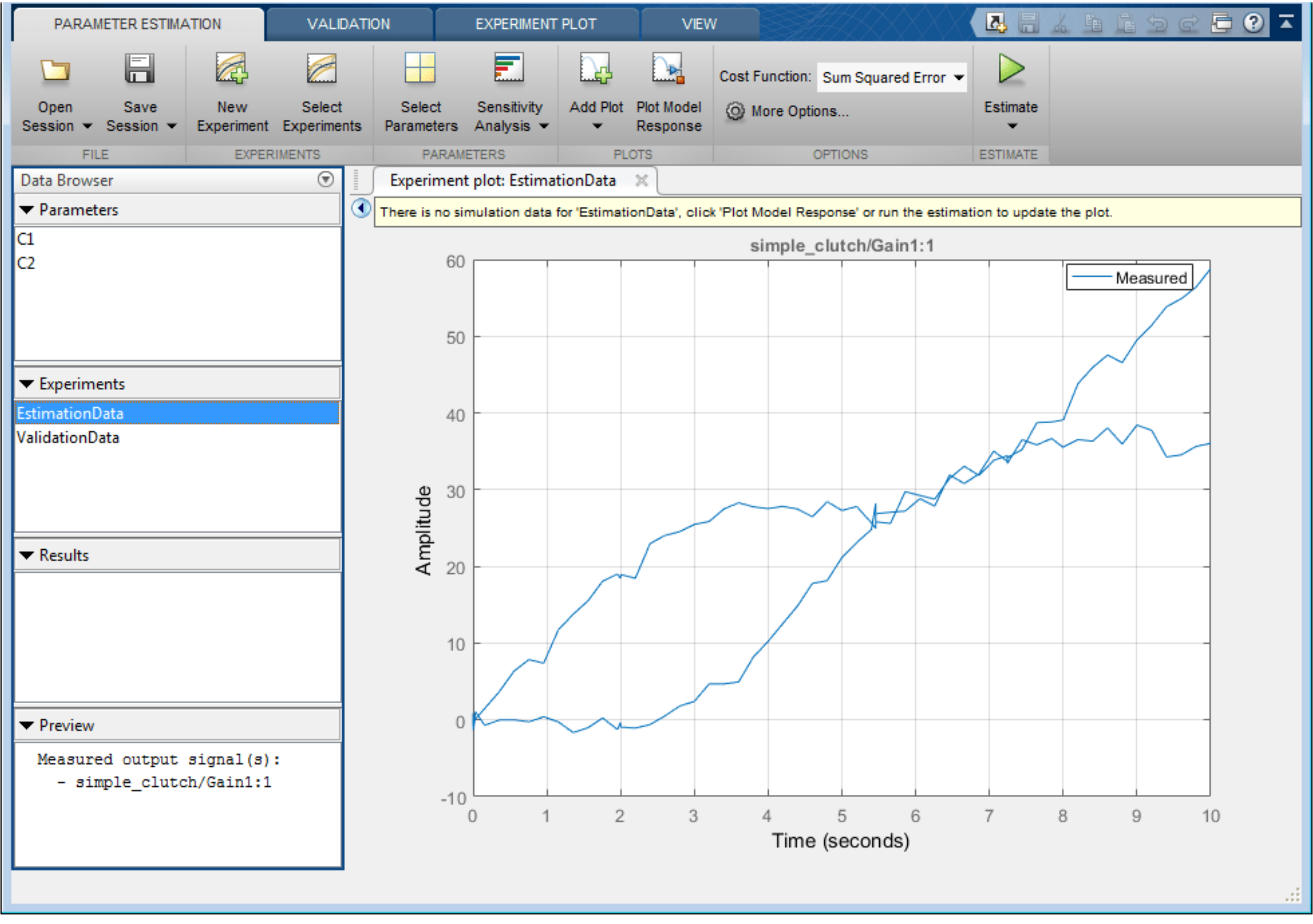
Alternatively, you can double-click the orange colored block at the lower left corner of the Simulink diagram. This will reload a project that has already been saved.

In general, estimating model parameters consists of three main steps: importing experimental data sets into the project, selecting the model parameters for estimation, and running an estimation and analyzing the results.

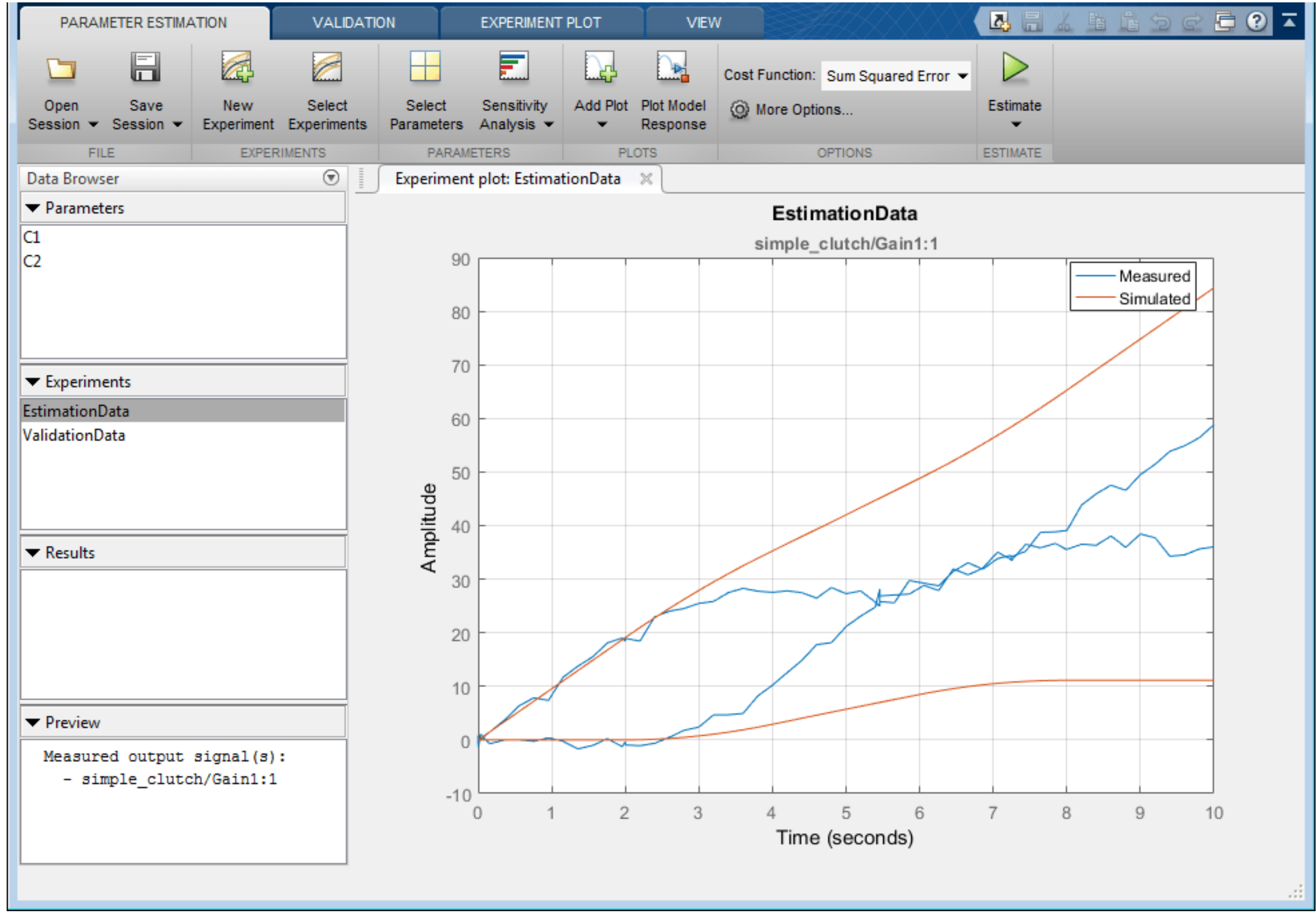
Experimental Data for Estimation

We have two sets of output data on this clutch system. The first one, **EstimationData**, will be used for parameter estimation and the other one, **ValidationData**, for validating the response of the Simulink model with the estimated parameters.

In the first experiment the clutch pressure follows the profile of **Signal 1** supplied by the **Clutch Pressure** block in the Simulink model. This signal applies a ramp-up and a ramp-down pressure on the clutch plates. Click **Add Plot** in the Parameter Estimation UI, and select **EstimationData** to view the output velocities of the inertias in response to this input. Such data sets could also be imported from various sources including MATLAB® variables, MAT files, Excel® files, or comma-separated-value files.



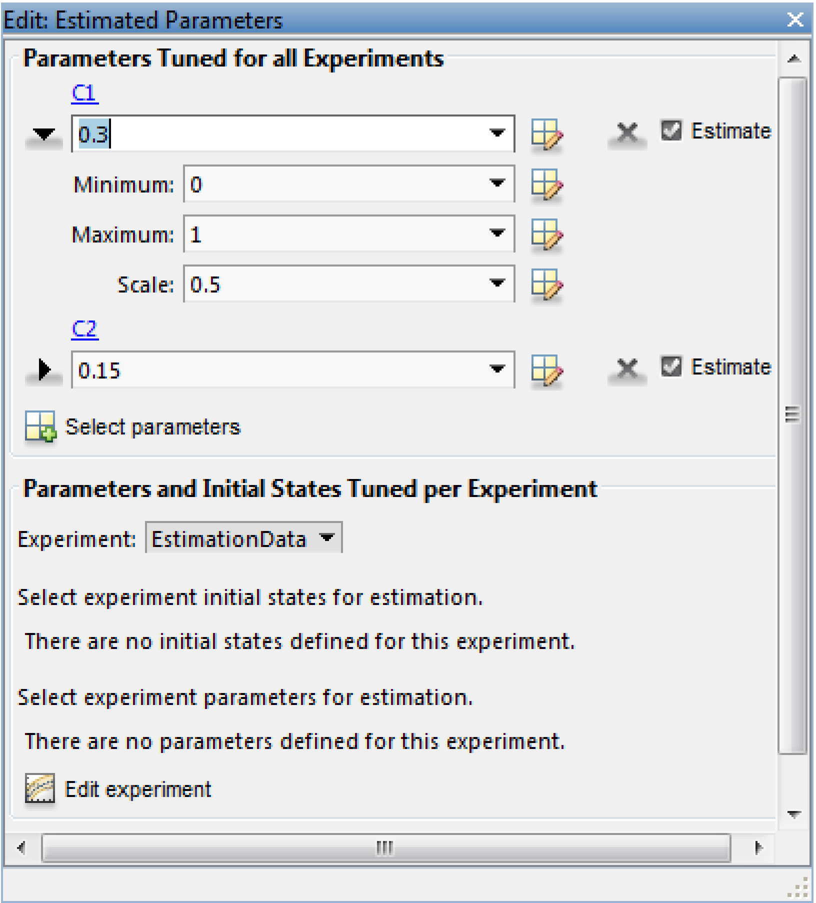
The parameter values for the friction coefficients are not known accurately. Clicking **Plot Model Response** provides a look at the response of this system, and shows that it does not match the experimental data, hence the parameters need to be estimated for a better fit.



Setting up and Running the Estimation

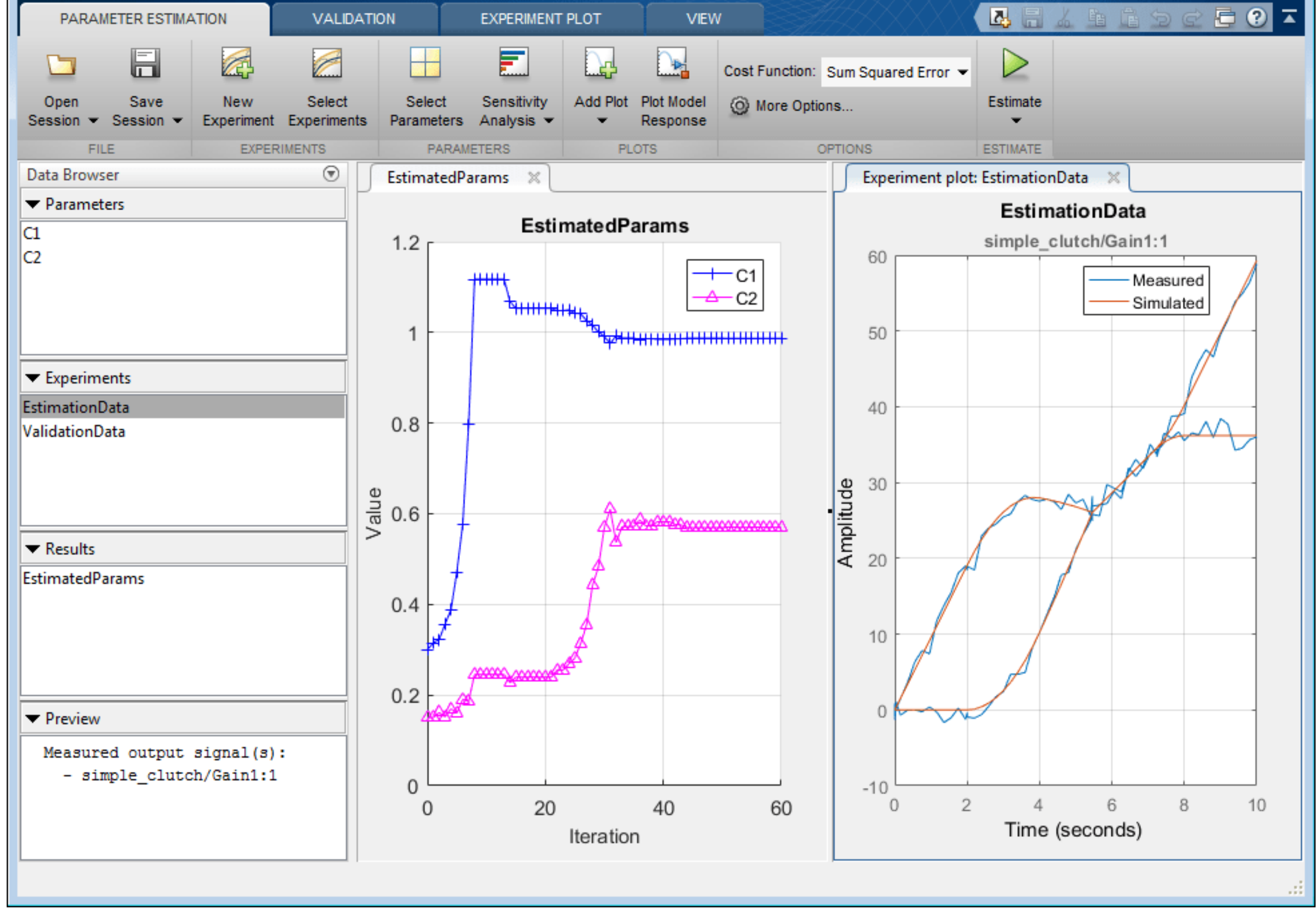
We will use the experimental data set **EstimationData** to estimate friction parameters of the clutch system.

The first step is to define the variables to be estimated. This establishes which parameters of the simulation can be adjusted, and any rules governing their values. Click **Select Parameters** to specify parameters to be estimated. Here we wish to estimate the friction coefficients `C1` and `C2` in the **Controllable Friction Clutch** block of the Simulink model. In the pre-loaded parameter estimation example, these parameters have already been specified for estimation. If there are known bounds on the parameter values, they can be set in the minimum and maximum fields.



Next, click **Select Experiments** to specify which experiments are to be used for estimation. It is possible to use one or more data sets at once in a given estimation. For our example, we will use the data set called **EstimationData**.

You are now ready to run the estimation. Click **Estimate** to start the estimation process. We provide a number of estimation methods, including nonlinear least-squares minimization, gradient descent, pattern search, or simplex search. Running estimation will vary the model parameters in order to reduce the error between the simulation outputs and the experimental data. During estimation, the experiment plot showing measured data and simulation response will updated. As the parameter values improve, the simulation curve should get closer to the experimental data curve. Also, a trajectory plot will show the parameter values at each iteration. These curves should reach steady-state as the parameter values get closer to their physical values.

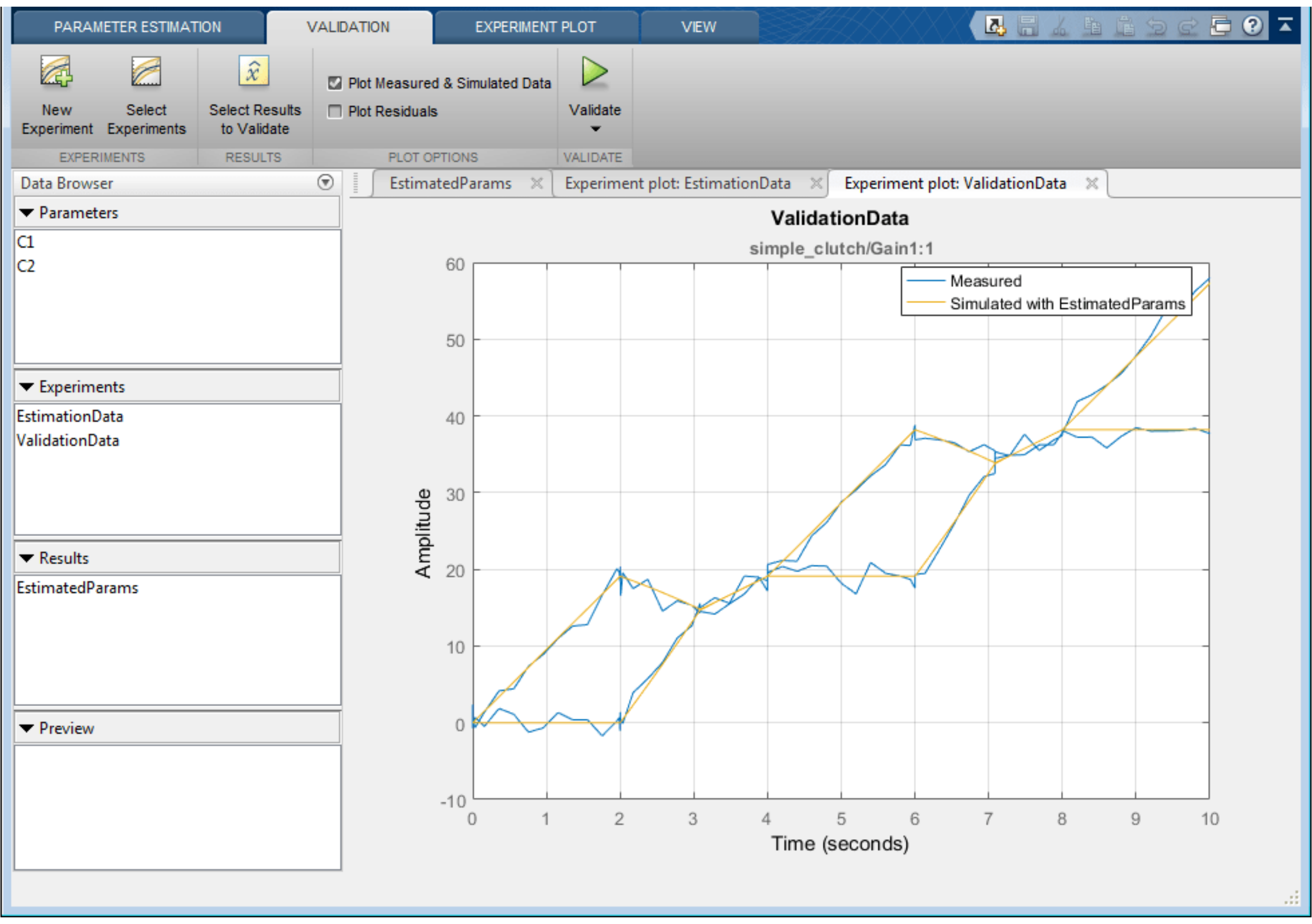


In addition, the table in the Estimation Progress Report will show data regarding the estimation process such as the number of iterations, the number of simulations, and the cost function. The cost function value represents the degree of fit between the simulation response and the estimation data. This value would decrease at each iteration, indicating the amount of improvement in the fit.

Validation

Once we complete the estimation, it is important to validate the results against other data sets. A successful estimation should be able to not only match the experimental data that we used for estimation, but also the other data sets that we collected in our experiments.

In the second set of experimental data we have for the clutch system, the clutch pressure follows the profile of **Signal 2** supplied by the **Clutch Pressure** block in the Simulink model. This signal applies a periodic pressure on the clutch plates. To use this, **first double-click on the Manual Switch block to change the input signal to the one used for validation data (Signal 2)**. Then in the Parameter Estimation UI, click the **Validation** tab, click **Select Experiments** and select the experiment **ValidationData** for validation. This contains output data corresponding to input from **Signal 2**. Finally, click **Validate** to carry out the validation. An experiment plot will compare the simulation response against experimental data. We see that the match is very good.



In summary, we have carried out estimation by specifying an experiment with measured output data, and designating certain parameters to be estimated. We then checked the parameter values by validating with a different data set, giving confidence in the parameter values.

Close the model

```
bdclose('simple_clutch')
```

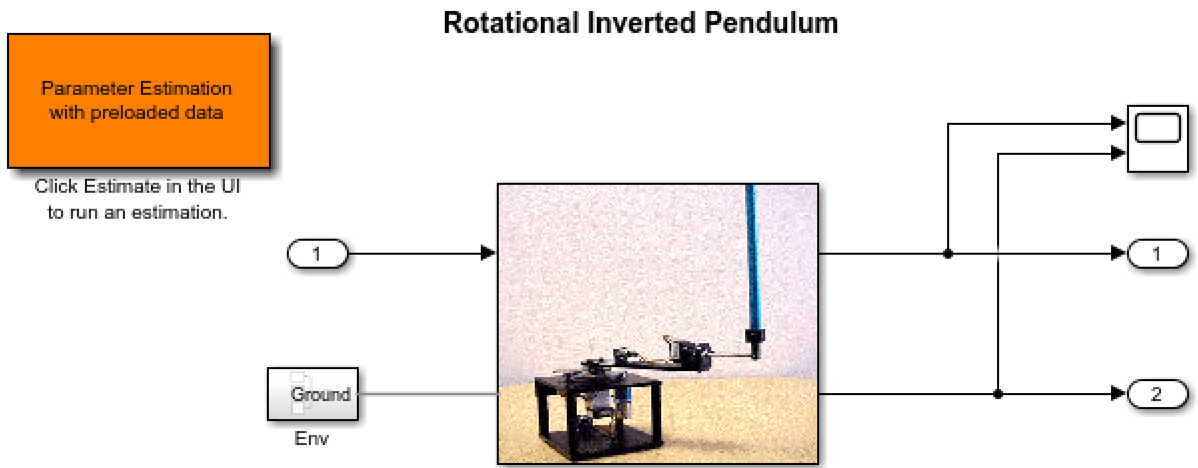
Inverted Pendulum Parameter Estimation

This example shows how to use Simulink® Design Optimization™ to estimate multiple parameters of a model by iterated estimations.

This example requires Simscape™ Multibody™ software.

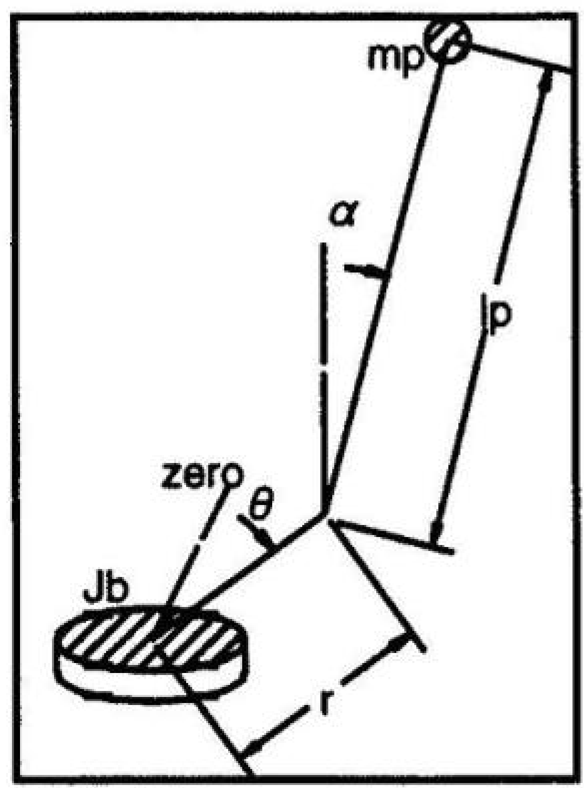
Simscape Multibody Model of the Inverted Pendulum System

The Simulink® model for the inverted pendulum, `spe_mech_invpend`, is shown below.



Inverted Pendulum Model Description

The pendulum system has an arm that swings in the horizontal plane, driven by a DC motor. The purpose of the arm is to provide a balancing torque to a swinging pendulum, to keep the pendulum in an upright position. The angle of both the arm and pendulum is monitored and used as feedback to control the motion of the system. For this example we will only concentrate on estimating parameters of the uncontrolled system shown below.



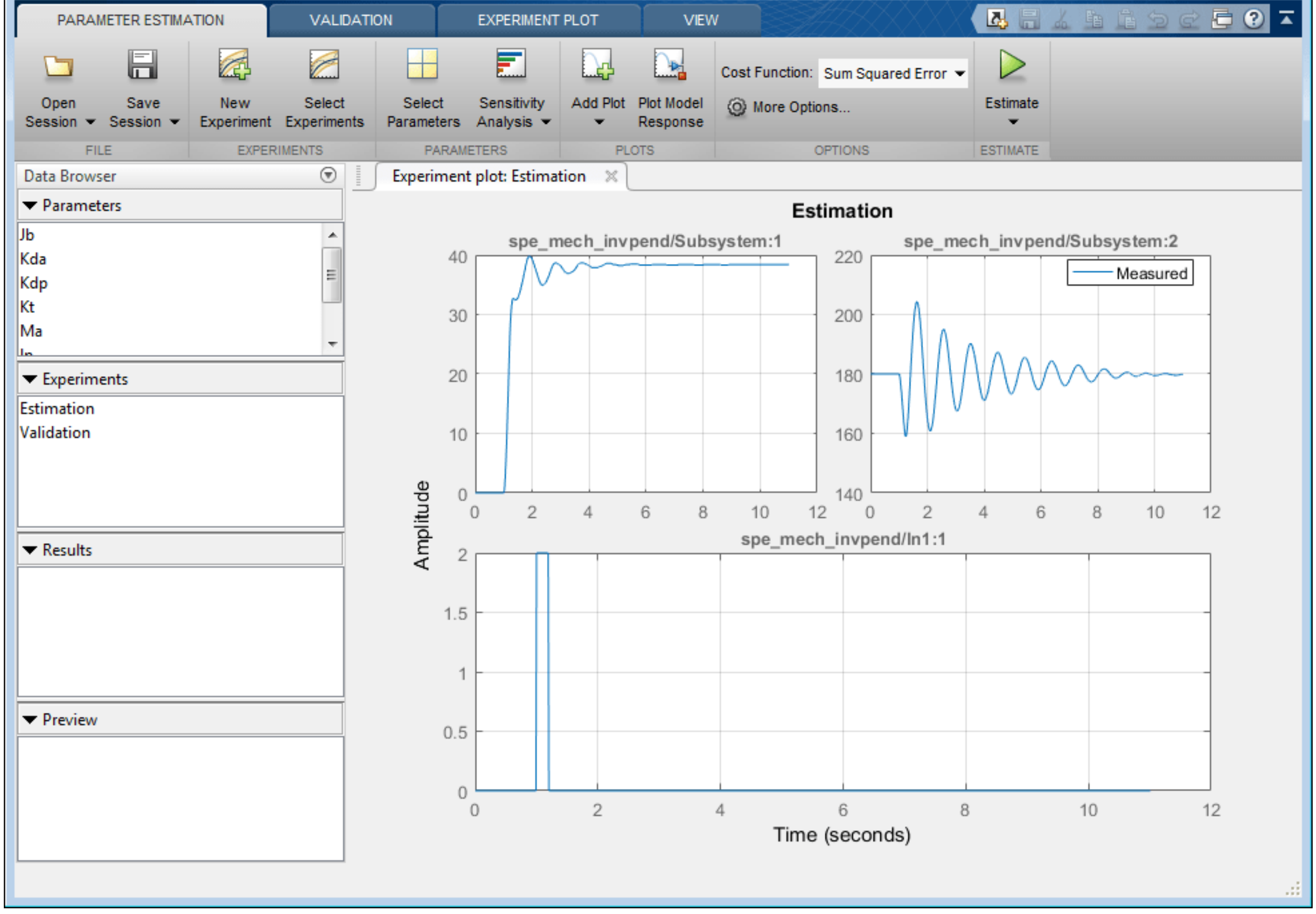
The system is modeled using Simscape Multibody. There are two bodies modeled in this system. The machine consists of one body representing the rotational arm and the other representing the pendulum. The bodies are connected by revolute joints that constrain the motion of the bodies relative to each other. An input voltage is delivered to a DC motor that provides the torque to the rotational arm.

The motor is modeled as a torque gain `Kt`. The arm of the pendulum has mass `Ma`, inertia `Jb` and length `r`. The pendulum has length `lp` and mass `mp`. For this example damping is modeled in the revolute joints using gains `Kda` and `Kdp`. The outputs of the system are the angles of the arm and the pendulum.

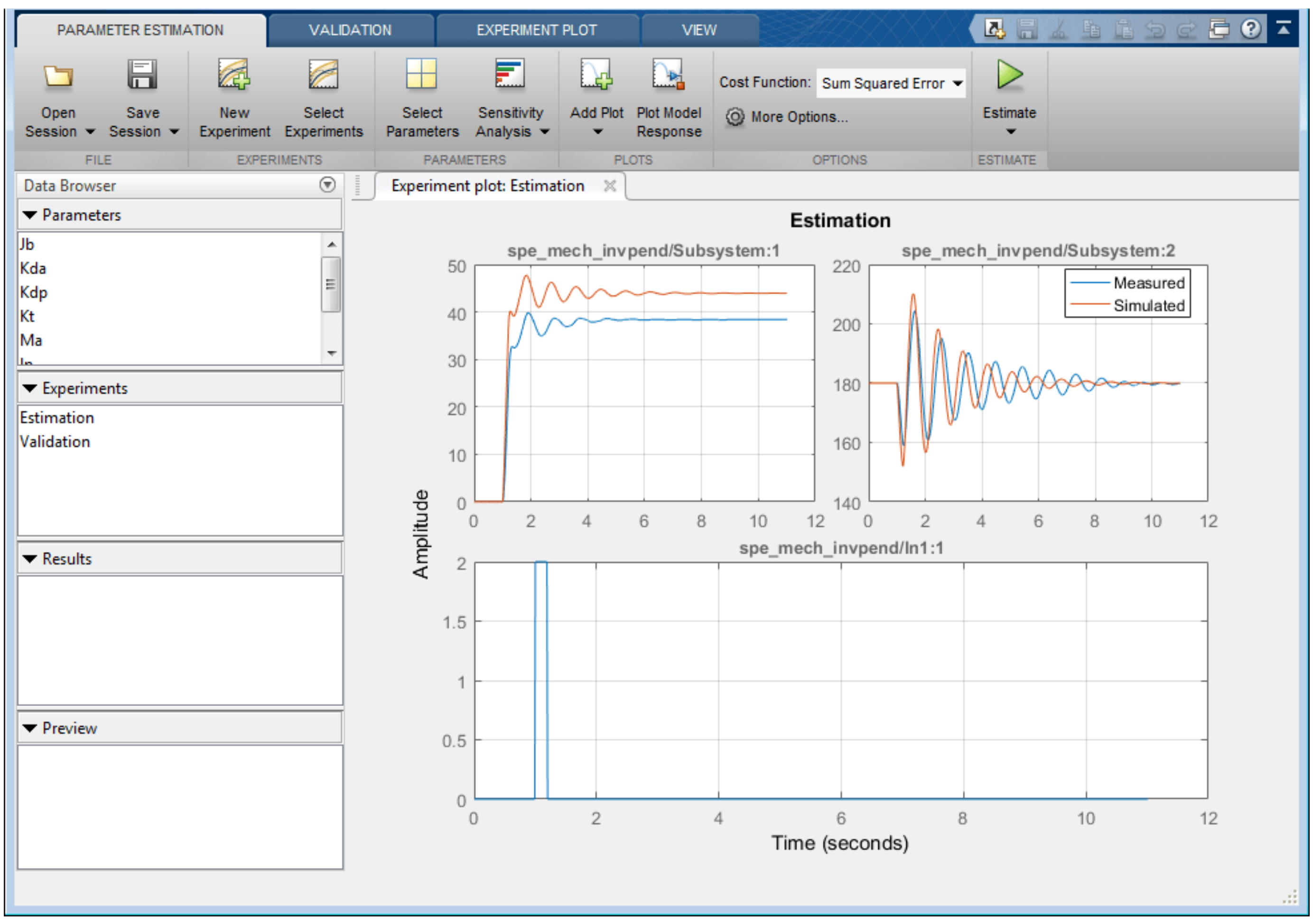
For this example we will run two estimations using different parameter sets for each estimation. This allows us to customize our estimation and can result in a more efficient solution.

Estimation Data

Double-click the orange block in the upper left corner of the inverted pendulum model to launch the **Parameter Estimator**, pre-loaded with data for this project. This is configured with measured experiment data `Estimation`. For other uses you can import experimental data sets from various sources including MATLAB® variables, MAT files, Excel® files, or comma-separated-value files. It is also configured with validation data `Validation` which we will use later, after estimation. The measured data in `Estimation` is shown in the experiment plot. There is only one data set used for estimation in this example.

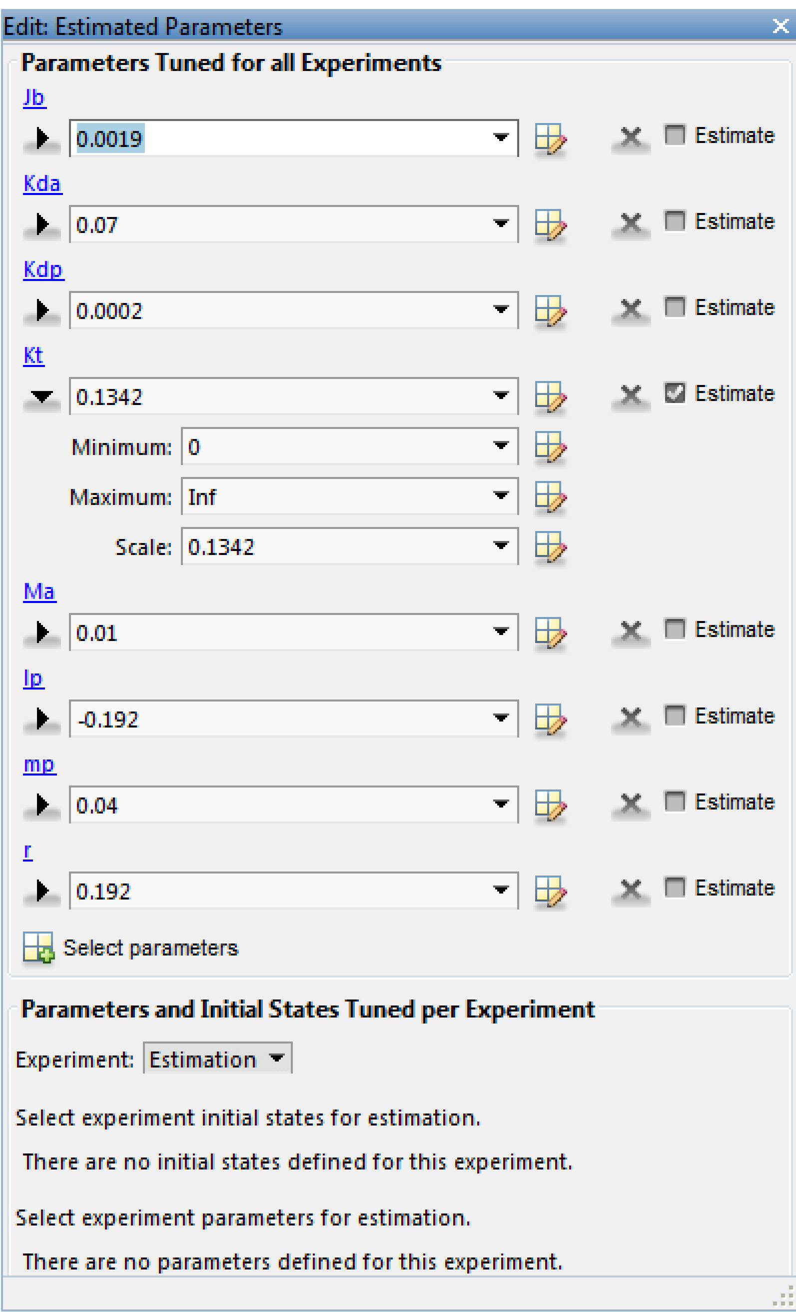


The experiment plot is also used to see how well the measured data matches the current model. Click **Plot Model Response** in the **Parameter Estimation** tab to display simulated signal data on the experiment plots. The simulation does not match the measured data, showing that the model parameters need to be estimated.



Define Variables

The next step is to define the variables for the estimation. This establishes which parameters of the simulation can be adjusted, and any rules governing their values. Click **Select Parameters** in the **Parameter Estimation** tab. For our inverted pendulum example, we have already selected the torque gain parameter, `Kt`, for estimation. Since we know from our physical insight that this parameter can not be negative we set its lower limit to zero.

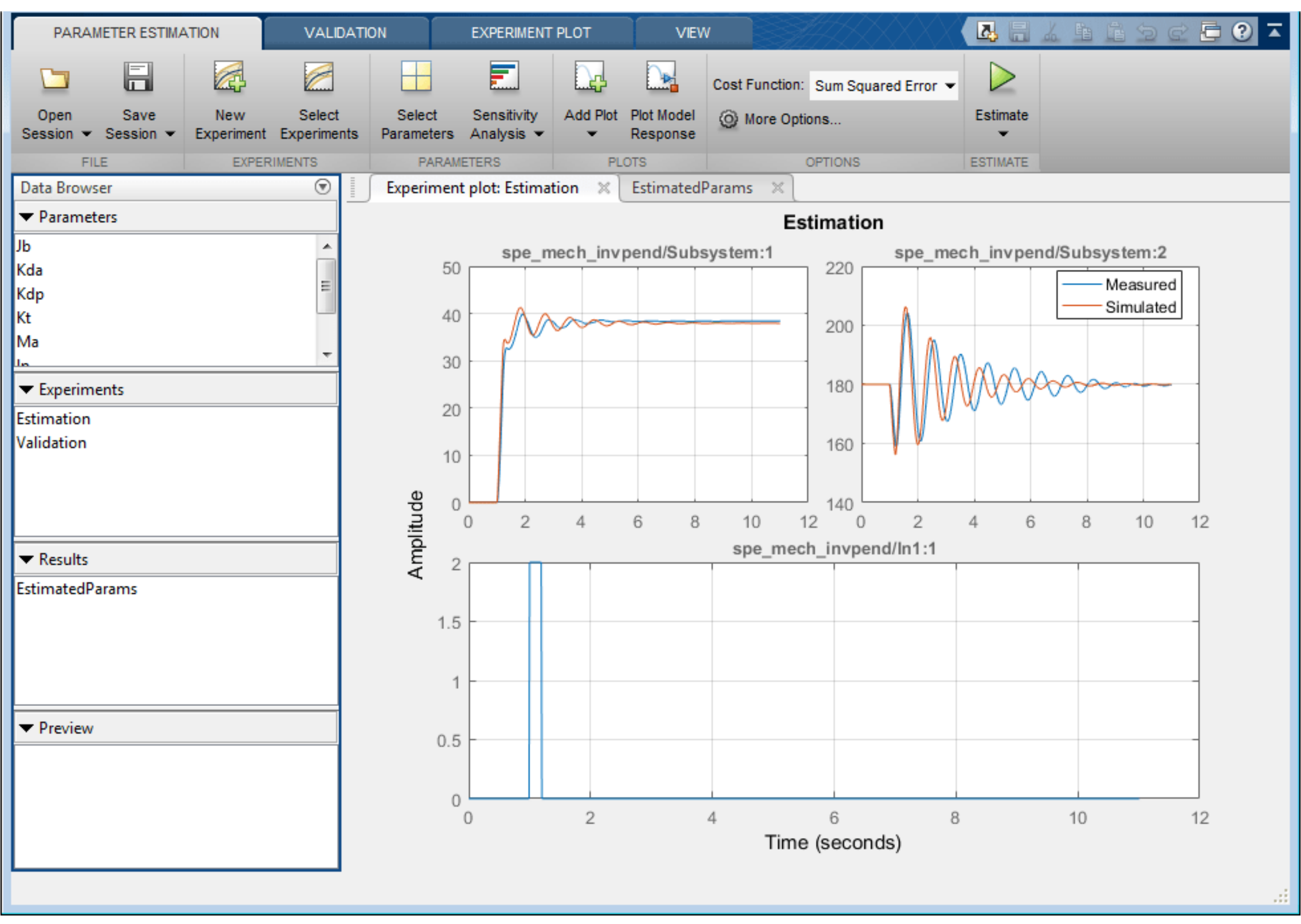


First Estimation

With the parameters for estimation specified, we select experiments to use for estimation. Click **Select Experiments** in the **Parameter Estimation** tab and select the experiment named `Estimation` for estimation.

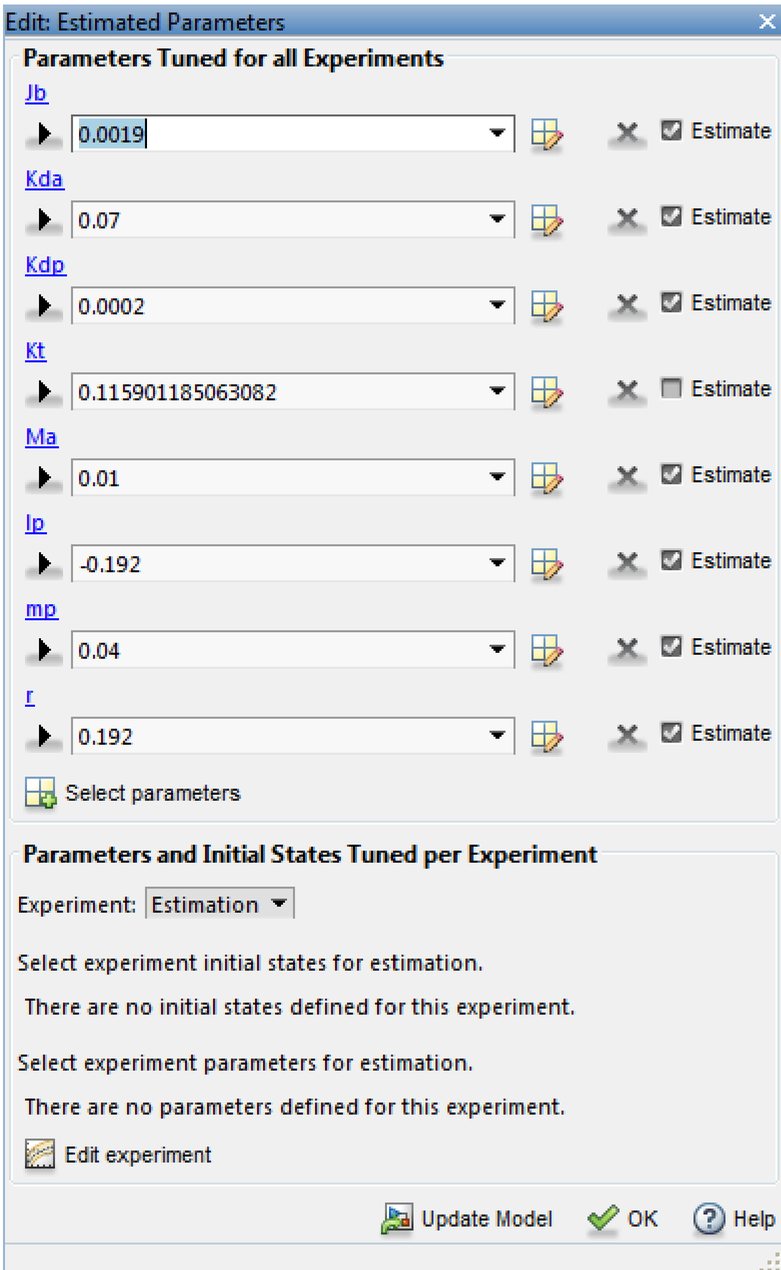
We are now ready to start our estimation. Click **Estimate** in the **Parameter Estimation** tab to start the estimation. The estimation will keep iterating the parameter value until the estimation converges and terminates.

The plot below shows the experimental data overlaid with the simulated data. The simulated data comes from the model with the estimated parameter `Kt`. The results of the estimation show that the first output (the position of the arm) matches, however we can see that the second output (the position of the pendulum) does not show very satisfactory results. It is clear that additional estimation is needed to obtain better results.

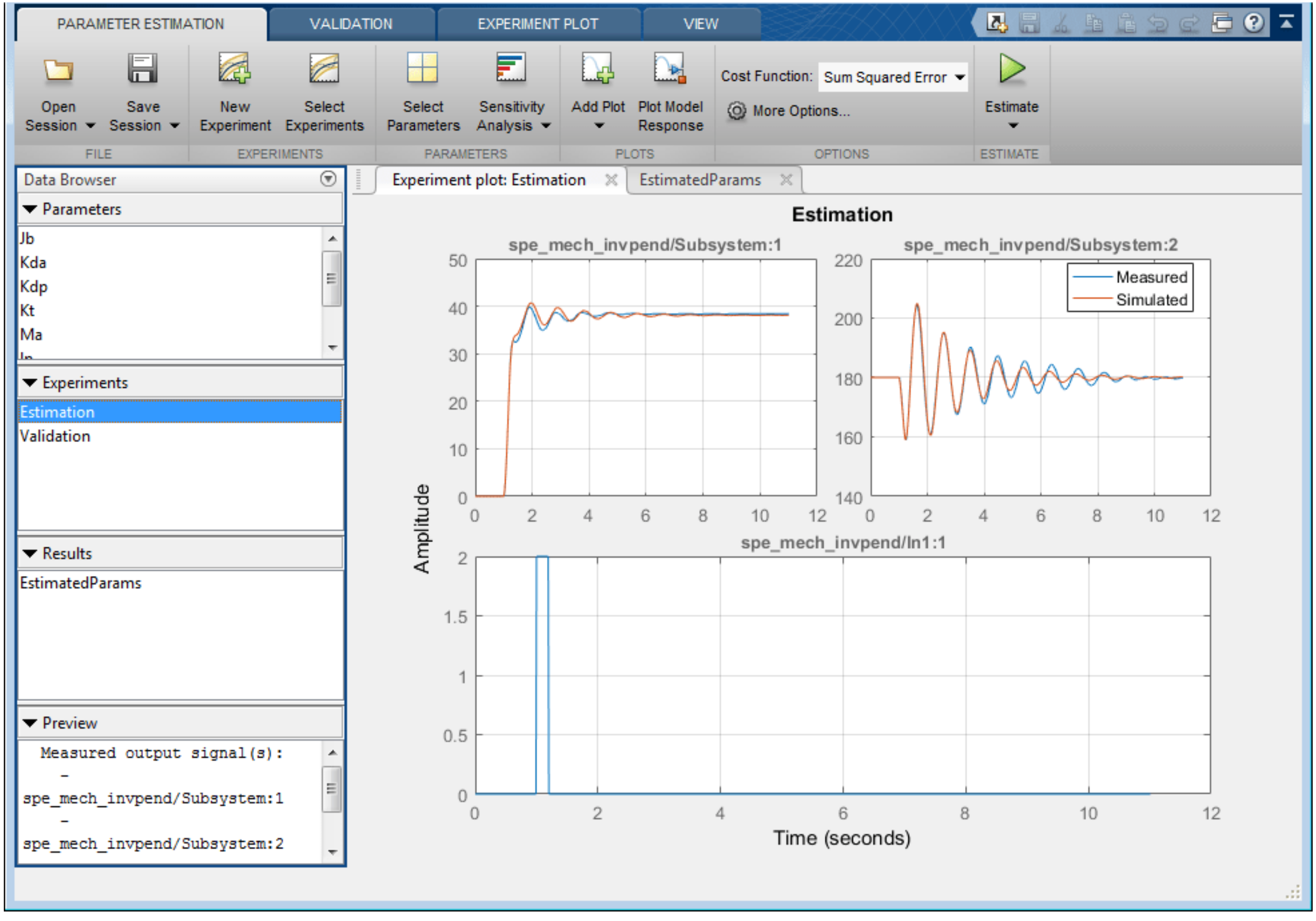


Running an Additional Estimation

This time we will leave the torque gain, `Kt`, constant and estimate the other parameters of the model. Click **Select Parameters** in the **Parameter Estimation** tab. Uncheck `Kt`, and check the other parameters as shown below.



Click **Estimate** to start the new estimation. The results of the second estimation are shown below.

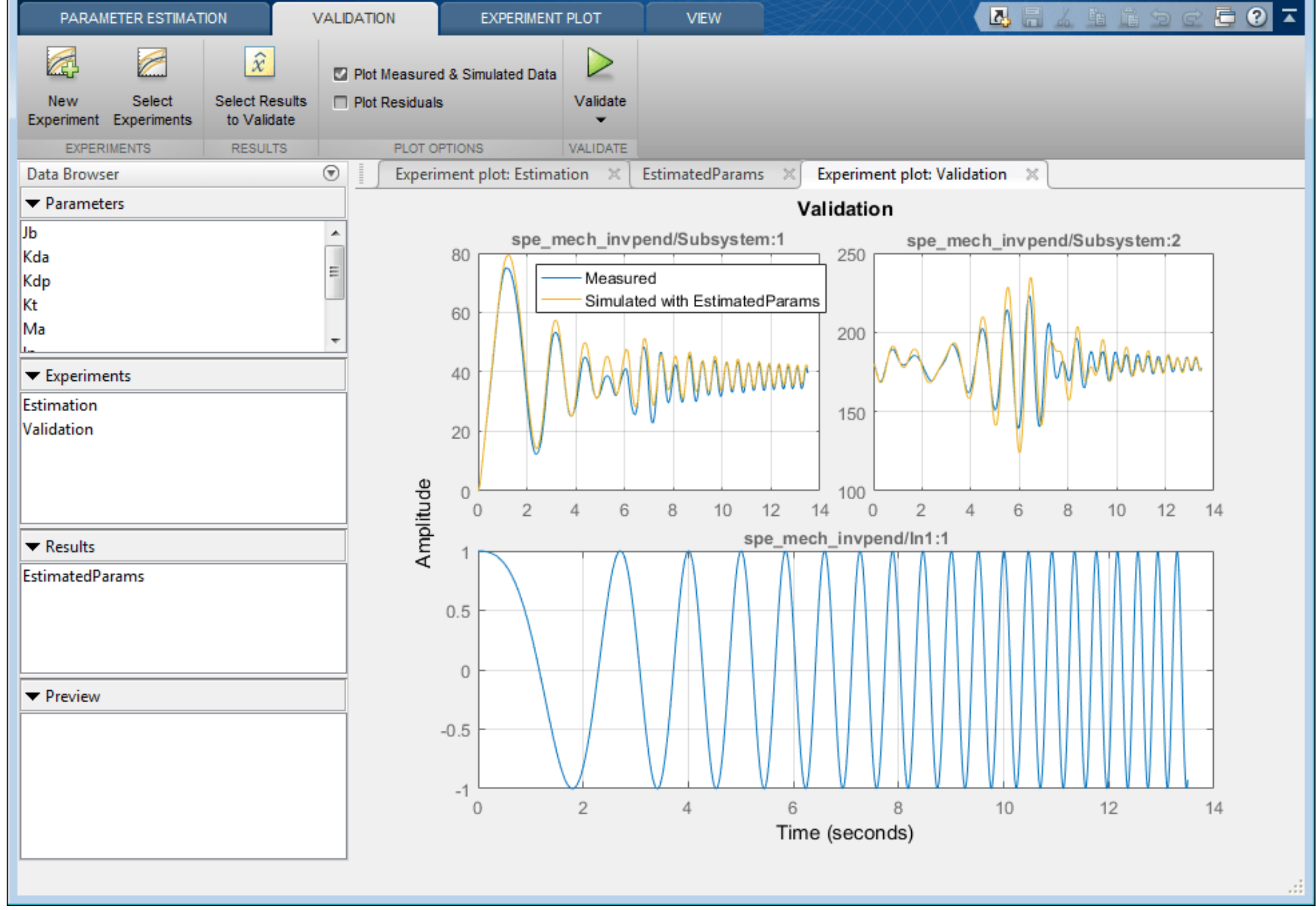


This is clearly a better result. This shows that in order to complete an estimation task it is not necessary to estimate all the parameters in the model at the same time. We can run multiple estimations keeping some parameters constant while varying others.

Validation

It is important to validate the results against other data sets. A successful estimation will not only match the experimental data that was used for estimation, but also the other data sets that were collected in experiments. An experiment named `Validation` has already been created for this project. Click **Add Plot** in the **Parameter Estimation** tab and select `Validation` to view the data.

Click **Plot Model Response** to see the simulation output overlaid on the data. The figure below shows how the inverted pendulum system responds to the validation input data. The validation shows that this model does handle the lower frequencies of the input validation data well and the model parameters were successfully estimated.



Conclusion

This example shows the flexibility of Parameter Estimation for segmenting an estimation task into multiple estimations. This allows for estimations to be run on different parameter sets which can help in the speed of estimating a given model.

Close the model.

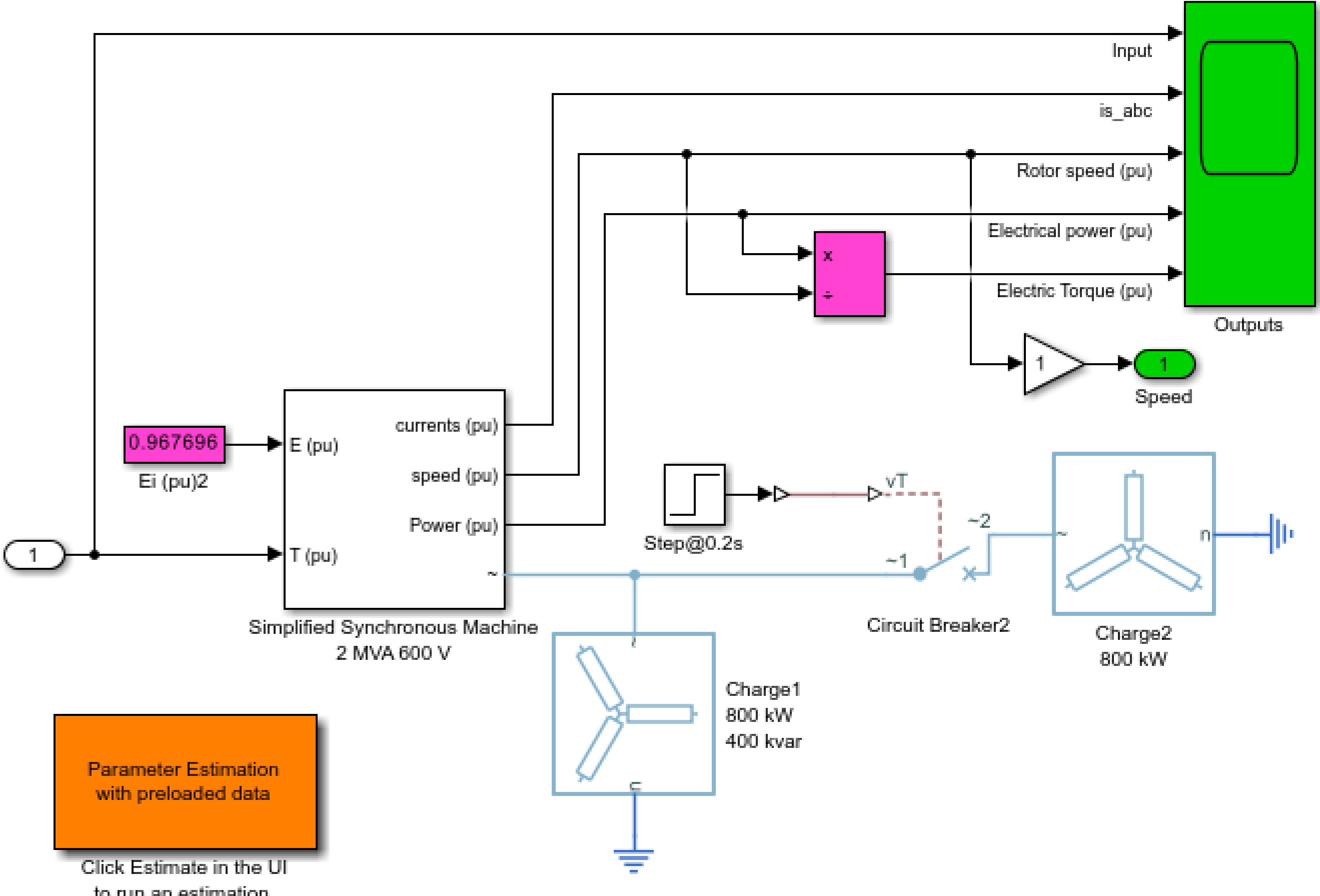
Simplified Alternator Parameter Estimation

This example shows how to use parameter bounds to improve estimation performance. This is illustrated by estimating the power rating, P, of a synchronous machine.

This example requires Simscape™ and Simscape™ Electrical™.

Simulink Model of the Simplified Alternator

The Simulink® model for the alternator system, `spe_psbloadshed_machine`, is shown below.



Model Description

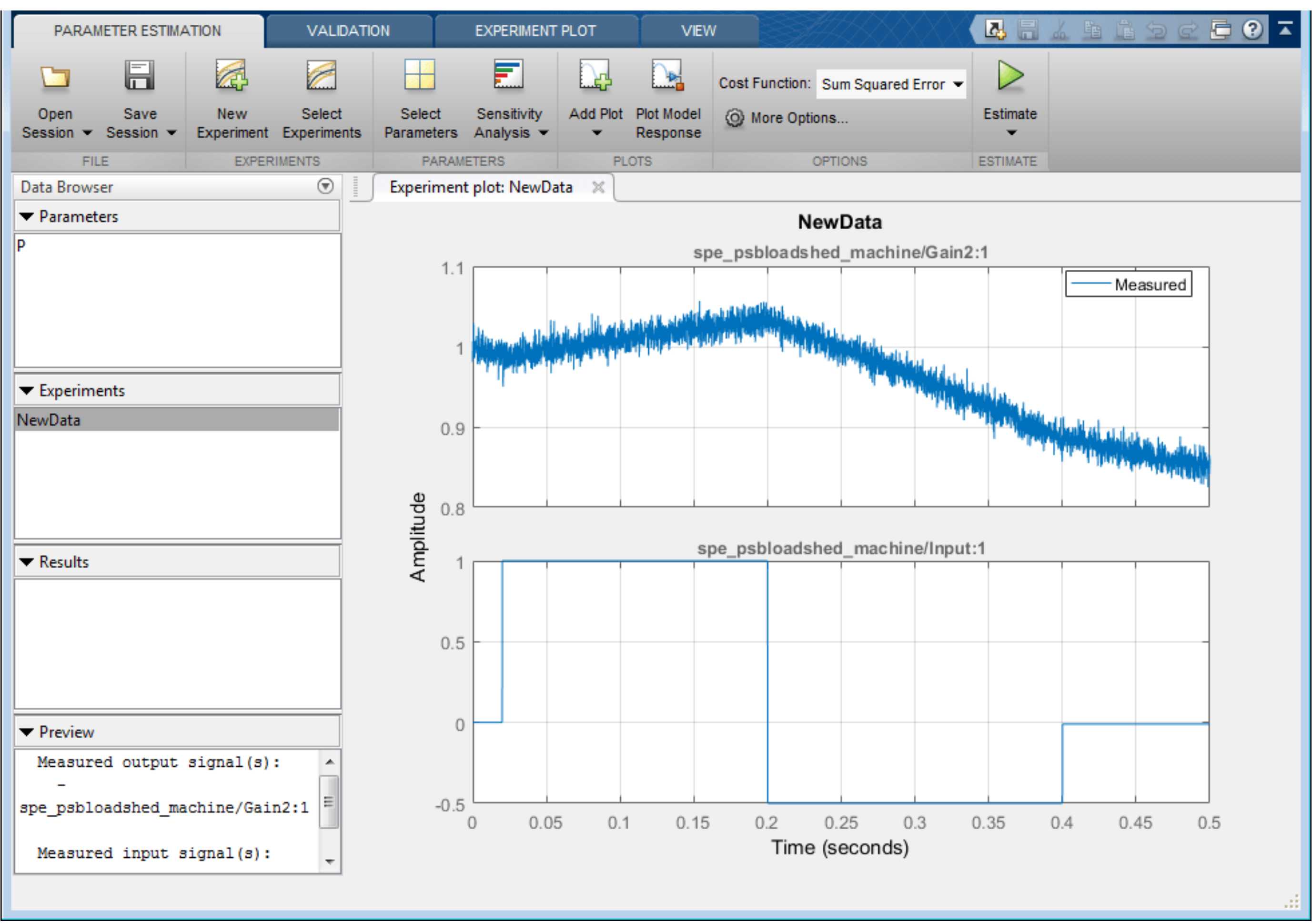
A three-phase, four-wire alternator rated 2000 kVA, 1600 kW, 0.8 power factor, 600 V, 1800 rpm is connected to a 1600 kW, 400 kvar inductive load. The stator neutral point is grounded. The internal impedance of the generator (Zg = 0.0036 + j*0.16 pu) represents the armature winding resistance Ra and direct axis transient reactance X'd. The total inertia constant of the generator and prime mover is H = 0.6 s, corresponding to J = 67.5 kg.m^2.

A three-phase breaker is used to switch out a 800 kW resistive load. The breaker is initially closed and it is opened at t = 0.2 s, resulting in a 50% load shedding.

The machine is excited with a constant voltage. The mechanical torque is modeled as a two-step signal. The first step has a magnitude of 1.0 and a duration of 0.18s. The second step has a magnitude of -0.5 for a duration of 0.2s.

Estimation Data

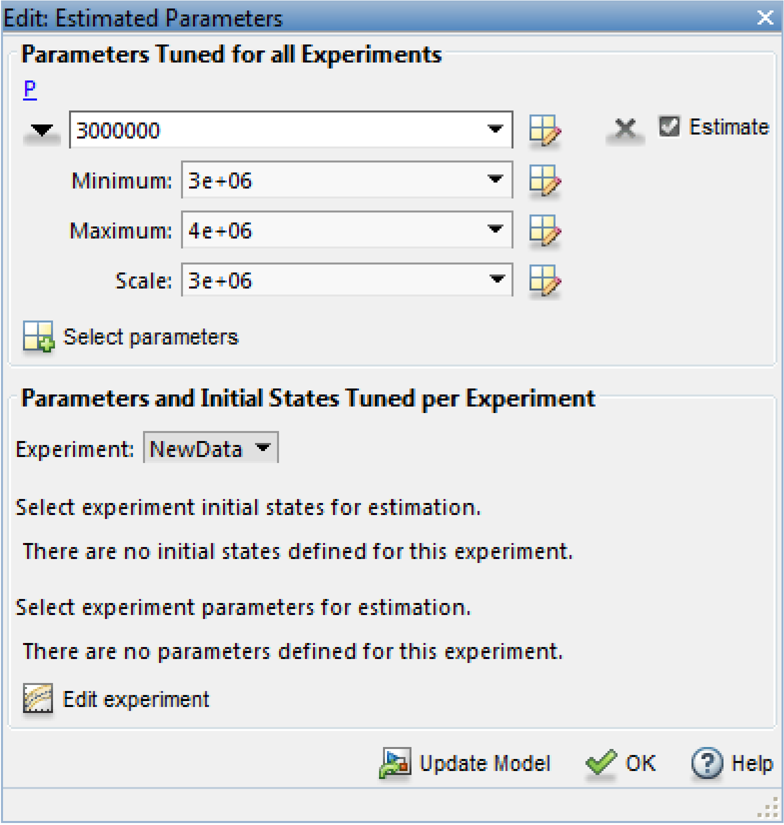
Double-click the orange block on the left side of the model to open the **Parameter Estimator** already loaded with experimental data, `NewData`. The input and output data from this experiment are shown in the plot. There is only one data set used for this example.



Define Variables

Click **Select Parameters** in the **Parameter Estimation** tab to specify parameters for estimation. Here, we have already loaded the parameters for this model. There is only one parameter in this model that we are interested in estimating, the nominal power, `P`, of the Simplified Synchronous Machine.

We know from the specs that this value should be around 2000kW but here we assume that we only have an initial guess of 3000kW. We also set the minimum value of the nominal power to be 3000kW, and the maximum value to be 4000kW.

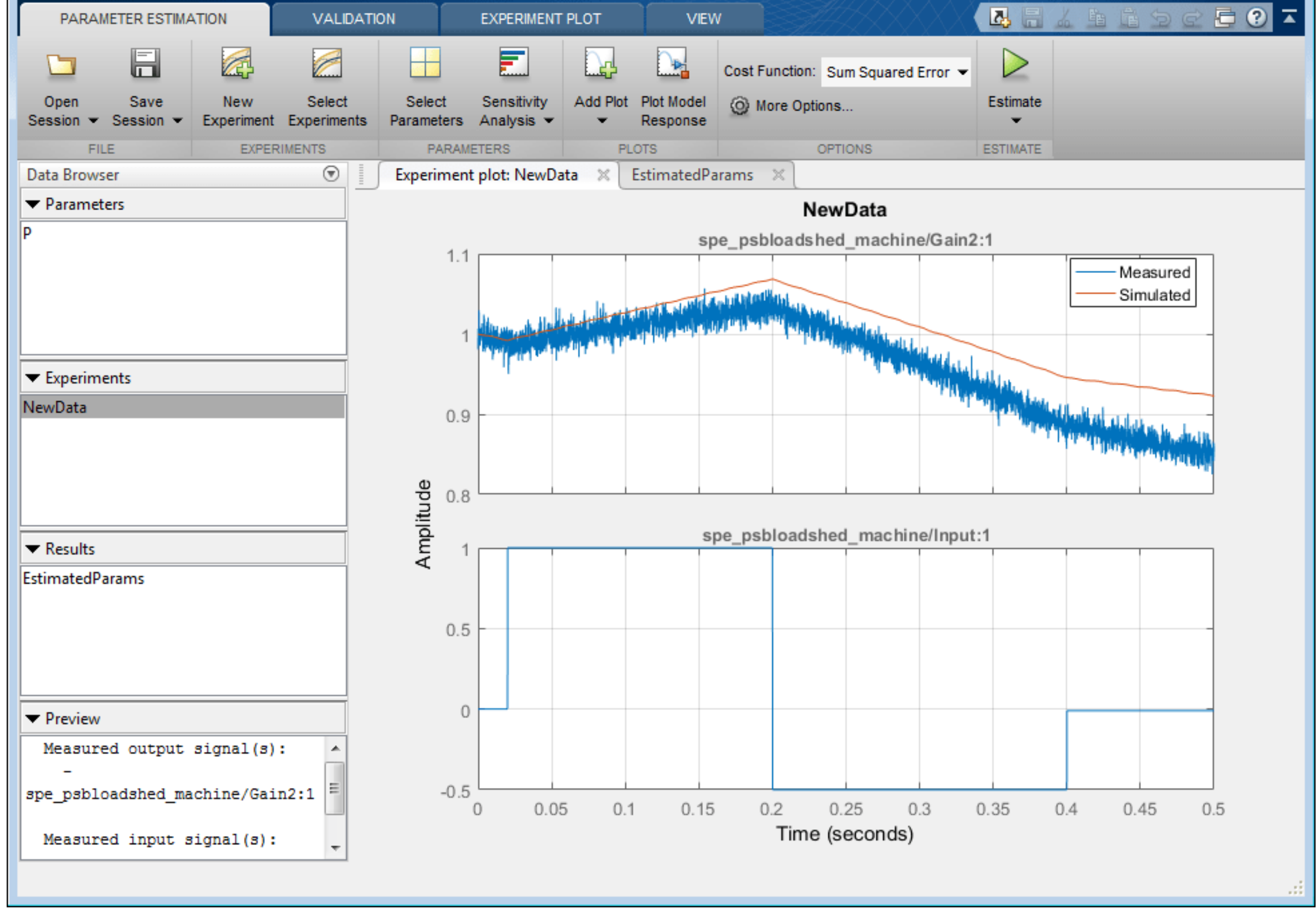


The Estimation Task

With the parameters for estimation specified, we select experiments to use for estimation. Click **Select Experiments** in the **Parameter Estimation** tab and select `NewData` for estimation.

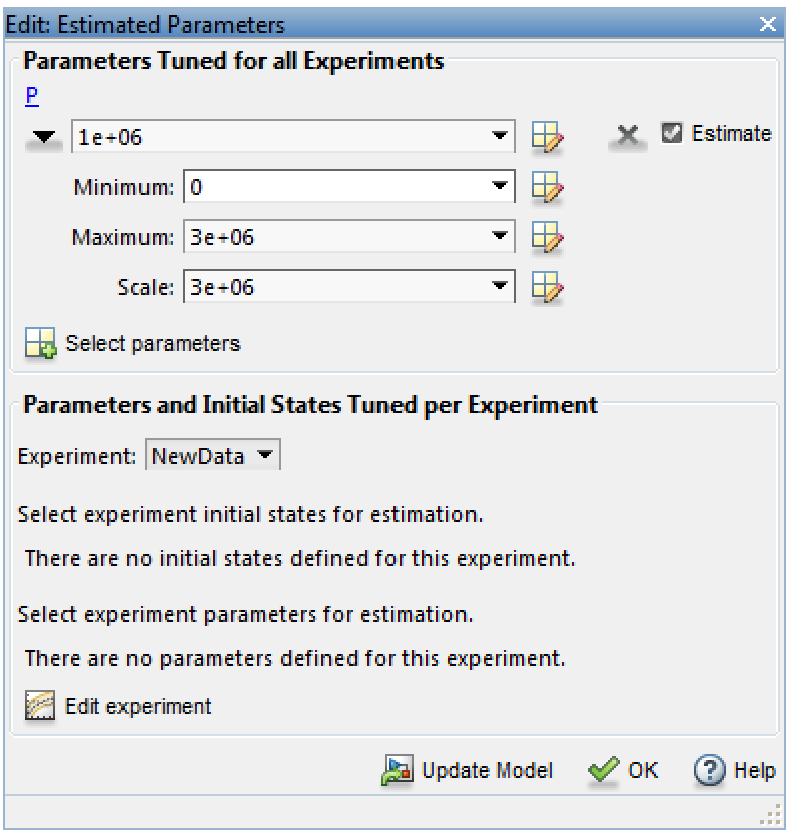
Click **Estimate** to start the estimation. The estimation will keep iterating the parameter value and the experiment plot will continue to update, until the estimation converges and terminates.

The plot below shows the experimental data overlaid with the simulated data. The simulated data comes from the model with the estimated parameters. As expected the estimation terminated quickly and the results were not so good because of our initial guess and bounds of the parameter `P`.

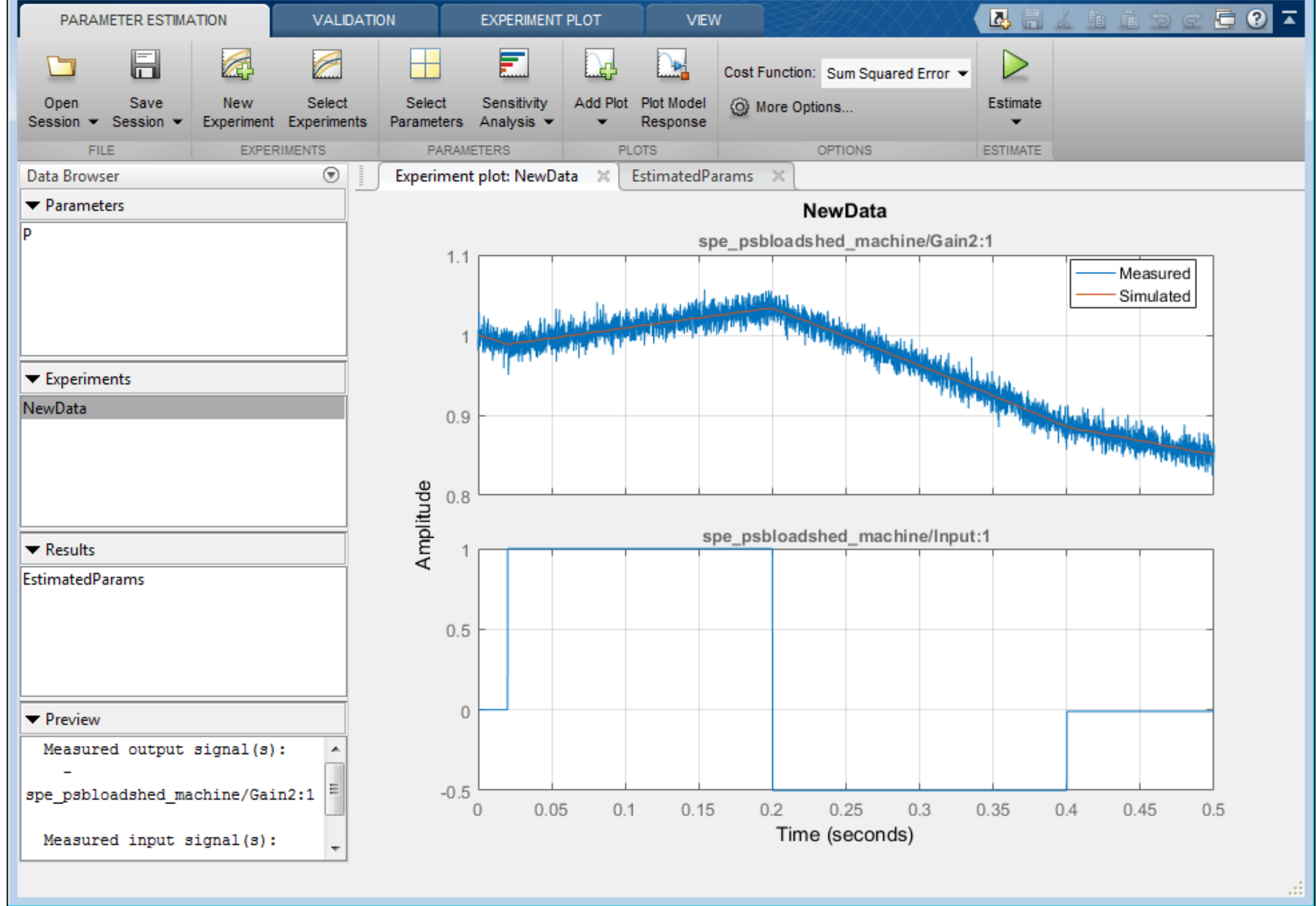


Running the Estimation with a Different Initial Guess

Since we are not satisfied with our results, we will choose a different initial guess. This is quite simple to do with the Simulink® Design Optimization™ **Parameter Estimator**. Click **Select Parameters** in the **Parameter Estimation** tab and change the value to 1000 kV and the **Minimum** and **Maximum** bounds to 0 kV and 3000 kV respectively.



Click **Estimate** to run another estimation. Once the estimation is complete we can verify that our results are more accurate by looking once again at the measured vs. simulated response.



Conclusion

Placing inappropriate bounds on your parameters can lead to inaccurate results and most often the estimation will not converge successfully. However, with the parameter estimation GUI, it is simple to change these bounds to run another estimation without creating a new estimation project.

Close the model.

Generate MATLAB Code for Deployed Parameter Estimation Problems (GUI)

This example shows how to automatically generate MATLAB® code to solve a deployed parameter estimation problem. You use the **Parameter Estimator** to define an estimation problem for a battery and generate MATLAB code to solve this estimation problem in deployed mode using Simulink® Compiler™.

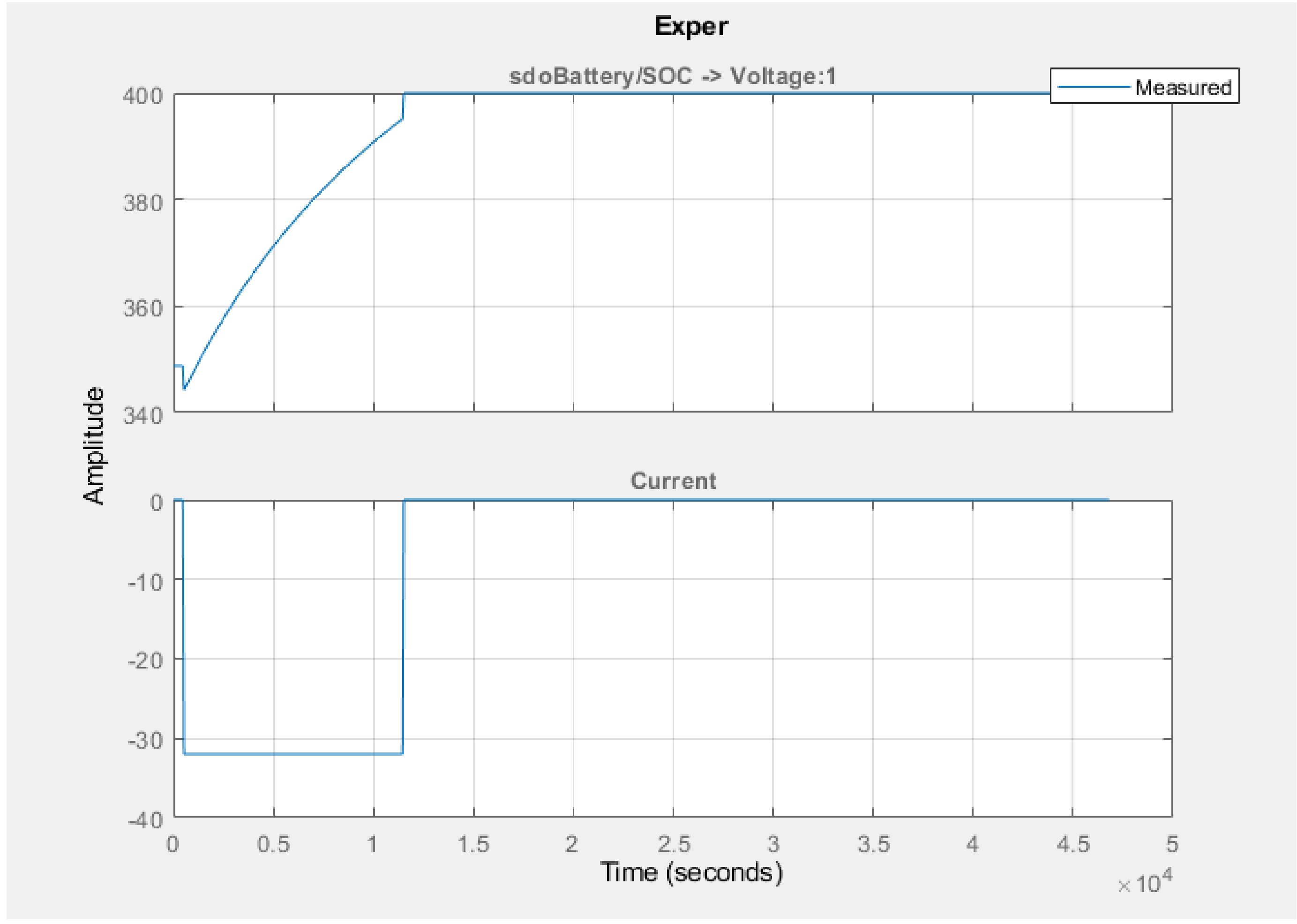
Parameter Estimation for Battery Model

The "Deployed Application of Parameter Estimation" openExample('sldo/BatteryDegradationParameterEstimationDeploymentExample') example shows how to use **Parameter Estimator** to estimate parameters for a battery in an electric vehicle. In this example, you load a pre-configured **Parameter Estimator** session based on that example. Open the battery model.

```
open_system('sdoBattery')
```

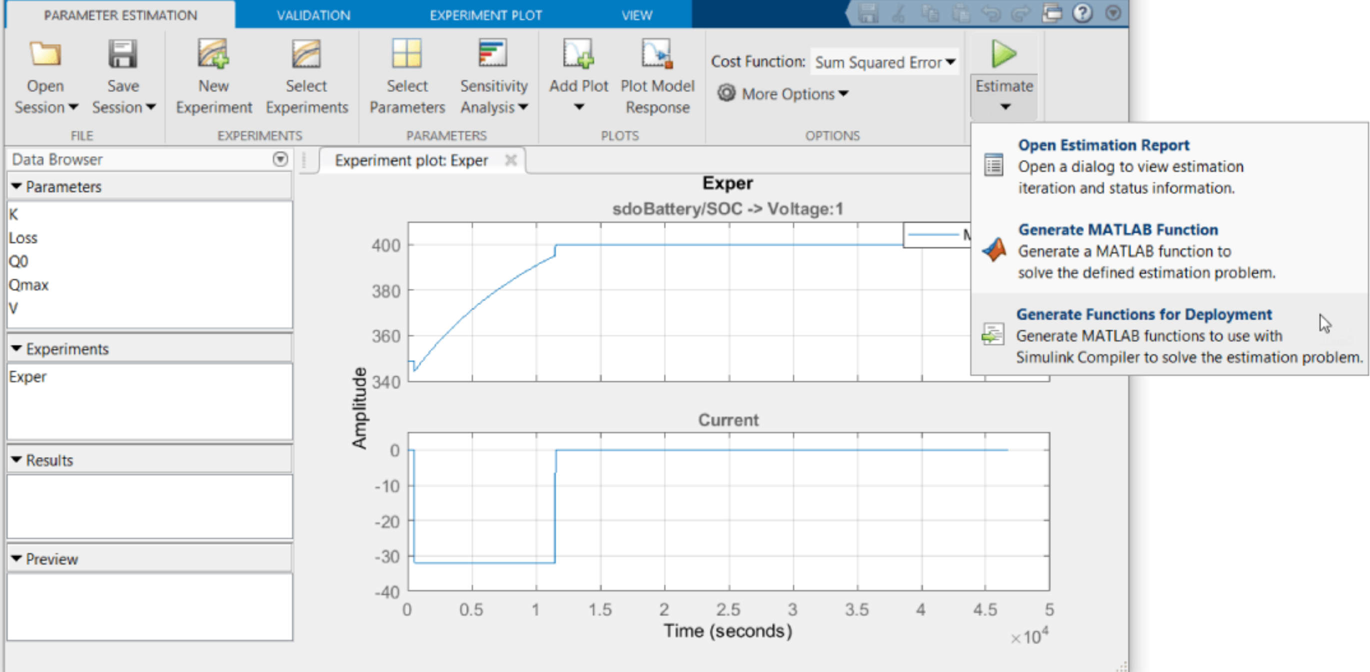
Open **Parameter Estimator** app with a preconfigured session for parameter estimation.

```
load sdoBattery_spesession_forDeployment
spetool(SDOSessionData)
```



Generate MATLAB Code

From the **Estimate** button, select **Generate Functions for Deployment**. This generates two MATLAB functions which are added to the MATLAB editor.



The generated code is added to the MATLAB editor as two unsaved MATLAB functions. The first is a "setup" function.

```
function parameterEstimationSdoBattery_setup(p)
%PARAMETERESTIMATIONSDOBATTERY_SETUP
%
% Set up a parameter estimation problem for the sdoBattery model.
%
% The function creates objects that can be used to solve a parameter
% estimation problem with Simulink Compiler. The input argument, p,
% defines the model parameters to estimate, if omitted the parameters
% specified in the function body are estimated.
%
% Modify the function to include or exclude new experiments. To
% see an example, type:
% openExample('sldo/BatteryDegradationParameterEstimationDeploymentExample')

%
% Auto-generated by SPETOOL on 13-Jan-2022 05:56:20.
%

%% Open the model.
open_system('sdoBattery')

%% Specify Model Parameters to Estimate
%
if nargin < 1 || isempty(p)
    p = sdo.getParameterFromModel('sdoBattery',{'K','Loss','Q0','Qmax','V'});
    p(1).Value = 0.32;
    p(1).Free = 0;
    p(2).Value = 0.012;
    p(2).Free = 0;
    p(3).Value = 150;
    p(3).Minimum = 0;
```

The "setup" function sets up the parameter estimation problem and prepares it to be solved in deployed mode. Significant portions of the function are:

- **Specify Model Parameters to Estimate -** Defines the model parameters being estimated.
- **Define the Estimation Experiments -** Specifies the measured data, and the signals they are associated with in the model. After parameter estimation, the model output should be close to the measured data.
- **Create a Simulator -** Creates a simulator for running the model to compare whether its output is similar to the measured data in the experiments.
- **Prepare for Deployment -** Prepares the experiments and simulator for deployment, for parameter estimation in deployed mode with Simulink Compiler. Saves these prepared objects to a MATLAB data file.

Select **Save** from the MATLAB editor to save the generated "setup" function.

The second generated function is a "run" function.

```
function [pOpt,Info] = parameterEstimationSdoBattery_run(dataFilename)
%PARAMETERESTIMATIONSDOBATTERY_RUN
%
% Solve up a parameter estimation problem for the sdoBattery model.
% Can be made into a standalone executable using Simulink Compiler.
%
% The function returns estimated parameter values, pOpt
% and estimation termination information, Info.
%
% The input argument, dataFilename, defines the file name to read for
% experiment data. The code here assumes the measured experiment data
% is in a CSV file or spreadsheet whose column headers are Time, Input,
% and Output. Modify the code here as appropriate for your data. To see
% an example, type:
% openExample('sldo/BatteryDegradationParameterEstimationDeploymentExample')
%
% Modify the function to change the data file or data variables,
% or to change the estimation options.
%
% Auto-generated by SPETOOL on 13-Jan-2022 05:56:20.
%

%% Ensure model is compiled
%#function sdoBattery.slx

%% Load configured experiment and simulator objects, and parameters
load sdoBatteryObjectsToDeploy.mat Exper Simulator p

%% Load new data and update experiments.
%% *** Change the file name and data format to match your data. ***
if nargin < 1
```

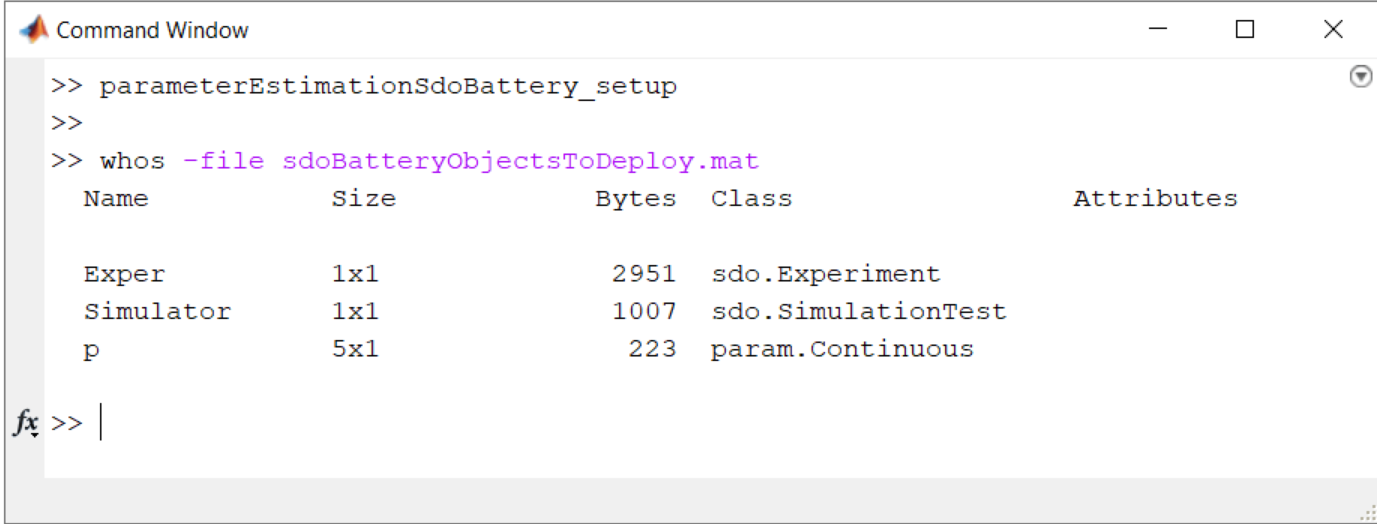
The "run" function can be compiled to a stand-alone executable to be used in deployed mode with Simulink Compiler. Significant portions of the code in the "run" function are:

- **Load Objects** - Load the objects that were prepared for deployment by the "setup" function.
- **Update Experiments** - Update the experiments with new data. **You will probably want to modify this portion of the code to suit the format of your data.**
- **Create Estimation Objective Function** - Create an anonymous function that calls the subfunction `sdoBattery_optFcn`, which evaluates the model using each experiment and compares simulation and measured experiment outputs. This anonymous function is called by `sdo.optimize` at each iteration of the optimization problem to solve the estimation problem.
- **Estimate the Parameters** - Solve the estimation problem using the `sdo.optimize` command.

Select **Save** from the MATLAB editor to save the generated "run" function.

Run Generated Code

Execute the setup file. This prepares the parameter estimation problem and saves prepared objects into the file `sdoBatteryObjectsToDeploy.mat`. Then you can run `parameterEstimationSdoBattery_run.m` in an environment with Simulink Compiler.



Execute the "run" file. This can be compiled to a stand-alone executable using `mcc`, and run in deployed mode using Simulink Compiler.

Command Prompt

```
C:\Users\Michael\CarBattery>parameterEstimationSdoBattery_run sdoBattery_Data1_forGeneratedCode.csv

 Optimization started 20-Jan-2022 10:05:51

                                          First-order
 Iter F-count        f(x)      Step-size  optimality
    0      5   0.00467119            1
    1     10  2.04632e-06      0.01003      0.00712
    2     15  1.63009e-07     0.001241      0.00108
Local minimum possible.

lsqnonlin stopped because the final change in the sum of squares relative to
its initial value is less than the value of the function tolerance.

C:\Users\Michael\CarBattery>
```

Modify the Generated Code

You can modify the "setup" function to:

- Estimate different parameters, or specify different lower/upper bounds
- Include new experiments

You can modify the "run" function to:

- Modify the update-data portion to suit your data format.

- Change the options, such as the optimization solver, tolerances, etc.

See Also

`prepareToDeploy(Experiment)` | `prepareToDeploy(SimulationTest)` | `updateIOData(Experiment)` | `sdo.Experiment` | `sdo.SimulationTest`

Related Examples

- “Parameter Tuning for Digital Twins” on page 2-192

Response Optimization

- “How the Optimization Algorithm Formulates Minimization Problems” on page 3-3
- “Specify Signals to Log” on page 3-10
- “Specify Custom Requirements in the App” on page 3-11
- “Move Constraints” on page 3-14
- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Edit Design Requirements” on page 3-29
- “Specify Variable Requirements in the App” on page 3-31
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43
- “Specify Design Variables” on page 3-56
- “Update Model with Design Variables Set” on page 3-60
- “Specify Optimization Options” on page 3-62
- “Create Linearization I/O Sets” on page 3-64
- “Interact with Plots” on page 3-67
- “Compare Requirements and Design Variables Using Spider Plot” on page 3-71
- “Save Design Variable Values for Specific Iteration” on page 3-74
- “Design Optimization to Meet Time-Domain and Frequency-Domain Requirements (GUI)” on page 3-76
- “Discrete-Valued Variables in Response Optimization (Code)” on page 3-88
- “Design Optimization Tuning Parameters in Referenced Models (GUI)” on page 3-95
- “Design Optimization Tuning Parameters in Referenced Models (Code)” on page 3-102
- “Specify Steady-State Operating Point for Response Optimization” on page 3-108
- “Design Optimization to Meet a Custom Objective (GUI)” on page 3-110
- “Design Optimization to Meet a Custom Objective (Code)” on page 3-125
- “Design Optimization to Meet Custom Signal Requirements (GUI)” on page 3-132
- “Design Optimization to Meet Frequency-Domain Requirements (GUI)” on page 3-136
- “Specify Custom Signal Objective with Uncertain Variable (GUI)” on page 3-150
- “Design Optimization with Uncertain Variables (Code)” on page 3-159
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- “Skip Model Simulation Based on Parameter Constraint Violation (GUI)” on page 3-170
- “Optimizing Parameters for Robustness” on page 3-177
- “Use Accelerator Mode During Simulations” on page 3-186
- “Speed Up Response Optimization Using Parallel Computing” on page 3-187
- “Use Parallel Computing for Response Optimization” on page 3-190
- “Use Fast Restart Mode During Response Optimization” on page 3-196
- “Optimization Does Not Make Progress” on page 3-198

- “Optimization Convergence” on page 3-199
- “Optimization Speed and Parallel Computing” on page 3-201
- “Undesirable Parameter Values” on page 3-203
- “Reverting to Initial Parameter Values” on page 3-205
- “Save and Load Optimization Sessions” on page 3-206
- “Improving Optimization Performance Using Parallel Computing” on page 3-208
- “Optimizing Time-Domain Response of Simulink Models Using Parallel Computing” on page 3-217
- “Design Optimization to Meet Frequency-Domain Requirements (Code)” on page 3-224
- “PID Tuning with Actuator Constraints” on page 3-230
- “PID Tuning with Reference Tracking and Plant Uncertainty” on page 3-235
- “Engine Design and Cost Tradeoffs” on page 3-240
- “Magnetic Levitation Controller Tuning” on page 3-248
- “LQG Controller Tuning” on page 3-256
- “Inverted Pendulum Controller Tuning” on page 3-260
- “Pitch Rate Controller Tuning” on page 3-264
- “Tuning of Airframe Autopilot Gains” on page 3-268
- “Distillation Controller Tuning” on page 3-272
- “Heat Exchanger Controller Tuning” on page 3-276
- “Power Converter Tuning” on page 3-280
- “Servomechanism Tuning” on page 3-284
- “Stewart Platform Controller Tuning” on page 3-288
- “Phase Lock Loop Tuning” on page 3-292
- “Surrogate Optimization in Simulink Design Optimization” on page 3-296
- “Surrogate Optimization using the Response Optimizer App” on page 3-302

How the Optimization Algorithm Formulates Minimization Problems

When you optimize parameters of a Simulink model to meet design requirements, Simulink Design Optimization software automatically converts the requirements into a constrained optimization problem and then solves the problem using optimization techniques. The constrained optimization problem iteratively simulates the Simulink model, compares the results of the simulations with the constraint objectives, and uses optimization methods to adjust tuned parameters to better meet the objectives.

This topic describes how the software formulates the constrained optimization problem used by the optimization algorithms. For each optimization algorithm, the software formulates one of the following types of minimization problems:

- Feasibility on page 3-3
- Tracking on page 3-5
- Mixed feasibility and tracking

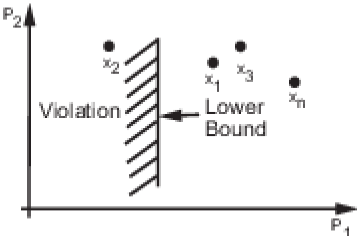
For more information on how each optimization algorithm formulates these problems, see:

- “Gradient Descent Method Problem Formulations” on page 3-6
- “Simplex Search Method Problem Formulations” on page 3-7
- “Pattern Search Method Problem Formulations” on page 3-7
- “Gradient Computations” on page 3-8

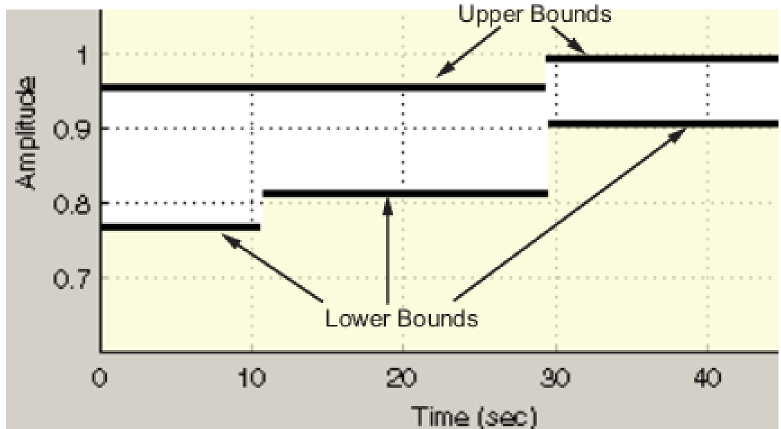
Feasibility Problem and Constraint Formulation

Feasibility means that the optimization algorithm finds parameter values that satisfy all constraints to within specified tolerances but does not minimize any objective or cost function in doing so.

In the following figure, x_1, x_3, and x_n represent a combination of parameter values P_1 and P_2 and are feasible solutions because they do not violate the lower bound constraint.



In a Simulink model, you constrain a signal by specifying lower and upper bounds in a Check block (Check Step Response Characteristics, ...) or a requirement object (`sdo.requirements.StepResponseEnvelope`, ...), as shown in the following figure.



These constraints are piecewise linear bounds. A piecewise linear bound y_{bnd} with n edges can be represented as:

$$y_{bnd}(t) = \begin{cases} y_1(t) & t_1 \le t \le t_2 \\ y_2(t) & t_2 \le t \le t_3 \\ \vdots & \vdots \\ y_n(t) & t_n \le t \le t_{n+1} \end{cases},$$

The software computes the signed distance between the simulated response and the edge. The signed distance for lower bounds is:

$$c = \begin{bmatrix} \max\limits_{t_1 \le t \le t_2} y_{bnd} - y_{sim} \\ \max\limits_{t_2 \le t \le t_3} y_{bnd} - y_{sim} \\ \max\limits_{t_n \le t \le t_{n+1}} y_{bnd} - y_{sim} \end{bmatrix},$$

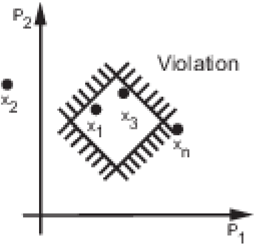
where y_{sim} is the simulated response and is a function of the parameters being optimized.

The signed distance for upper bounds is:

$$c = \begin{bmatrix} \max\limits_{t_1 \le t \le t_2} y_{sim} - y_{bnd} \\ \max\limits_{t_2 \le t \le t_3} y_{sim} - y_{bnd} \\ \max\limits_{t_n \le t \le t_{n+1}} y_{sim} - y_{bnd} \end{bmatrix}.$$

At the command line, “optimFcn” supplies `c` directly from the `Cleq` field of `vals`.

If *all* the constraints are met ($c \le 0$) for some combination of parameter values, then that solution is said to be feasible. In the following figure, x_1 and x_3 are feasible solutions.



When your model has multiple requirements or vector signals feeding a requirement, the constraint vector is extended with the constraint violations for each signal and bound:

$$C = [c_1; c_2; \cdots; c_n].$$

Tracking Problem

In addition to lower and upper bounds, you can specify a reference signal in a Check Against Reference block or `sdo.requirements.SignalTracking` object, which the Simulink model output can track. The tracking objective is a sum-squared-error tracking objective.

You specify the reference signal as a sequence of time-amplitude pairs:

$$y_{ref}(t_{ref}), t_{ref} \in \left\{T_{ref0}, T_{ref1}, \cdots, T_{refN}\right\}.$$

The software computes the simulated response as a sequence of time-amplitude pairs:

$$y_{sim}(t_{sim}), t_{sim} \in \{T_{sim0}, T_{sim1}, \cdots, T_{simN}\},$$

where some values of t_{sim} may match the values of t_{ref}.

A new time base, t_{new}, is formed from the union of the elements of t_{ref} and t_{sim}. Elements that are not within the minimum-maximum range of both t_{ref} and t_{sim} are omitted:

$$t_{new} = \left\{t: t_{sim} \cup t_{ref}\right\}$$

Using linear interpolation, the software computes the values of y_{ref} and y_{sim} at the time points in t_{new} and then computes the scaled error:

$$e(t_{new}) = \frac{\left(y_{sim}(t_{new}) - y_{ref}(t_{new})\right)}{\max\limits_{t_{new}}\left|y_{ref}\right|}.$$

Finally, the software computes the weighted, integral square error:

$$f = \int w(t)e(t)^2 dt.$$

Note The weight $w(t)$ is 1 by default. You can specify a different value of weight only at the command line.

When your model has requirements or vector signals feeding a requirement, the tracking objective equals the sum of the individual tracking integral errors for each signal:

$$F = \sum f_i \,.$$

Gradient Descent Method Problem Formulations

The Gradient Descent method uses the function `fmincon` to optimize model parameters to meet design requirements.

Problem Type	Problem Formulation
Feasibility Problem	The software formulates the constraint $C(x)$ as described in “Feasibility Problem and Constraint Formulation” on page 3-3. • If you select the maximally feasible solution option (i.e., the optimization continues after an initial feasible solution is found), the software uses the following problem formulation: $$\min_{[x,\gamma]} \gamma \quad s.t. \quad C(x) \le \gamma, \quad \underline{x} \le x \le \bar{x}, \quad \gamma \le 0$$ γ is a slack variable that permits a feasible solution with $C(x) \le \gamma$ rather than $C(x) \le 0$. • If you do not select the maximally feasible solution option (i.e., the optimization terminates as soon as a feasible solution is found), the software uses the following problem formulation: $$\min_{x} 0 \quad s.t. \quad C(x) \le 0, \quad \underline{x} \le x \le \bar{x}$$
Tracking Problem	The software formulates the tracking objective $F(x)$ as described in “Tracking Problem” on page 3-5 and minimizes the tracking objective: $$\min_{x} F(x) \quad s.t. \quad \underline{x} \le x \le \bar{x}$$
Mixed Feasibility and Tracking Problem	The software minimizes following problem formulation: $$\min_{x} F(x) \quad s.t. \quad C(x) \le 0, \quad \underline{x} \le x \le \bar{x}$$ **Note** When tracking a reference signal, the software ignores the maximally feasible solution option.

Simplex Search Method Problem Formulations

The Simplex Search method uses the function `fminsearch` and `fminbnd` to optimize model parameters to meet design requirements. `fminbnd` is used if one scalar parameter is being optimized, otherwise `fminsearch` is used. You cannot use parameter bounds $\underline{x} \le x \le \bar{x}$ with `fminsearch`.

Problem Type	Problem Formulation
Feasibility Problem	The software formulates the constraint $C(x)$ as described in "Feasibility Problem and Constraint Formulation" on page 3-3 and then minimizes the maximum constraint violation: $\min_x \max(C(x))$
Tracking Problem	The software formulates the tracking objective $F(x)$ as described in "Tracking Problem" on page 3-5 and then minimizes the tracking objective: $\min_x F(x)$
Mixed Feasibility and Tracking Problem	The software formulates the problem in two steps: **1** Finds a feasible solution. $\min_x \max(C(x))$ **2** Minimizes the tracking objective. The software uses the results from step 1 as initial guesses and maintains feasibility by introducing a discontinuous barrier in the optimization objective. $\min_x \Gamma(x)$ where $\Gamma(x) = \begin{cases} \infty & \text{if} \max(C(x)) > 0 \\ F(x) & \text{otherwise.} \end{cases}$

Pattern Search Method Problem Formulations

The Pattern Search method uses the function `patternsearch` to optimize model parameters to meet design requirements.

Problem Type	Problem Formulation
Feasibility Problem	The software formulates the constraint $C(x)$ as described in "Feasibility Problem and Constraint Formulation" on page 3-3 and then minimizes the maximum constraint violation: $\min_x \max(C(x)) \quad s.t. \quad \underline{x} \le x \le \bar{x}$

Problem Type	Problem Formulation
Tracking Problem	The software formulates the tracking objective $F(x)$ as described in "Tracking Problem" on page 3-5 and then minimizes the tracking objective: $\min_x \; F(x)$ $s.t. \quad \underline{x} \leq x \leq \bar{x}$
Mixed Feasibility and Tracking Problem	The software formulates the problem in two steps: **1** Finds a feasible solution. $\min_x \max(C(x))$ $s.t. \quad \underline{x} \leq x \leq \bar{x}$ **2** Minimizes the tracking objective. The software uses the results from step 1 as initial guesses and maintains feasibility by introducing a discontinuous barrier in the optimization objective. $\min_x \Gamma(x)$ $s.t. \; \underline{x} \leq x \leq \bar{x}$ where $\Gamma(x) = \begin{cases} \infty & \text{if} \max(C(x)) > 0 \\ F(x) & \text{otherwise.} \end{cases}$

Gradient Computations

For the `Gradient descent` (`fmincon`) optimization solver, the gradients are computed using numerical perturbation:

$$dx = \sqrt[3]{eps} \times \max\left(\left|x\right|, \frac{1}{10} x_{typical}\right)$$
$$dL = \max(x - dx, x_{\min})$$
$$dR = \min(x + dx, x_{\max})$$
$$F_L = opt_fcn(dL)$$
$$F_R = opt_fcn(dR)$$
$$\frac{dF}{dx} = \frac{(F_L - F_R)}{(dL - dR)}$$

- x is a scalar design variable.
- x_{min} is the lower bound of x.
- x_{max} is the upper bound of x.
- $x_{typical}$ is the scaled value of x.
- *opt_fcn* is the objective function.

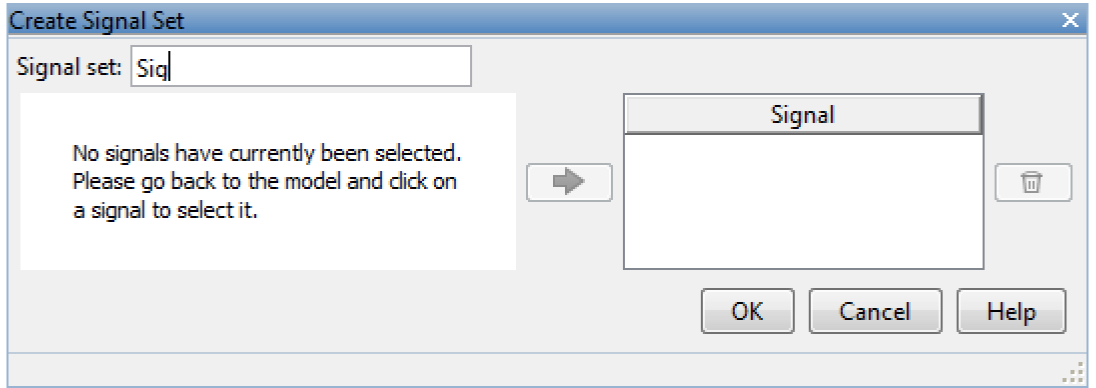
dx is relatively large to accommodate simulation solver tolerances.

If you want to compute the gradients in any other way, you can do so in the cost function you write for performing design optimization programmatically. See `sdo.optimize` and `GradFcn` of `sdo.OptimizeOptions` for more information.

Specify Signals to Log

Design requirements require logged model signals. During optimization, the model is simulated using the current value of the design variables and the logged signal is used to evaluate the design requirements.

1. In the **Response Optimizer**, select **Signal** in the **New** drop-down list. A window opens where you select a signal to log.
2. In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.
3. Select the signal and click to add it to the signal set.
4. In **Signal set** field, enter a name for the selected signal set.

Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

See Also

- “Design Optimization to Track Reference Signal (GUI)”
- `sdo.SimulationTest`

Specify Custom Requirements in the App

This topic shows how to specify custom requirements in the **Response Optimizer**.

You can specify custom requirements, such as minimizing system energy. To specify custom requirements:

1. In the **Response Optimizer**, in **New** drop-down menu, select **Custom Requirement**. The Create Requirement dialog box opens where you specify the custom requirement.
2. Specify a requirement name in **Name**.
3. Specify the requirement type in the **Type** drop-down menu.
4. Specify the name of the function that contains the custom requirement in **Function**. The field must be specified as a function handle using `@`. The function must be on the MATLAB path. Click to review or edit the function.

   If the function does not exist, clicking opens a template MATLAB file. Use this file to implement the custom requirement. The default function name is `myCustomRequirement`.
5. (Optional) To prevent the solver from considering specific parameter combinations, select **Error if constraint is violated**. Use this option for parameter-only constraints.

   During an optimization iteration, the solver first evaluates requirements with this option selected.

   - If the constraint is violated, the solver skips evaluating any remaining requirements and proceeds to the next iteration.
   - If the constraint is *not* violated, the solver evaluates the remaining requirements for the current iteration. If any of the remaining requirements bound signals or systems, then the solver simulates the model.

   For more information, see “Skip Model Simulation Based on Parameter Constraint Violation (GUI)” on page 3-170.

   Note If you select this check box, then do not specify signals or systems to bound. If you *do* specify signals or systems, then this check box is ignored.

   ---
6. (Optional) Specify the signal or system, or both, to be bound.

   You can apply this requirement to model signals, or a linearization of your Simulink model (requires Simulink Control Design), or both.

   Click **Select Signals and Systems to Bound (Optional)** to view the signal and linearization I/O selection area.

   - To apply this requirement to a model signal:

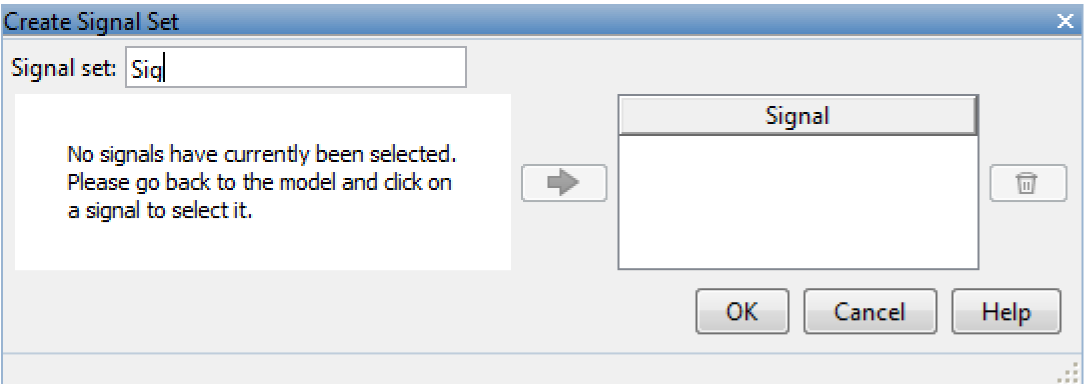
     In the **Signal** area, select a logged signal to which you will apply the requirement.

     If you have already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, it appears in the list. Select the corresponding check box.

     If you have not selected a signal to log:

a Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.

b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [⇨] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

- To apply this requirement to a linear system:

  a Specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.

  b Select the linearization input/output set from the **Linearization I/O** area.

  If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

  If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box. For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

  For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

7 Click **OK**.

A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**. A graphical display of the requirement also appears in the **Response Optimizer** app window.

See Also

Related Examples

- “Design Optimization to Meet a Custom Objective (GUI)” on page 3-110

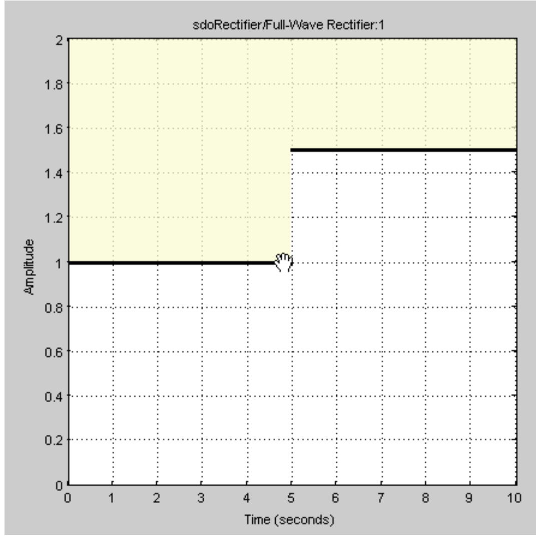
- “Design Optimization to Meet Custom Signal Requirements (GUI)” on page 3-132
- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43

Move Constraints

Constraint-bound edges define time-domain constraints you would like to place on a particular signal in your model. You can position these edges, which appear as a yellow shaded region bordered by a black line, graphically on page 3-14 or exactly on page 3-15.

Move Constraints Graphically

Use the mouse to click and drag edges in the amplitude versus time plot, as shown in the following figure.



- To move a constraint edge boundary or to change the slope of a constraint edge, position the pointer over a constraint edge endpoint, and press and hold down the left mouse button. The pointer should change to a hand symbol. While still holding the button down, drag the pointer to the target location, and release the mouse button. Note that the edges on either side of the boundary might not maintain their slopes.
- To move an entire constraint edge up, down, left, or right, position the mouse pointer over the edge and press and hold down the left mouse button. The pointer should change to a four-way arrow. While still holding the button down, drag the pointer to the target location, and release the mouse button. Note that the edges on either side of the boundary might not maintain their slopes.

To move a constraint edge to a perfectly horizontal or vertical position, hold down the **Shift** key while clicking and dragging the constraint edge. This causes the constraint edge to *snap* to a horizontal or vertical position.

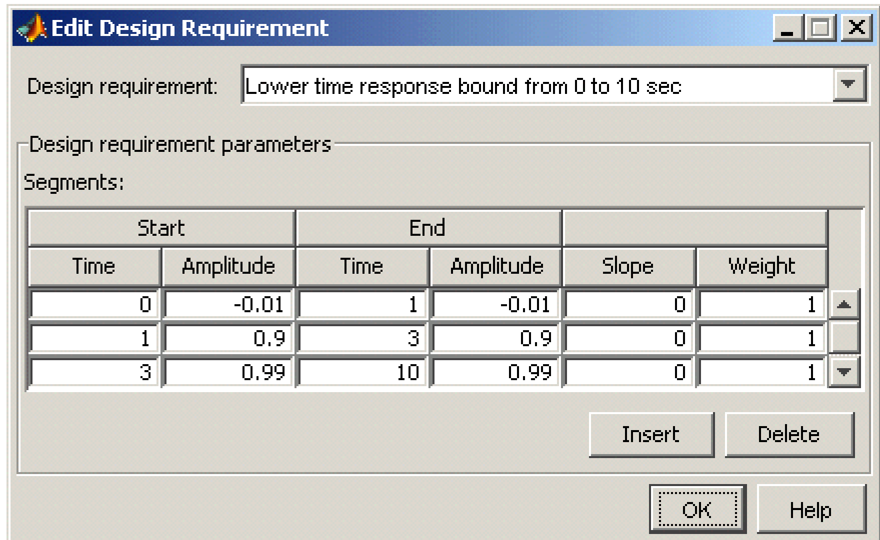
When moving constraint bound edges, it is sometimes helpful to display gridlines on the axes for careful alignment of the constraint bound edges. To turn the gridlines on or off, right-click within the axes and select **Grid**.

Note You can move a lower bound constraint edge above an upper bound constraint edge, or vice versa, but this produces an error when you attempt to run the optimization.

Position Constraints Exactly

To position a constraint edge exactly:

1. Position the pointer over the edge you want to move and right-click. Select **Edit** to open the Edit Design Requirement dialog box.



2. Specify the position of each constraint edge in the **Time** and **Amplitude** columns.

See Also

More About

- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43

Specify Time-Domain Design Requirements in the App

In the **Response Optimizer**, you can specify the following time-domain requirements:

- **Signal Bound** — "Specify Piecewise-Linear Lower and Upper Bounds" on page 3-16
- **Signal Property** — "Specify Signal Property Requirements" on page 3-17
- **Step Response Envelope** — "Specify Step Response Characteristics" on page 3-19
- **Signal Tracking** — "Track Reference Signals" on page 3-21
- **Ellipse Region Constraint** — "Impose Elliptic Bound on Phase Plane Trajectory of Two Signals" on page 3-22
- **Custom Requirement** — "Specify Custom Requirements" on page 3-24

After you specify the constraints, you can see if the requirements are satisfied by optimizing the design variables. For more information, see "Specify Optimization Options" on page 3-62.

Specify Piecewise-Linear Lower and Upper Bounds

To specify upper and lower bounds on a signal:

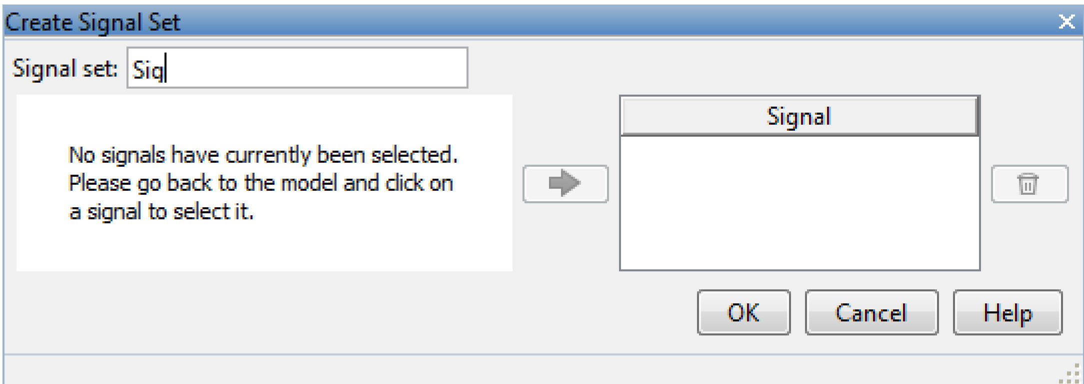
1. In the **Response Optimizer** , select **Signal Bound** in the **New** drop-down list. A window opens where you specify upper or lower bounds on a signal.
2. Specify a requirement name in the **Name** box.
3. Select the requirement type using the **Type** list.
4. Specify the edge start and end times and corresponding amplitude in the **Time (s)** and **Amplitude** columns.
5. Click [+] to specify additional bound edges.

   Select a row and click [delete] to delete a bound edge.
6. In the **Select Signals to Bound** area, select a logged signal to apply the requirement to.

   If you have already selected signals, as described in "Specify Signals to Log" on page 3-10, they appear in the list. Select the corresponding check-box.

   If you have not selected a signal to log:

   a. Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.
   b. In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [→] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

  Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

7 Click **OK**.

  A variable with the specified requirement name appears in the **Data** area of the app. A graphical display of the requirement also appears in the **Response Optimizer** app window.

8 (Optional) In the graphical display, you can:

   - “Move Constraints Graphically” on page 3-14
   - “Position Constraints Exactly” on page 3-15

Alternatively, you can add a Check Custom Bounds block to your model to specify piecewise-linear bounds.

Specify Signal Property Requirements

To specify signal property requirements:

1 In the **Response Optimizer**, select **Signal Property** in the **New** drop-down list. A Create Requirement window opens where you specify signal property requirements.

2 In the **Name** box, specify a requirement name.

3 In the **Specify Property** area, specify a signal property requirement using the **Property** and **Type** lists and the **Bound** box.

  Property List

Property	Description	Time weighting available
`Signal minimum`	Minimum of the signal	No
`Signal maximum`	Maximum of the signal	No

Property	Description	Time weighting available
`Signal final value`	Last signal value	No
`Signal mean`	Average of signal value	Yes
`Signal median`	Middle value of signal	Yes
`Signal variance`	Variance of signal	Yes
`Signal interquartile range`	Difference between the 75th and 25th percentiles of signal values	No
`Signal sum`	$\sum_{i=t_0}^{t_N} S(i)$, where $S(t_0), \ldots, S(t_N)$ is the signal to constrain.	Yes
`Signal sum square`	$\sum_{i=t_0}^{t_N} S(i)^2$	Yes
`Signal sum absolute`	$\sum_{i=t_0}^{t_N} \lvert S(i) \rvert$	Yes

For signal properties where the **Time-Weighted** option is available, you can select it to weight the property computation by the time intervals between samples.

Custom Signal Property

You can add a custom signal property to the **Property** list by editing the function `sdo.requirements.signalPropertyFcns`.

- **a** At the MATLAB command prompt, enter `edit sdo.requirements.signalPropertyFcns`.
- **b** Add your signal property function to the `FcnData` cell array.

  Your signal property function must be on the path.

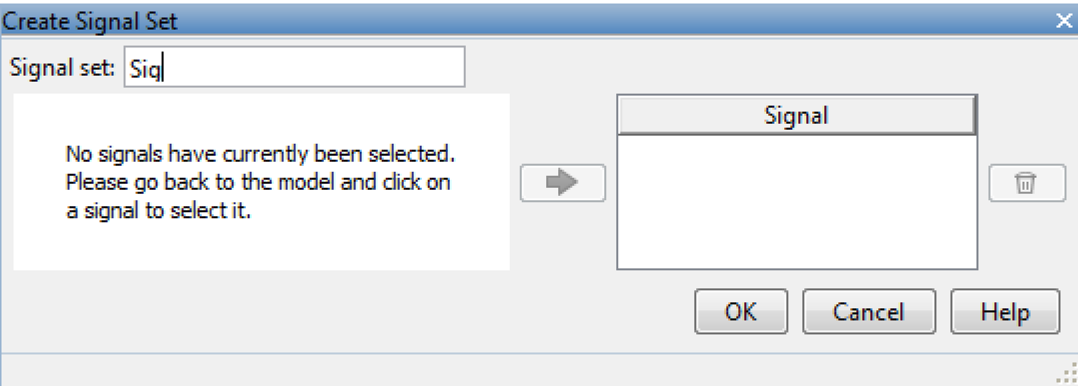
4 In the **Select Signals to Bound** area, select the logged signal to which you want to apply the requirement.

The signal selected must have numeric type data (either floating-point or integer). Also, if the property selected is `Signal median`, `Signal variance`, or `Signal interquartile range`, then the signal data must be floating-point (either double or single).

If you have already selected a signal, as described in “Specify Signals to Log” on page 3-10, the signal appears in the list. Select the corresponding check box for that signal.

If you have not selected a signal to log:

- **a** Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.
- **b** In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

5. Click **OK**.

   A variable with the specified requirement name appears in the **Data** area of the app. An iteration plot depicting the signal property for each iteration also appears in the **Response Optimizer** app window.

Specify Step Response Characteristics

To apply a step response requirement to a signal in your model, specify the step response characteristics as follows:

1. Select a step response requirement from the **Response Optimizer**.

   In the **New** drop-down menu of the app, in the **New Time Domain Requirement** section, select **Step Response Envelope**.

   A Create Requirement dialog box opens where you specify the step response requirements on a signal.
2. Specify a requirement name in the **Name** field of the dialog box.
3. Specify the step response characteristics:

   - **Initial value** — Input level before the step occurs
   - **Step time** — Time at which the step takes place
   - **Final value** — Input level after the step occurs
   - **Rise time** — The time taken for the response signal to reach a specified percentage of the step range. The step range is the difference between the final and initial values.
   - **% Rise** — The percentage of the step range used with **Rise time** to define the overall rise time characteristics.

- **Settling time** — Time taken until the response signal settles within a specified region around the final value. This settling region is defined as the final step value plus or minus the settling range, defined in **% Settling**.
- **% Settling** — The percentage of the step range value that defines the settling range of settling time characteristic specified in **Settling time**.
- **% Overshoot** — The amount by which the response signal can exceed the final value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
- **% Undershoot** — The amount by which the response signal can undershoot the initial value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.

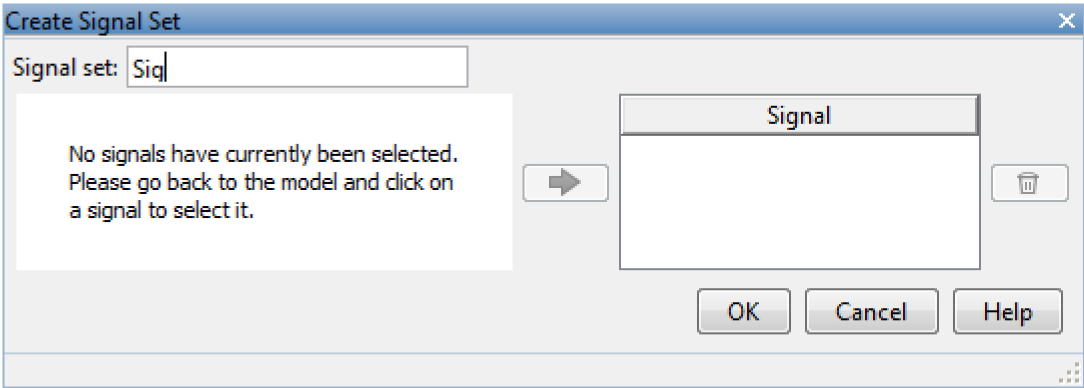
4. Specify the signal to be bound.

   To apply this requirement to a model signal, in the **Select Signals to Bound** area, select a logged signal to which you will apply the requirement.

   If you have already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, it appears in the list. Select the corresponding check-box.

   If you have not selected a signal to log:

   a. Click . The Create Signal Set dialog box opens where you specify the logged signal.
   b. In the Simulink model window, click the signal to which you want to add a requirement.



   The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

   c. Select the signal and click to add it to the signal set.
   d. In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

Alternatively, you can use the Check Step Response Characteristics block to specify step response bounds for a signal.

See Also

“Design Optimization to Meet Step Response Requirements (GUI)”

Track Reference Signals

Use reference tracking to force a model signal to match a desired signal. To track a reference signal:

1. In the **Response Optimizer**, select **Signal Tracking** in the **New** drop-down list. A window opens where you specify the reference signal to track.
2. Specify a requirement name in the **Name** box.
3. Define the reference signal by entering vectors, or variables from the workspace, in the **Time vector** and **Amplitude** fields.

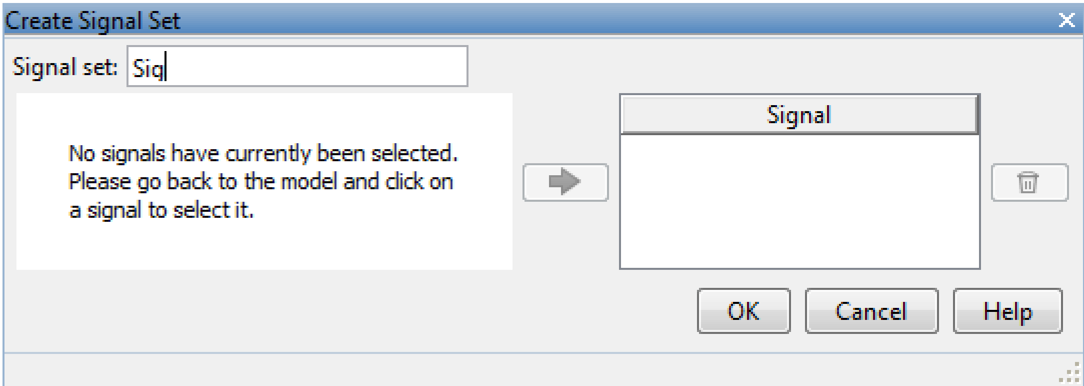
   Click **Update reference signal data** to use the new amplitude and time vector as the reference signal.
4. Specify how the optimization solver minimizes the error between the reference and model signals using the **Tracking Method** list:

   - SSE — Reduces the sum of squared errors
   - SAE — Reduces the sum of absolute errors
5. In the **Specify Signal to Track Reference Signal** area, select a logged signal to apply the requirement to.

   If you already selected a signal to log, as described in "Specify Signals to Log" on page 3-10, they appear in the list. Select the corresponding check-box.

   If you have not selected a signal to log:

   a. Click . A Create Signal Set dialog box opens where you specify the logged signal.
   b. In the Simulink model window, click the signal to which you want to add a requirement.



   The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

   c. Select the signal and click to add it to the signal set.
   d. In **Signal set** field, enter a name for the selected signal set.

      Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.
   e. Select the check-box corresponding to the signal and click **OK**.

A variable with the specified requirement name appears in the **Data** area of the app. A graphical display of the signal bound also appears in the **Response Optimizer** app window.

Note When tracking a reference signal, the software ignores the maximally feasible solution option. For more information on this option, in the **Response Optimization** tab, click **Options** > **Optimization Options**, and click **Help**.

Alternatively, you can use the Check Against Reference block to specify a reference signal to track.

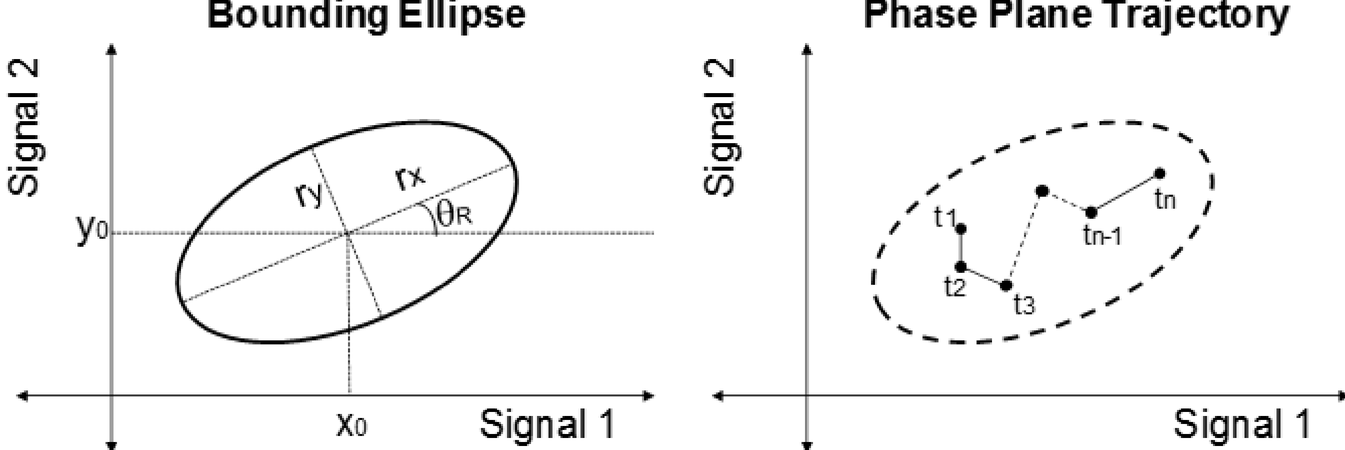
See Also

"Design Optimization to Track Reference Signal (GUI)"

Impose Elliptic Bound on Phase Plane Trajectory of Two Signals

You can impose an elliptic bound on the phase plane trajectory of two signals in your Simulink model. The phase plane trajectory is a plot of the two signals against each other. You specify the radii, center, and rotation of the bounding ellipse. You also specify whether you require the trajectory of the two signals to lie inside or outside the ellipse.

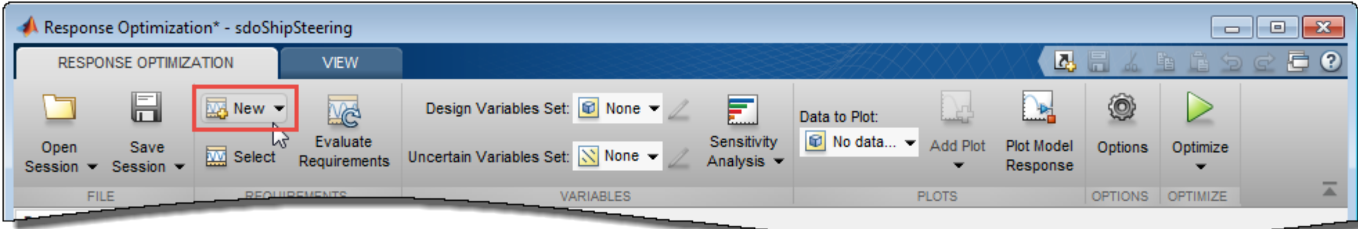
The following image shows the bounding ellipse and an example of the phase plane trajectory of two signals.



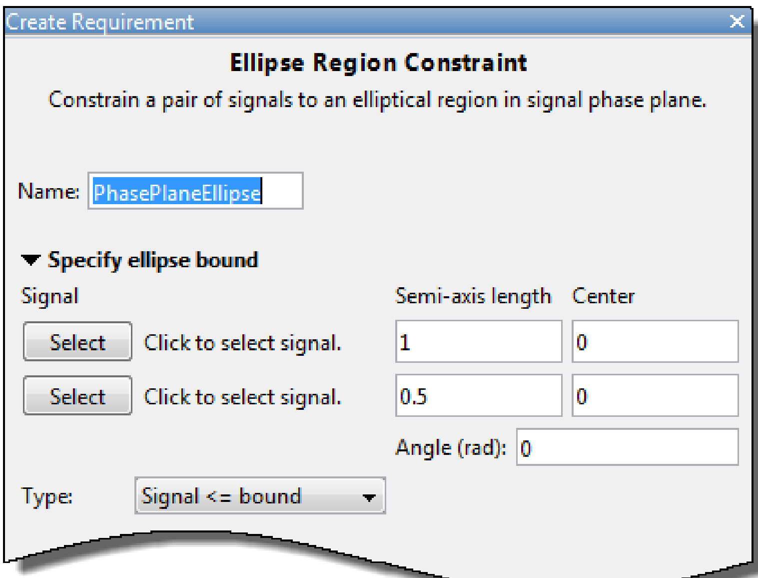
The X-Y plane is the phase plane defined by the two signals. r_x and r_y are the radii of the bounding ellipse along the *x* and *y* axes, and θ_R is the rotation of the ellipse about the center. The ellipse center is at (x_0,y_0). In the image, the phase plane trajectory of the signals lies within the bounding ellipse for all time points t_1 to t_n.

To specify the elliptical bound requirement:

1 In the **Response Optimizer**, in **New** drop-down list, select **Ellipse Region Constraint**.

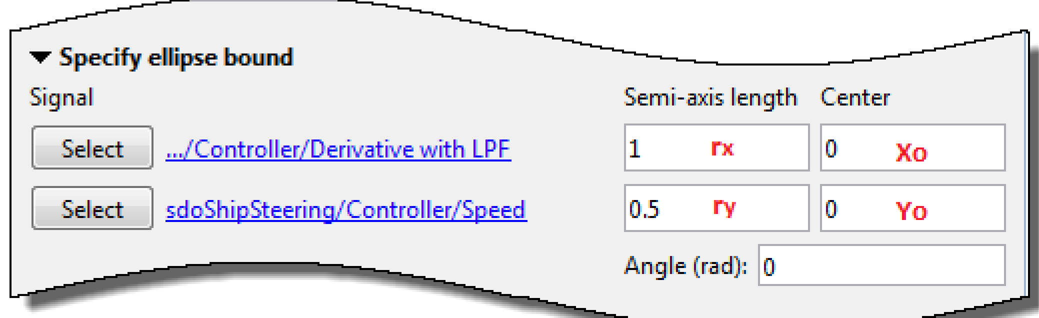


In the Create Requirement dialog box, specify the requirement.

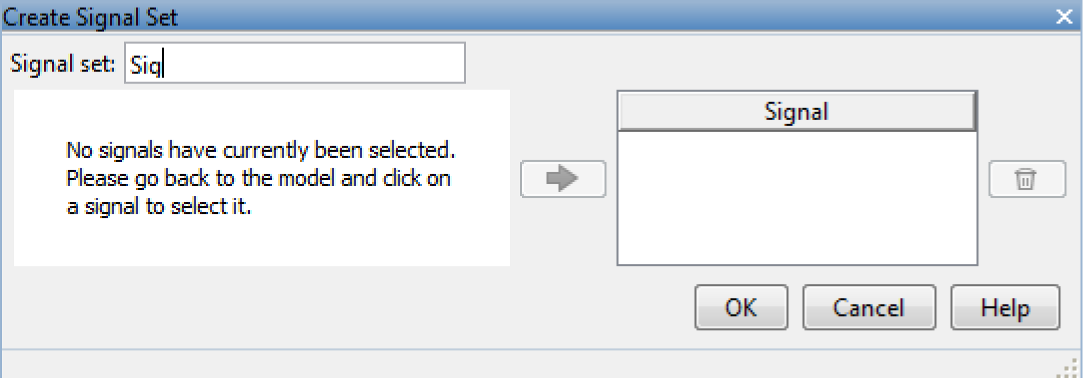


2 Specify a requirement name in **Name**.

1 Specify the two signals that you want to impose the requirement on. The signals define the X-Y plane of the bounding ellipse. To specify the signals, click the corresponding **Select** buttons.



When you click **Select**, the Create Signal Set dialog box opens.



In the Simulink model window, click the signal to which you want to add the requirement. The Create Signal Set dialog box updates with the name of the block and the port number where the selected signal is located. Select the signal, and click to add it to the signal set.

Once you have specified the logged signal in the Create Signal Set dialog box, the signal appears in the Create Requirement dialog box.

2. Specify the radii of the bounding ellipse as real positive finite values in **Semi-axis length**. You specify r_x and r_y that are the *x*-axis and *y*-axis radii before any rotation about the ellipse center.
3. Specify the location of the center of the bounding ellipse in **Center**. You specify x_0 and y_0, the *x* and *y* coordinates of the center, as real finite values.
4. Specify the angle of rotation of the ellipse about its center as a real finite scalar in **Angle (rad)**.
5. Specify the bound **Type** as one of the following:

   - `'<='` — Ellipse is an upper bound. The phase plane trajectory of the two signals should lie inside or on the ellipse.
   - `'>='` — Ellipse is a lower bound. The phase plane trajectory of the two signals should lie outside or on the ellipse.

1. (Optional) To create an iteration plot that shows the evaluated requirement value for each optimization iteration, select **Create Plot**. The plot is populated when you perform optimization. During optimization, the software computes the signed minimum distance of each point in the phase plane trajectory to the bounding ellipse. The maximum of these signed distances is returned and plotted at each iteration. A positive value indicates that the requirement has been violated and at least one of the trajectory points lies outside the bounding region.
2. Click **OK**.

   A new variable, with the specified requirement name, appears in the **Data** area of the **Response Optimizer**. A graphical display of the requirement also appears in the **Response Optimizer** app window.

Specify Custom Requirements

You can specify custom requirements, such as minimizing system energy. To specify custom requirements:

1. In the **Response Optimizer**, in **New** drop-down menu, select **Custom Requirement**. The Create Requirement dialog box opens where you specify the custom requirement.

2. Specify a requirement name in **Name**.
3. Specify the requirement type in the **Type** drop-down menu.
4. Specify the name of the function that contains the custom requirement in **Function**. The field must be specified as a function handle using `@`. The function must be on the MATLAB path. Click to review or edit the function.

   If the function does not exist, clicking opens a template MATLAB file. Use this file to implement the custom requirement. The default function name is `myCustomRequirement`.
5. (Optional) To prevent the solver from considering specific parameter combinations, select **Error if constraint is violated**. Use this option for parameter-only constraints.

   During an optimization iteration, the solver first evaluates requirements with this option selected.

   - If the constraint is violated, the solver skips evaluating any remaining requirements and proceeds to the next iteration.
   - If the constraint is *not* violated, the solver evaluates the remaining requirements for the current iteration. If any of the remaining requirements bound signals or systems, then the solver simulates the model.

   For more information, see "Skip Model Simulation Based on Parameter Constraint Violation (GUI)" on page 3-170.

   Note If you select this check box, then do not specify signals or systems to bound. If you *do* specify signals or systems, then this check box is ignored.

   ---
6. (Optional) Specify the signal or system, or both, to be bound.

   You can apply this requirement to model signals, or a linearization of your Simulink model (requires Simulink Control Design), or both.

   Click **Select Signals and Systems to Bound (Optional)** to view the signal and linearization I/O selection area.

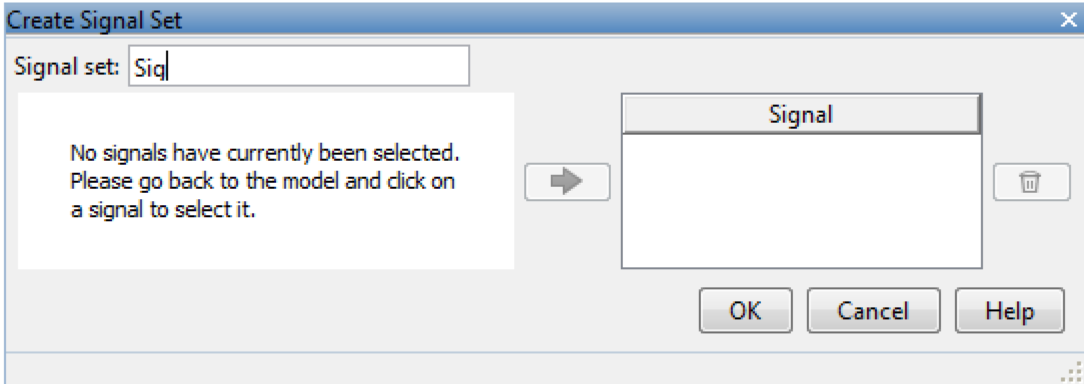
   - To apply this requirement to a model signal:

     In the **Signal** area, select a logged signal to which you will apply the requirement.

     If you have already selected a signal to log, as described in "Specify Signals to Log" on page 3-10, it appears in the list. Select the corresponding check box.

     If you have not selected a signal to log:

     a. Click . A Create Signal Set dialog box opens where you specify the logged signal.
     b. In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c. Select the signal and click [arrow button] to add it to the signal set.
d. In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

- To apply this requirement to a linear system:

  a. Specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.
  b. Select the linearization input/output set from the **Linearization I/O** area.

     If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

     If you have not created a linearization input/output set, click [+ button] to open the Create linearization I/O set dialog box. For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

  For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

7. Click **OK**.

   A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**. A graphical display of the requirement also appears in the **Response Optimizer** app window.

See Also

- “Design Optimization to Meet a Custom Objective (GUI)” on page 3-110
- “Design Optimization to Meet a Custom Objective (Code)” on page 3-125

Edit Design Requirements

The Edit Design Requirement dialog box allows you to exactly position constraint segments and to edit other properties of these constraints. The dialog box has two main components:

- An upper panel to specify the constraint you are editing
- A lower panel to edit the constraint parameters

The upper panel of the Edit Design Requirement dialog box resembles the image in the following figure.

In the **Control System Designer** app in Control System Toolbox™, you can edit design requirements from the analysis plots. The **Design requirement** drop-down list will contain all the requirements on that plot.

Edit Design Requirement Dialog Box Parameters

The particular parameters shown within the lower panel of the Edit Design Requirement dialog box depend on the type of constraint/requirement. In some cases, the lower panel contains a grid with one row for each segment and one column for each constraint parameter. The following table summarizes the various constraint parameters.

Edit Design Requirement Dialog Box Parameters

Parameter	Found in	Description
Time	Upper and lower time response bounds on step and impulse response plots	Defines the time range of a segment within a constraint/requirement.
Amplitude	Upper and lower time response bounds on step and impulse response plots	Defines the beginning and ending amplitude of a constraint segment.
Slope (1/s)	Upper and lower time response bounds	Defines the slope, in 1/s, of a constraint segment. It is an alternative method of specifying the magnitude values. Entering a new **Slope** value changes any previously defined magnitude values.
Final value	Step response bounds	Defines the input level after the step occurs.
Rise time	Step response bounds	Defines a constraint segment for a particular rise time.
% Rise	Step response bounds	The percentage of the step range used to describe the rise time.
Settling time	Step response bounds	Defines a constraint segment for a particular settling time.
% Settling	Step response bounds	The percentage of the step range that defines the settling region used to describe the settling time.
% Overshoot	Step response bounds	The percentage amount by which the signal can exceed the final value before settling.
% Undershoot	Step response bounds	Defines the constraint segments for a particular percent undershoot.

See Also

Related Examples

- “Specify Design Variables” on page 3-56
- “Specify Variable Requirements in the App” on page 3-31
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43
- “Specify Optimization Options” on page 3-62
- “Design Optimization Using Lookup Table Requirements for Gain Scheduling (GUI)” on page 6-59

Edit Design Requirements

The Edit Design Requirement dialog box allows you to exactly position constraint segments and to edit other properties of these constraints. The dialog box has two main components:

- An upper panel to specify the constraint you are editing
- A lower panel to edit the constraint parameters

The upper panel of the Edit Design Requirement dialog box resembles the image in the following figure.

In the context of the **Control System Designer** app in Control System Toolbox, **Design requirement** is associated with both the analysis plot or editor that contains the requirement and the particular requirement itself. To edit other constraints within the app, select another design requirement from the drop-down menu.

Edit Design Requirement Dialog Box Parameters

The particular parameters shown within the lower panel of the Edit Design Requirement dialog box depend on the type of constraint/requirement. In some cases, the lower panel contains a grid with one row for each segment and one column for each constraint parameter. The following table summarizes the various constraint parameters.

Edit Design Requirement Dialog Box Parameters

Parameter	Found in	Description
Time	Upper and lower time response bounds on step and impulse response plots	Defines the time range of a segment within a constraint/requirement.
Amplitude	Upper and lower time response bounds on step and impulse response plots	Defines the beginning and ending amplitude of a constraint segment.
Slope (1/s)	Upper and lower time response bounds	Defines the slope, in 1/s, of a constraint segment. It is an alternative method of specifying the magnitude values. Entering a new **Slope** value changes any previously defined magnitude values.
Final value	Step response bounds	Defines the input level after the step occurs.
Rise time	Step response bounds	Defines a constraint segment for a particular rise time.
% Rise	Step response bounds	The percentage of the step range used to describe the rise time.
Settling time	Step response bounds	Defines a constraint segment for a particular settling time.
% Settling	Step response bounds	The percentage of the step range that defines the settling region used to describe the settling time.
% Overshoot	Step response bounds	The percentage amount by which the signal can exceed the final value before settling.
% Undershoot	Step response bounds	Defines the constraint segments for a particular percent undershoot.

Specify Variable Requirements in the App

In the **Response Optimizer**, you can specify the following constraints on Simulink model parameters that are specified as variables:

- **Monotonic Variable** — "Impose Monotonic Constraint Requirement on Variable" on page 3-31
- **Smoothness Constraint** — "Impose Upper Bound on Gradient Magnitude of Variable" on page 3-33
- **Function Matching** — "Specify Linear or Quadratic Function Matching Constraint" on page 3-36
- **Vector Property** — "Specify Requirement on a Vector Property" on page 3-39
- **Relational Constraint** — "Impose Relational Constraint Between Two Variables" on page 3-41

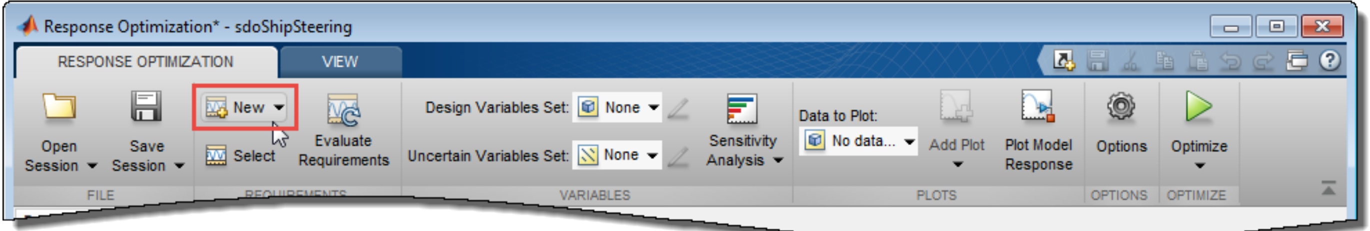
For information about how to specify a model parameter as a variable, see "Add Model Parameters as Variables for Optimization" on page 3-56. After you specify the constraints, you can see if the requirements are satisfied by optimizing the design variables. For more information, see "Specify Optimization Options" on page 3-62.

Impose Monotonic Constraint Requirement on Variable

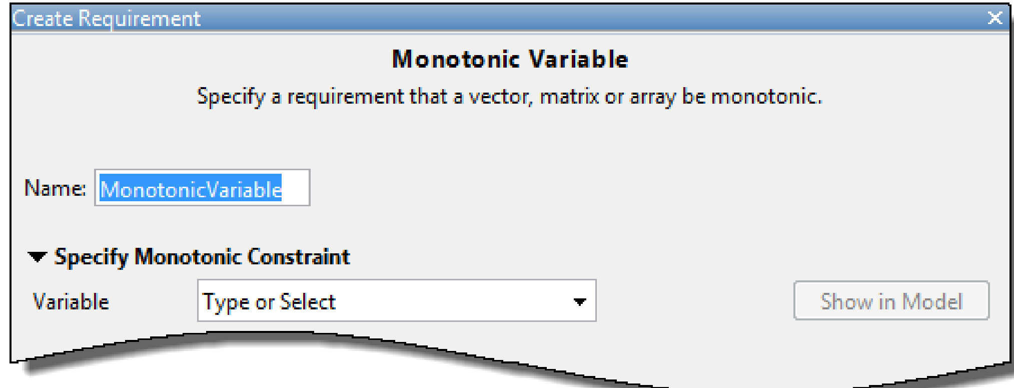
You can impose a monotonic constraint requirement on a design variable in your Simulink model. For example, constrain a variable to be monotonically increasing. The variable can be a vector, matrix, or multidimensional array that is a parameter in your model, such as the breakpoints of a lookup table.

To specify the requirement:

1 In the **Response Optimizer**, in **New** drop-down menu, select **Monotonic Variable**.



In the Create Requirement dialog box, specify the requirement.



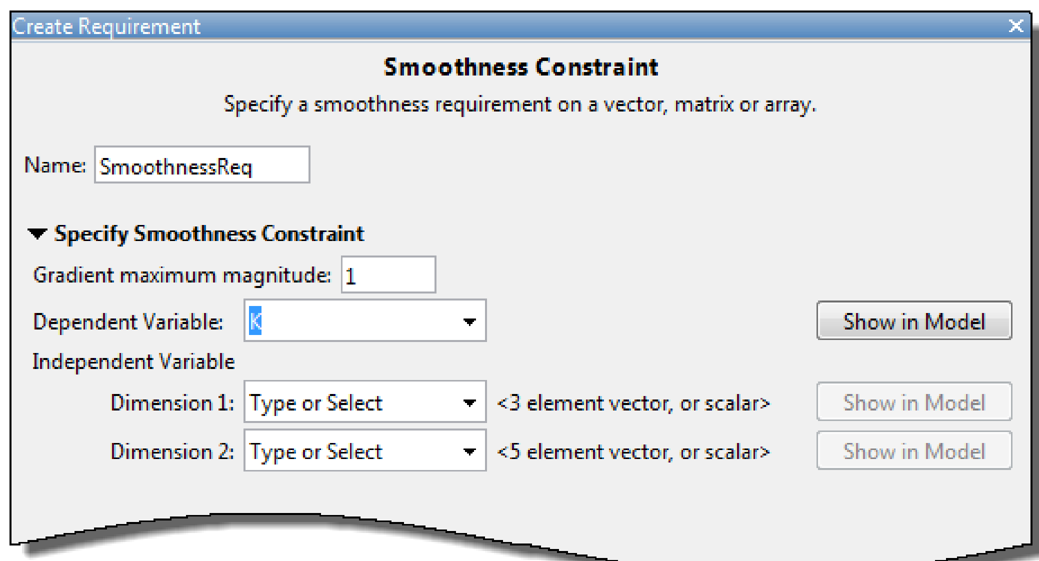
2. Specify a requirement name in **Name**.
3. Specify the name of the variable in **Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single`.

   You can type the name of a nonscalar variable, or select the variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

   Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the **Response Optimizer**, see “Add Model Parameters as Variables for Optimization” on page 3-56.

1. Specify the monotonicity for each dimension of the variable.

   After you select the variable, the dialog updates to show **Dimension 1** to **Dimension n**, corresponding to the *n* dimensions of the variable. For example, for a 2-dimensional variable `K` of size 3-by-5, the dialog updates as shown.



   Specify the monotonicity for the first dimension in **Dimension 1** and for the nth-dimension in **Dimension n** as one of the following options:

   - `Strictly increasing` — Each element of the variable is greater than the previous element in that dimension.
   - `Increasing` — Each element of the variable is greater than or equal to the previous element in that dimension.
   - `Decreasing` — Each element of the variable is less than or equal to the previous element in that dimension.
   - `Strictly decreasing` — Each element of the variable is less than the previous element in that dimension.

- `Not constrained` — No constraint exists between the elements of the variable in that dimension.

1. (Optional) To create an iteration plot that shows the evaluated requirement value for each optimization iteration, select **Create Plot**. The plot is populated when you perform optimization. The plot shows the evaluated requirement value corresponding to each dimension of the variable. A positive value indicates that the requirement has been violated.
2. Click **OK**.

   A new variable, with the specified requirement name, appears in the **Data** area of the **Response Optimizer** app.

Impose Upper Bound on Gradient Magnitude of Variable

You can impose an upper bound on the gradient magnitude of a variable in your Simulink model. The variable can be a vector, matrix, or multidimensional array that is a parameter in your model, such as the data of a lookup table. For example, consider a car engine controller whose gain changes under different operating conditions determined by the car speed. You can use a gradient bound constraint to limit the rate at which the controller gain changes per unit change in vehicle speed.

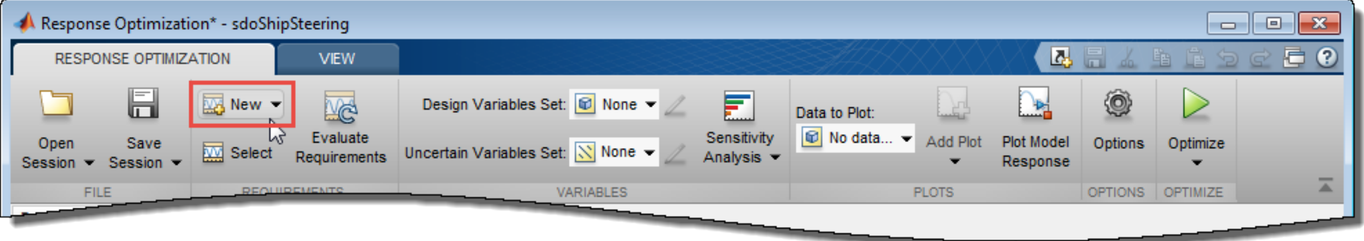
For an *N*-dimensional variable `F` that is a function of independent variables $x_1,\ldots, x_N$, the gradient magnitude is defined as:

$$|\nabla F| = \sqrt{\left(\frac{\partial F}{\partial x_1}\right)^2 + \left(\frac{\partial F}{\partial x_2}\right)^2 + \cdots + \left(\frac{\partial F}{\partial x_N}\right)^2}$$

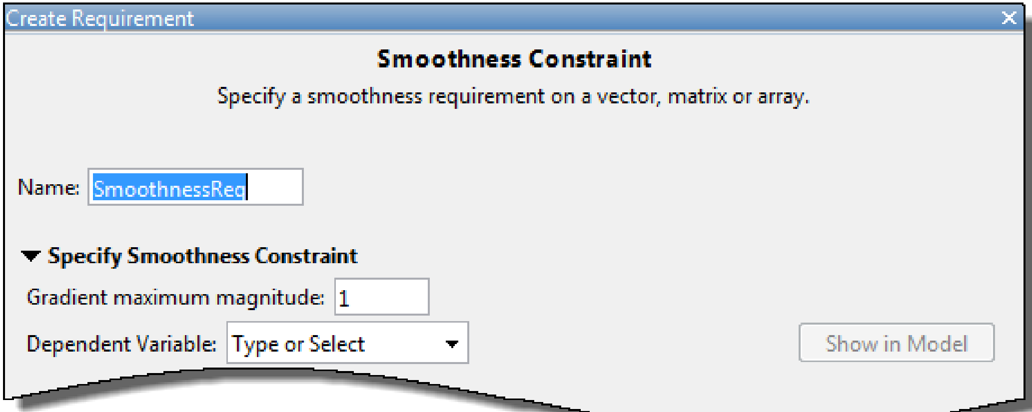
To compute the gradient magnitude, the software computes the partial derivative in each dimension by computing the difference between successive `F` data in that dimension and dividing by the spacing between the data in that dimension. You specify `F` and the spacing between the data. The software checks whether the gradient magnitude of the variable data is less than or equal to a specified bound. If the gradient magnitude of the data is greater than the required bound, the variable data is not smooth.

To specify the requirement:

1. In the **Response Optimizer**, in **New** drop-down list, select **Smoothness Constraint**.



   In the Create Requirement dialog box, specify the requirement.



2 Specify a requirement name in **Name**.

3 Specify the gradient magnitude bound as a nonnegative finite real scalar in **Gradient maximum magnitude**.

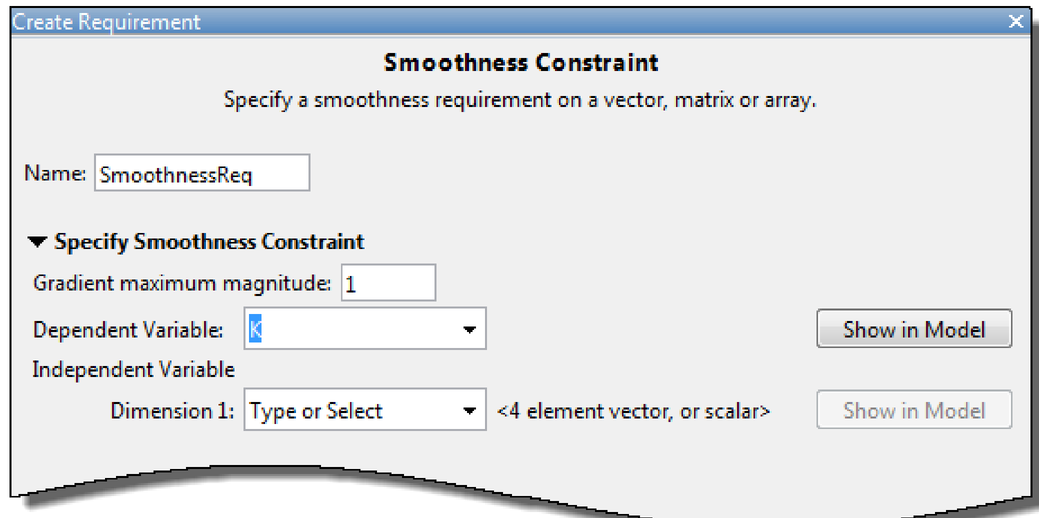
4 Specify the variable `F` that you want to impose the requirement on in **Dependent Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single`. The variable must be a parameter in your model or a constant that you enter.

   You can type the name of a nonscalar variable or constant, or select the variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

   Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the **Response Optimizer**, see “Add Model Parameters as Variables for Optimization” on page 3-56.

1 Specify the spacing between points of **Dependent Variable** data in each dimension in **Independent Variable**.

   After you select the **Dependent Variable**, the dialog updates to show **Dimension 1** to **Dimension n**, corresponding to the *n* dimensions of the dependent variable. For example, for a 1-dimensional variable `K`, the dialog updates as shown.



The first dimension specifies the spacing going down the dependent variable data rows, and the second specifies spacing across the columns. The *N*th dimension specifies the spacing along the *N*th dimension of dependent variable data. You can specify the independent variables in each dimension as scalars or vectors.

- Scalars — Specify the spacing between dependent variable data `F` in the corresponding dimension as a nonzero scalar. For example, suppose that **Dependent Variable** is two-dimensional, and the spacing between data in the first dimension is `5` and in the second dimension is `2`. In the **Independent Variable** section, specify **Dimension 1** as `5` and **Dimension 2** as `2`.
- Vectors — Specify the coordinates of `F` data in the corresponding dimension as real, numeric, monotonic vectors. The software uses the coordinates to compute the spacing between the dependent variable data points in the corresponding dimension. The length of the vector must match the length of `F` in the corresponding dimension. You do not have to specify coordinates with uniform spacing. For example, suppose that `F` is two-dimensional, and the length of the data in the first and second dimension is `3` and `5`, respectively. The coordinates of the data in the first dimension are `[1 2 3]`. In the second dimension, the spacing is not uniform and the coordinates of the data are `[1 2 10 20 30]`. In the **Independent Variable** section, specify **Dimension 1** as `[1 2 3]` and **Dimension 2** as `[1 2 10 20 30]`.

You can also specify the independent variables by typing the name of a variable, or selecting a variable from the drop-down list. The list is prepopulated with all the variables in your model that have the appropriate size. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify as `V(1,:)` to use the first row of the variable. To use a numeric field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

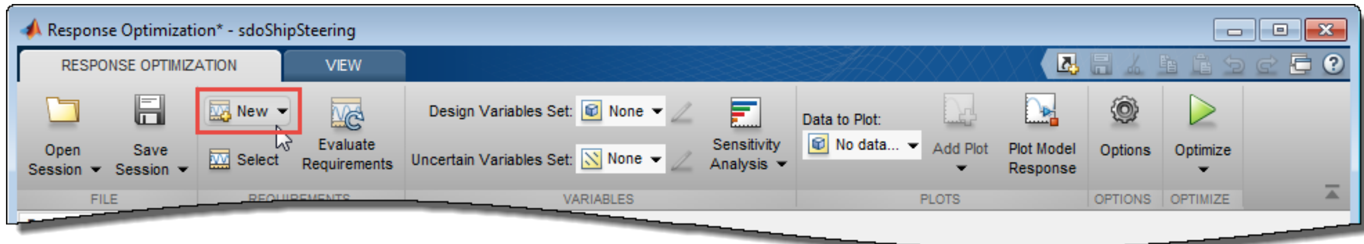
1. (Optional) To create an iteration plot that shows the evaluated requirement value for each optimization iteration, select **Create Plot**. The plot is populated when you perform optimization. A positive value indicates that the requirement has been violated.
2. Click **OK**.

   A new variable, with the specified requirement name, appears in the **Data** area of the **Response Optimizer**.

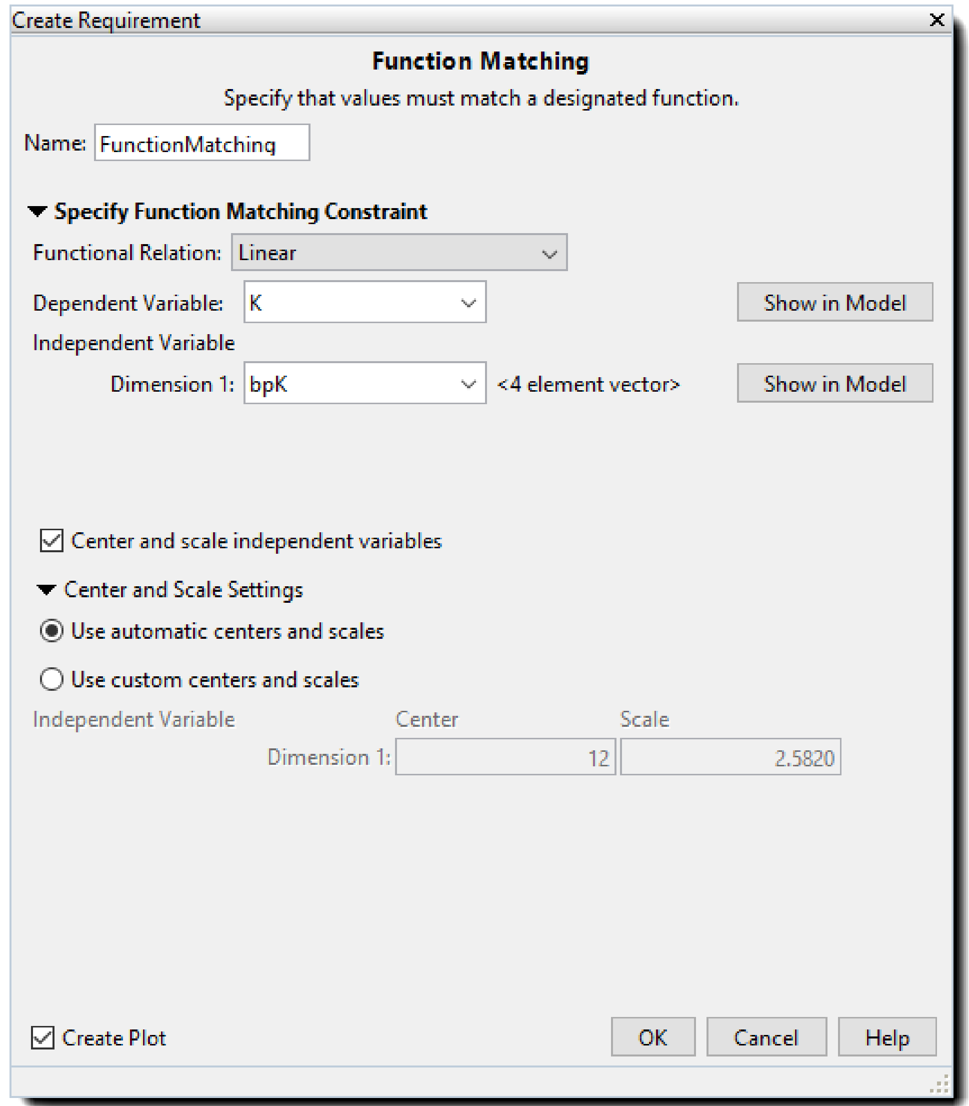
Specify Linear or Quadratic Function Matching Constraint

In the app, you can constrain a variable's values to match a linear or quadratic function. The variable can be a vector, matrix, or a multidimensional array that is a parameter in your model, such as the data of a lookup table in your model. To specify the requirement:

1 In **Response Optimizer**, from the **New** drop-down list, select **Function Matching**.



In the Create Requirement dialog box, specify the requirement. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



2 Specify the function to be matched. To do so, set **Functional Relation** to one of the following values:

- `Linear` — Data from variable V are fit to a linear function. For example, for a two-dimensional variable with independent variables, X_1 and X_2, the linear function has the form:

$$V = a_0 + a_1X_1 + a_2X_2$$

  The software calculates the fit coefficients a_0, a_1, and a_2 and then calculates the sum of squares of the error between the data and the linear function.

- `Quadratic with no cross-terms` — Data are fit to a quadratic function with no cross-terms. For a two-dimensional variable, the pure quadratic function has the form:

$$V = a_0 + a_1X_1 + a_2X_1^2 + a_3X_2 + a_4X_2^2$$

- `Quadratic with all cross-terms` — Variable data are fit to a quadratic function that includes cross-terms. For a two-dimensional variable, the quadratic function has the form:

$$V = a_0 + a_1X_1 + a_2X_1^2 + a_3X_2 + a_4X_2^2 + a_5X_1X_2$$

If the variable is one-dimensional, there are no cross-terms and so the computation is the same as when **Functional relation** is `Quadratic with no cross-terms`.

3. Specify the variable `V` to which you want to apply the requirement in **Dependent Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single` that is a parameter in your model.

   Type the name of a nonscalar variable, or select a variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To see where the selected variable is used on your model, click **Show in Model**. To choose a subset of an array or matrix variable `A`, type an expression. For example, specify `A(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

   Sometimes models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as design variables in the app, see "Add Model Parameters as Variables for Optimization" on page 3-56.

4. Specify the independent variable vectors used for computing the function in **Independent Variable**. The independent variables are specified as real, numeric, monotonic vectors.

   The number of independent variables must equal the number of dimensions of the dependent variable `V`. For example, you specify two independent variables when `V` is a matrix, and use three independent variables when `V` is three-dimensional. The first independent variable vector specifies coordinates going down the rows of `V`, and the second independent variable vector specifies coordinates going across the columns of `V`. The nth independent variable vector specifies coordinates along the nth dimension of `V`. The number of elements in each independent variable vector must match the size of `V` in the corresponding dimension. The independent variable vectors must be monotonically increasing or decreasing.

   You can also specify the independent variables by typing the name of a variable, or selecting a variable from the drop-down list. The list is prepopulated with all the variables in your model that have the appropriate size. To choose a subset of an array or matrix variable `A`, type an expression. For example, specify `A(1,:)` to use the first row of the variable. To use a numeric field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`. To use an equally spaced vector, select `[1 2 ...N]` from the drop-down menu.

5. Specify whether you want to center and scale the independent variables. When you select the **Center and scale independent variables** option, the independent variable vectors you specify are divided by a scale value after subtracting a center value. Centering can improve numerical conditioning when one or more independent variable vectors have a mean that differs from 0 by several orders of magnitude. Scaling can improve numerical conditioning when independent variable vectors differ from each other by several orders of magnitude.

   To specify the center and scale values for each independent variable, expand the **Center and Scale Settings** section, and select one of the following:

   - **Use automatic centers and scales** - The center and scale values are the mean and standard deviation for each independent variable. Using the mean and standard deviation values to center and scale the independent variables is the default option.

- **Use custom centers and scales** - Specify the **Center** and **Scale** values for each independent variable. The independent variable vectors are divided by the corresponding **Scale** value after subtracting the value you specify in **Center**.

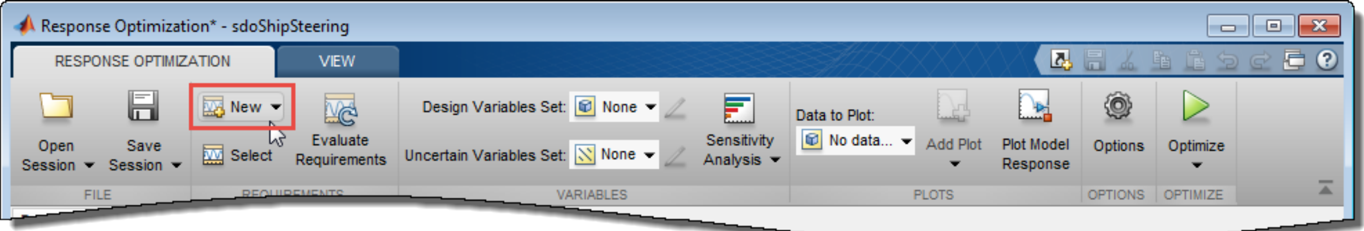
6. (Optional) Select the **Create Plot** option to create an iteration plot that shows the evaluated requirement value for each optimization iteration. The software computes an error signal that is the difference between the dependent variable data and the specified function of the independent variables. The sum of squares of this error is plotted when you perform optimization. A positive value indicates that the requirement has been violated, and `0` value indicates that the requirement is satisfied. The closer the value is to `0`, the better the match between the function and dependent variable data.
7. Close the Create Requirement dialog box.

   The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

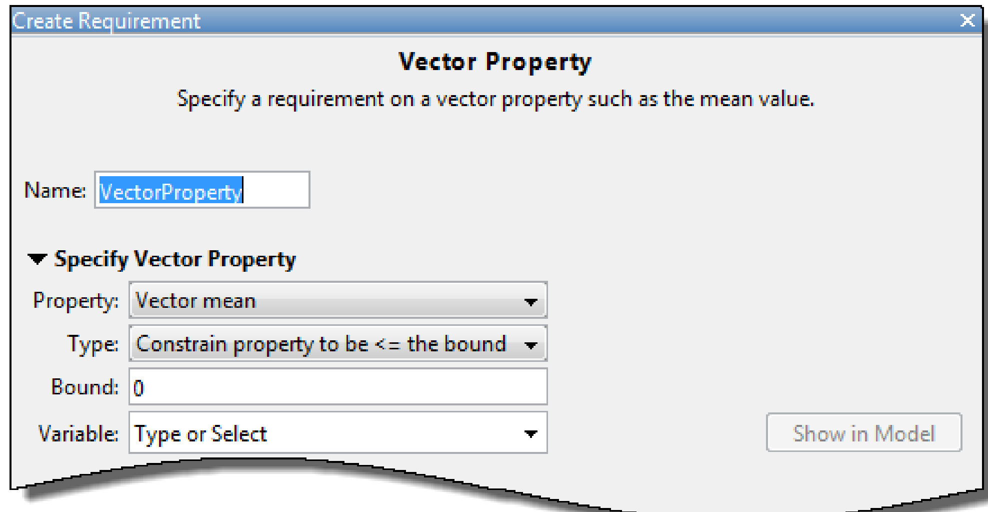
Specify Requirement on a Vector Property

You can specify a requirement on a vector property, such as the mean value of the vector. The vector must be a parameter in your model. To specify the requirement:

1. In the **Response Optimizer**, in **New** drop-down list, select **Vector Property**.



In the Create Requirement dialog box, specify the requirement.



2 Specify a requirement name in **Name**.

1 Specify the vector property in **Property**. For a vector *V* with *N* elements, you can specify one of the following properties:

- `Vector mean` — *mean*(*V*)
- `Vector median` — *median*(*V*)
- `Vector variance` — *variance*(*V*)
- `Vector inter-quartile range` — Difference between the 75th and 25th percentiles of the vector values.
- `Vector sum` — $\sum_{i=1}^{N} V(i)$
- `Vector sum of squares` — $\sum_{i=1}^{N} V(i)^2$
- `Vector sum of absolute values` — $\sum_{i=1}^{N} |V(i)|$
- `Vector minimum` — *min*(*V*)
- `Vector maximum` — *max*(*V*)

2 Specify the type of requirement you want to impose on the vector property in **Type**. You can set an upper or lower bound on the vector property, or require the property to equal a particular value. You can also choose to maximize or minimize the vector property. For example, to maximize the mean value of your vector, specify **Property** as `Vector mean` and **Type** as `Maximize the property`.

3 Specify the value of the bound imposed on the vector property in **Bound**. Specify the bound as a finite real scalar value. For example, if for a vector variable *V* you require `mean(V) = 5`, specify **Property** as `Vector mean`, **Type** as `Constrain property to be == the bound`, and **Bound** as `5`.

1 Specify the name of the variable in **Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single`.

You can type the name of a nonscalar variable, or select the variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the **Response Optimizer**, see “Add Model Parameters as Variables for Optimization” on page 3-56.

2 (Optional) To create an iteration plot that shows the evaluated requirement value for each optimization iteration, select **Create Plot**. The plot is populated when you perform optimization. A positive value indicates that the requirement has been violated.

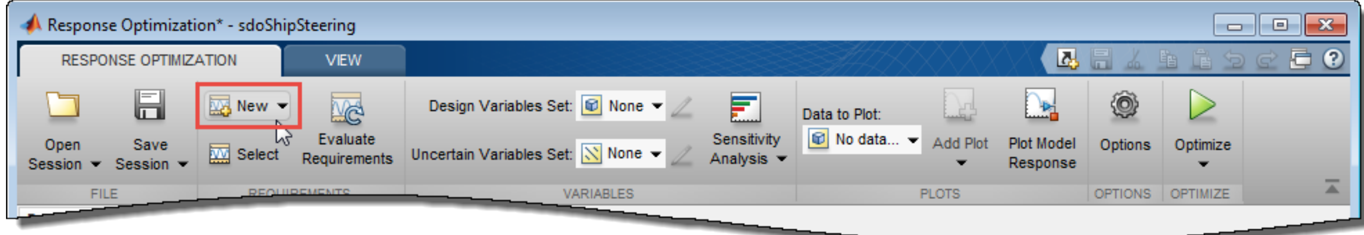
3 Click **OK**.

A new variable, with the specified requirement name, appears in the **Data** area of the **Response Optimizer** app.

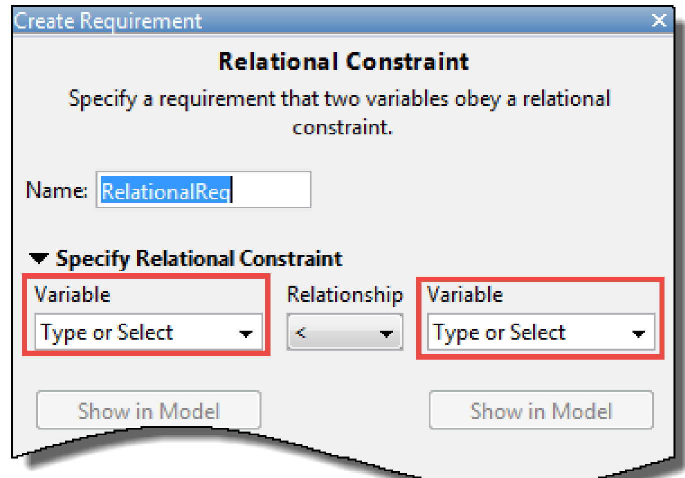
Impose Relational Constraint Between Two Variables

You can impose a relational constraint requirement on a pair of variables in your Simulink model. For example, require that variable *a* is always greater than variable *b*. To specify the requirement:

1 In the **Response Optimizer**, in **New** drop-down list, select **Relational Constraint**.



In the Create Requirement dialog box, specify the requirement.



2 Specify a requirement name in **Name**.

3 Specify the name of the two variables in **Variable**. The variables can be vectors or arrays but must be the same size.

Type the names of two variables, or select the variables from the drop-down lists. The lists are prepopulated with all the variables in your model. To see where a selected variable is used on your model, click **Show in Model**. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the **Response Optimizer**, see “Add Model Parameters as Variables for Optimization” on page 3-56.

1 Specify the relation between the elements of the two variables as one of the following in **Relationship**:

- `'<'` — Each data element in the first variable is less than the corresponding element in the second variable.
- `'<='` — Each data element in the first variable is less than or equal to the corresponding element in the second variable.
- `'>'` — Each data element in the first variable is greater than the corresponding element in the second variable.
- `'>='` — Each data element in the first variable is greater than or equal to the corresponding element in the second variable.
- `'=='` — Each data element in the first variable is equal to the corresponding element in the second variable.
- `'~='` — Each data element in the first variable is not equal to the corresponding element in the second variable.

1. (Optional) To create an iteration plot that shows the evaluated requirement value for each optimization iteration, select **Create Plot**. The plot is populated when you perform optimization. The plot shows the evaluated requirement value corresponding to each element of the variables. The interpretation of the evaluated requirement value depends on the requirement **Type**.

Type	Evaluated Requirement Value	
	Requirement is Satisfied	Requirement is Violated
`'>'` or `'<'`	Negative number	Positive number, or `0` if the elements are equal
`'>='` or `'<='`	Negative number, or `0` if the elements are equal	Positive number
`'=='`	`0`	Non-zero number
`'~='`	`0`	`1`

2. Click **OK**.

   A new variable, with the specified requirement name, appears in the **Data** area of the **Response Optimizer** app.

See Also

Related Examples

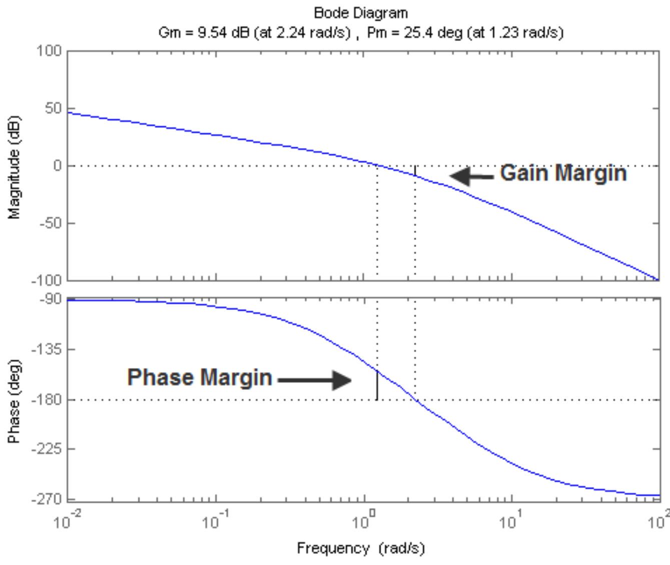
- “Specify Design Variables” on page 3-56
- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43
- “Specify Optimization Options” on page 3-62
- “Design Optimization Using Lookup Table Requirements for Gain Scheduling (GUI)” on page 6-59

Specify Frequency-Domain Design Requirements in the App

Specify Lower Bounds on Gain and Phase Margin

To specify lower bounds on the gain and phase margin of a linear system:

1. In the **Response Optimizer**, select **Gain and Phase Margin** in the **New** list. A window opens where you specify lower bounds on the gain and phase margin of your linear system.
2. Specify a requirement name in **Name**.
3. Specify bounds on the gain margin or phase margin, or both.



   - **Gain margin** — Amount of gain increase or decrease required to make the loop gain unity at the frequency where the phase angle is –180°.
   - **Phase margin** — Amount of phase increase or decrease required to make the phase angle –180° when the loop gain is 1.0

   To specify a lower bound on the gain margin or phase margin, or both, select the corresponding check box and enter the lower bound value.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

5. Click **OK**.

   A variable with the specified requirement name appears in the **Data** area of the app. A graphical display of the requirement also appears in the **Response Optimizer** app window.

6. (Optional) In the graphical display, you can:

   - “Move Constraints Graphically” on page 3-14
   - “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Gain and Phase Margins block to specify bounds on the gain and phase margin. (Requires Simulink Control Design.)

Specify Piecewise-Linear Lower and Upper Bounds on Frequency Response

To specify upper or lower bounds on the magnitude of a system response:

1. In the **Response Optimizer**, select **Bode Magnitude** in the **New** list. A window opens where you specify the lower or upper bounds on the magnitude of the system response.
2. Specify a requirement name in the **Name** box.
3. Specify the requirement type using the **Type** list.
4. Specify the edge start and end frequencies and corresponding magnitude in the **Frequency** and **Magnitude** columns.
5. Insert or delete bound edges.

   Click [+] to specify additional bound edges.

   Select a row and click [delete] to delete a bound edge.

6. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

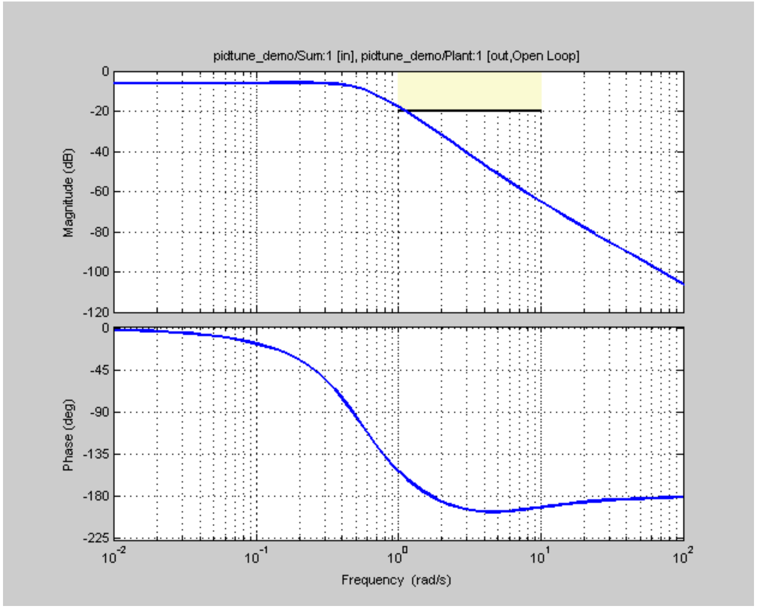
If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

7 Click **OK**.

A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app window. A graphical display of the requirement also appears in the **Response Optimizer** app window.



8 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Bode Characteristics block to specify bounds on the magnitude of the system response. (Requires Simulink Control Design.)

Specify Bound on Closed-Loop Peak Gain

To specify an upper bound on the closed-loop peak response of a system:

1. In the **Response Optimizer**, select **Closed-Loop Peak Gain** in the **New** list. A window opens where you specify an upper bound on the closed-loop peak gain of the system.
2. Specify a requirement name in the **Name** box.
3. Specify the upper bound on the closed-loop peak gain in the **Closed-Loop peak gain** box.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

a Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.

b Select the linearization input/output set from the **Linearization I/O** area.

  If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

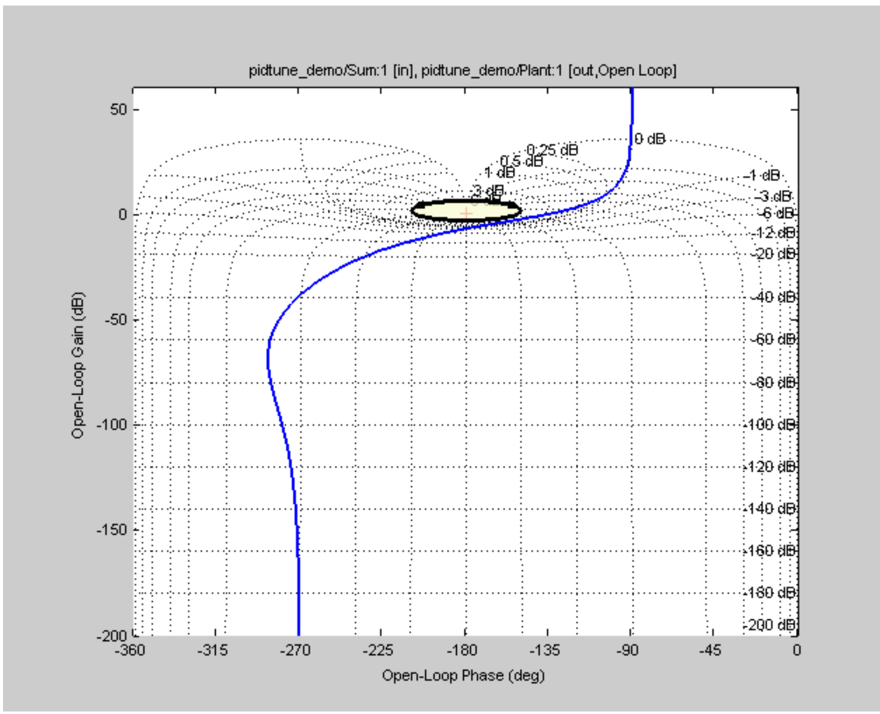
  If you have not created a linearization input/output set, click + to open the Create linearization I/O set dialog box.

  For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

5 Click **OK**.

  A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app window. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Nichols Characteristics block to specify bounds on the magnitude of the system response. (Requires Simulink Control Design.)

Specify Lower Bound on Damping Ratio

To specify a lower bound on the damping ratio of the system:

1. In the **Response Optimizer**, select **Damping Ratio** in the **New** list. A window opens where you specify a lower bound on the damping ratio of the system.
2. Specify a requirement name in the **Name** box.
3. Specify the lower bound on the damping ratio in the **Damping ratio** box.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

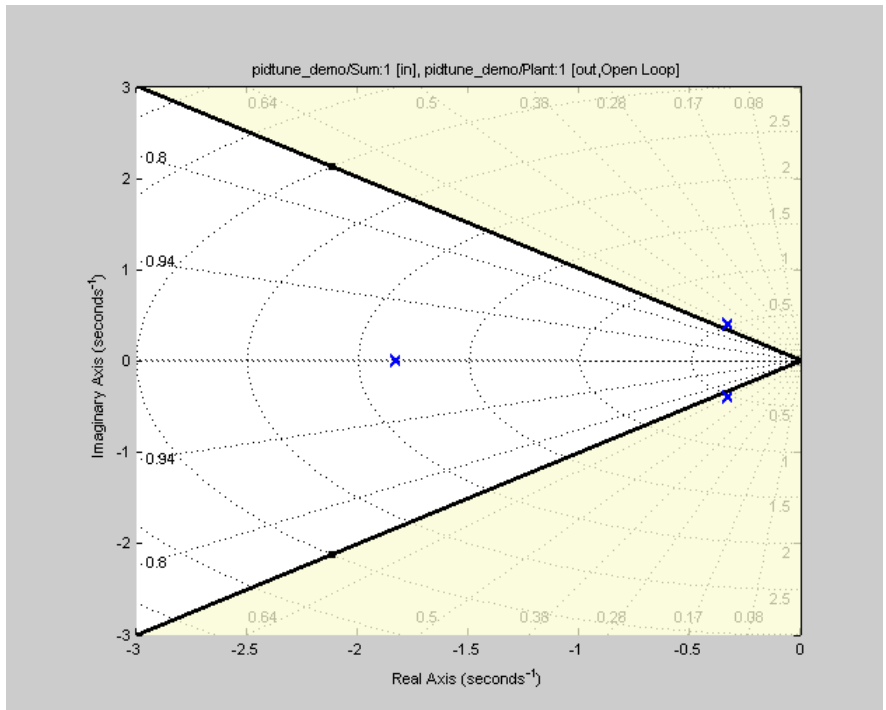
      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
5. Click **OK**.

   A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Pole-Zero Characteristics block to specify a bound on the damping ratio. (Requires Simulink Control Design.)

Specify Upper and Lower Bounds on Natural Frequency

To specify a bound on the natural frequency of the system:

1. In the **Response Optimizer**, select **Natural Frequency** in the **New** list. A window opens where you specify a bound on the natural frequency of the system.
2. Specify a requirement name in the **Name** box.
3. Specify a lower or upper bound on the natural frequency in the **Natural frequency** box.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

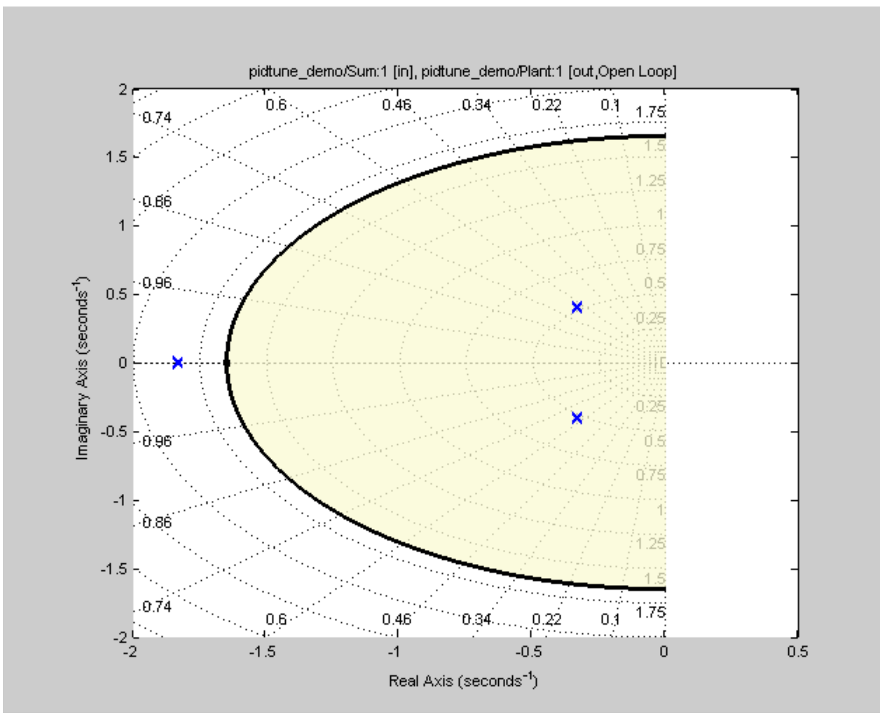
If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

5 Click **OK**.

A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Pole-Zero Characteristics block to specify a bound on the natural frequency. (Requires Simulink Control Design.)

Specify Upper Bound on Approximate Settling Time

To specify an upper bound on the approximate settling time of the system:

1 In the **Response Optimizer**, select **Settling Time** in the **New** list. A window opens where you specify an upper bound on the approximate settling time of the system.
2 Specify a requirement name in the **Name** box.

3. Specify the upper bound on the approximate settling time in the **Settling time** box.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

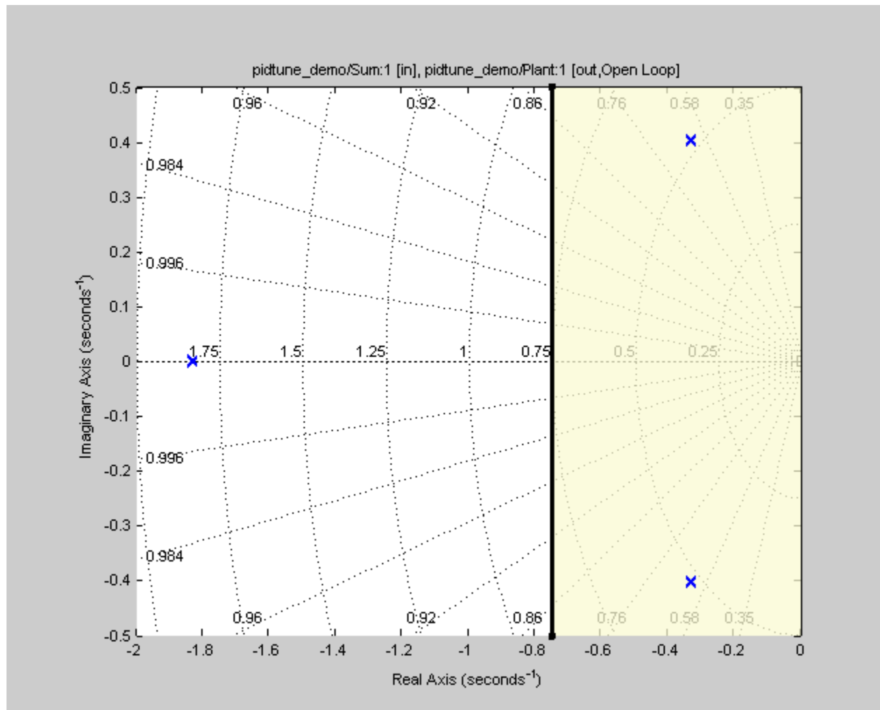
      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see "Create Linearization I/O Sets" on page 3-64.

   For more information on linearization, see "What Is Linearization?" (Simulink Control Design).
5. Click **OK**.

   A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6. (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Pole-Zero Characteristics block to specify the approximate settling time. (Requires Simulink Control Design.)

Specify Piecewise-Linear Upper and Lower Bounds on Singular Values

To specify piecewise-linear upper and lower bounds on the singular values of a system:

1. In the **Response Optimizer**, select **Singular Values** in the **New** list. A window opens where you specify the lower or upper bounds on the singular values of the system.
2. Specify a requirement name in the **Name** box.
3. Specify the requirement type using the **Type** list.
4. Specify the edge start and end frequencies and corresponding magnitude in the **Frequency** and **Magnitude** columns, respectively.
5. Insert or delete bound edges.

   Click [+] to specify additional bound edges.

   Select a row and click [delete] to delete a bound edge.
6. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

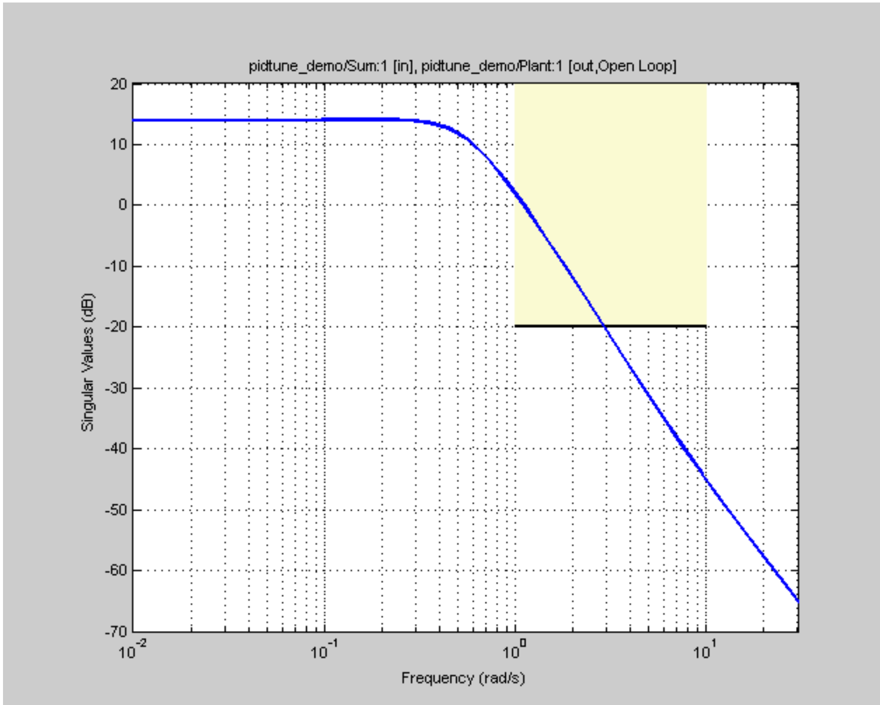
      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
7. Click **OK**.

   A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



8 (Optional) In the graphical display, you can:

- "Move Constraints Graphically" on page 3-14
- "Position Constraints Exactly" on page 3-15

Alternatively, you can use the Check Singular Value Characteristics block to specify bounds on the singular value. (Requires Simulink Control Design).

Specify Step Response Characteristics

To apply a step response requirement to a linearization of your model (requires Simulink Control Design), specify the step response characteristics as follows:

1 Select a step response requirement from the **Response Optimizer**.

   In the **New** drop-down menu of the app, in the **New Frequency Domain Requirement** section, select **Step Response Envelope**.

   A Create Requirement dialog box opens where you specify the step response requirements.
2 Specify a requirement name in the **Name** field of the dialog box.
3 Specify the step response characteristics:

   - **Initial value** — Input level before the step occurs
   - **Step time** — Time at which the step takes place
   - **Final value** — Input level after the step occurs
   - **Rise time** — The time taken for the response signal to reach a specified percentage of the step range. The step range is the difference between the final and initial values.

- **% Rise** — The percentage of the step range used with **Rise time** to define the overall rise time characteristics.
- **Settling time** — Time taken until the response signal settles within a specified region around the final value. This settling region is defined as the final step value plus or minus the settling range, defined in **% Settling**.
- **% Settling** — The percentage of the step range value that defines the settling range of settling time characteristic specified in **Settling time**.
- **% Overshoot** — The amount by which the response signal can exceed the final value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
- **% Undershoot** — The amount by which the response signal can undershoot the initial value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.

4. Specify the systems to be bound.

   To apply this requirement to a linearization of your Simulink model:

   a. In the **Select Systems to Bound** area, specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

Alternatively, you can use the Check Step Response Characteristics block to specify step response bounds for a signal.

Specify Custom Requirements

You can specify custom requirements, such as minimizing system energy. To specify custom requirements:

1. In the **Response Optimizer**, in **New** drop-down menu, select **Custom Requirement**. The Create Requirement dialog box opens where you specify the custom requirement.
2. Specify a requirement name in **Name**.
3. Specify the requirement type in the **Type** drop-down menu.
4. Specify the name of the function that contains the custom requirement in **Function**. The field must be specified as a function handle using `@`. The function must be on the MATLAB path. Click [folder icon] to review or edit the function.

If the function does not exist, clicking [folder icon] opens a template MATLAB file. Use this file to implement the custom requirement. The default function name is `myCustomRequirement`.

5 (Optional) To prevent the solver from considering specific parameter combinations, select **Error if constraint is violated**. Use this option for parameter-only constraints.

   During an optimization iteration, the solver first evaluates requirements with this option selected.

   - If the constraint is violated, the solver skips evaluating any remaining requirements and proceeds to the next iteration.
   - If the constraint is *not* violated, the solver evaluates the remaining requirements for the current iteration. If any of the remaining requirements bound signals or systems, then the solver simulates the model.

   For more information, see "Skip Model Simulation Based on Parameter Constraint Violation (GUI)" on page 3-170.

   Note If you select this check box, then do not specify signals or systems to bound. If you *do* specify signals or systems, then this check box is ignored.

6 (Optional) Specify the signal or system, or both, to be bound.

   You can apply this requirement to model signals, or a linearization of your Simulink model (requires Simulink Control Design), or both.

   Click **Select Signals and Systems to Bound (Optional)** to view the signal and linearization I/O selection area.

   - To apply this requirement to a model signal:

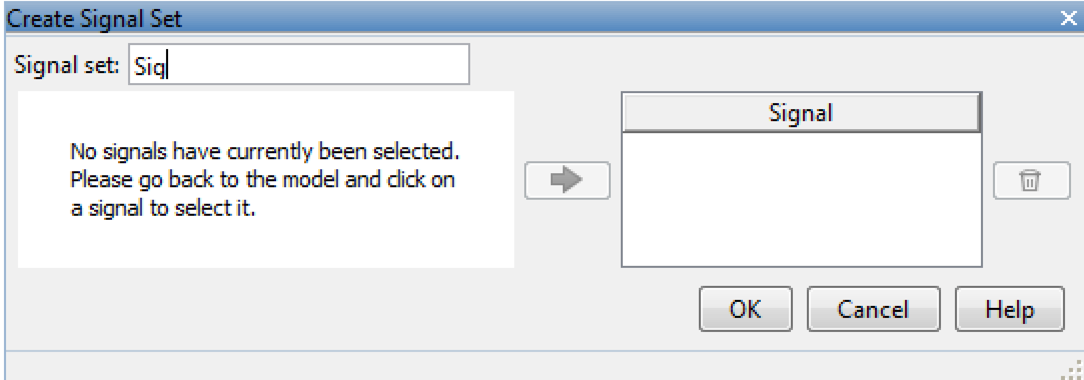
     In the **Signal** area, select a logged signal to which you will apply the requirement.

     If you have already selected a signal to log, as described in "Specify Signals to Log" on page 3-10, it appears in the list. Select the corresponding check box.

     If you have not selected a signal to log:

     a Click [+ button]. A Create Signal Set dialog box opens where you specify the logged signal.

     b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c. Select the signal and click [button] to add it to the signal set.
d. In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

- To apply this requirement to a linear system:

  a. Specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.
  b. Select the linearization input/output set from the **Linearization I/O** area.

     If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

     If you have not created a linearization input/output set, click [button] to open the Create linearization I/O set dialog box. For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

  For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

7. Click **OK**.

   A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**. A graphical display of the requirement also appears in the **Response Optimizer** app window.

See Also

- “Design Optimization to Meet a Custom Objective (GUI)” on page 3-110
- “Design Optimization to Meet a Custom Objective (Code)” on page 3-125

See Also

Related Examples

- “Specify Design Variables” on page 3-56
- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Variable Requirements in the App” on page 3-31
- “Specify Optimization Options” on page 3-62

Specify Design Variables

This topic shows how to specify design variables for optimization.

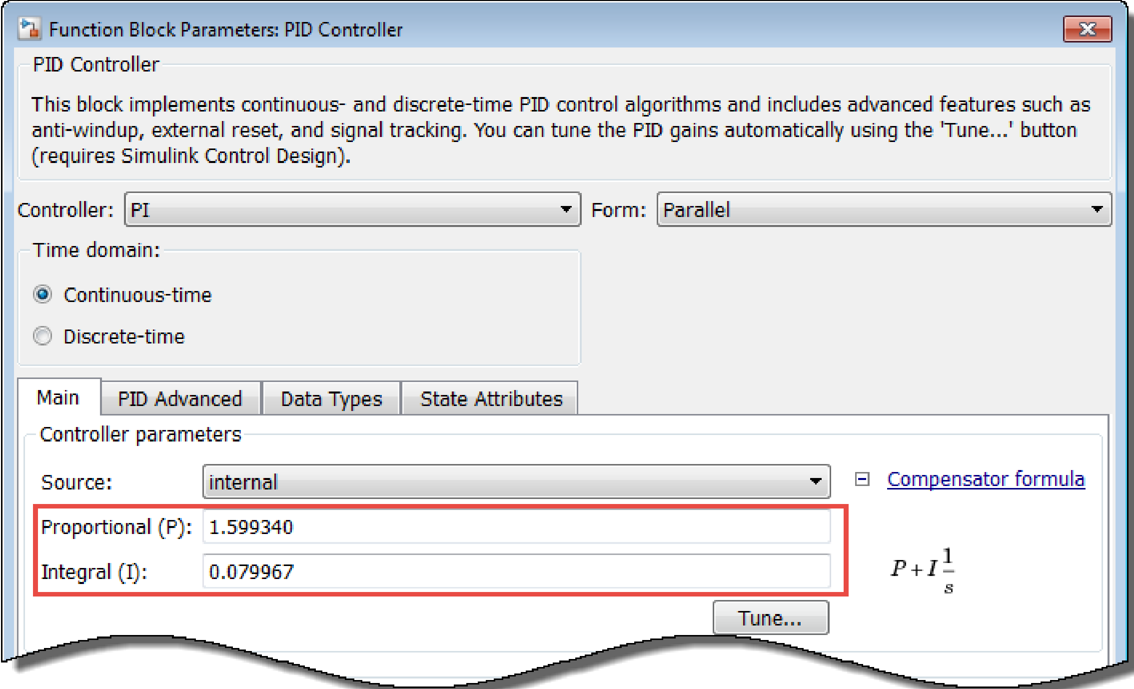
Before running the optimization, you must specify the model parameters to optimize. These parameters form the design variables set for optimization. By tuning these parameters, Simulink Design Optimization software attempts to make the signals meet the requirements. Simulink Design Optimization software optimizes the response signals of the model by varying the tuned parameters so that the response signals lie within the constraint bound segments or closely match a specified reference signal. The design variables can be scalar, vector, matrix, or an expression that evaluates to one of these values.

You can also use sensitivity analysis for finding the parameters that most influence the optimization problem and use these as design variables. To open the **Sensitivity Analyzer**, in the **Response Optimization** tab, click **Sensitivity Analysis**. In the **Sensitivity Analyzer** app, you can explore the response optimization design space by altering the design variables, identify the parameters that most influence the optimization problem, and compute initial values.

Add Model Parameters as Variables for Optimization

The software can only optimize variables that are in use by the Simulink model. Create variables for optimization in the MATLAB or model workspace, and specify your model or block parameters using these variables.

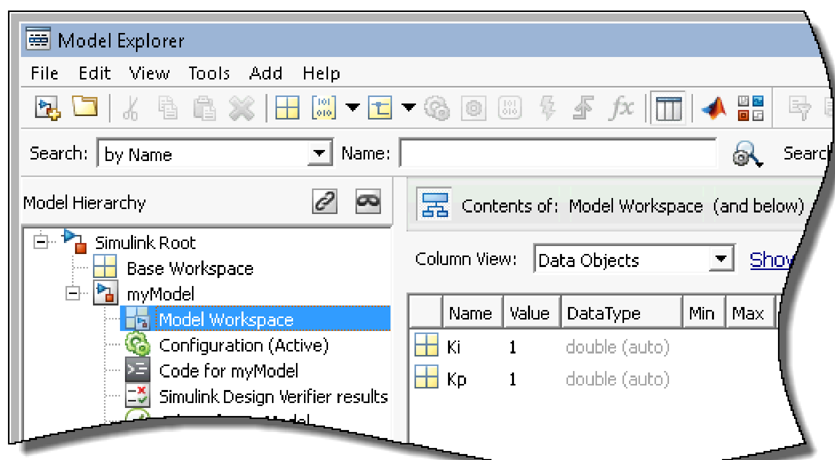
In this figure, the **Proportional (P)** and **Integral (I)** gain parameters of a PID Controller block are specified as numerical values.



To optimize the gain parameters, specify them as variables Kp and Ki:

1 Create the variables Kp and Ki in one of the following ways:

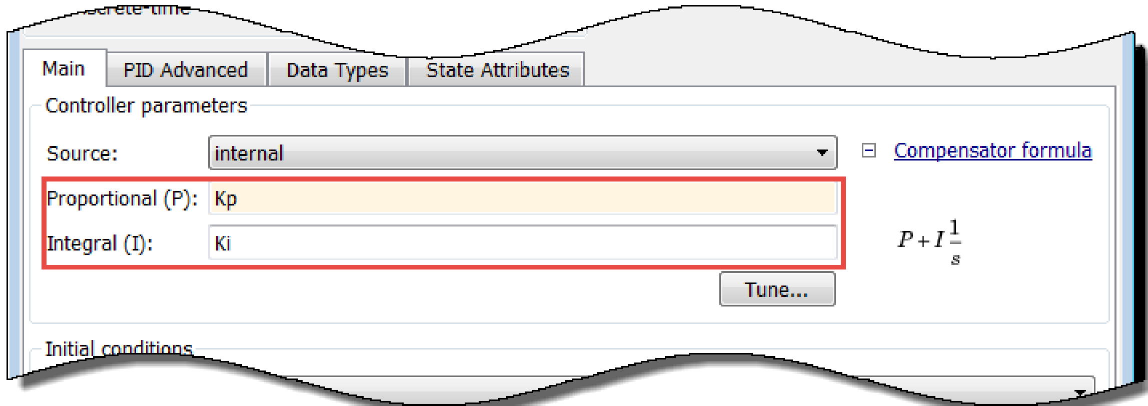
- Add the variables to the model workspace, and specify initial values.



- Write initialization code in the **PreloadFcn** callback of the model. For more information, see "Model Callbacks".

```
Kp = 1;
Ki = 1;
```

2 Specify the gain parameters as the variables Kp and Ki in the PID Controller block dialog box.



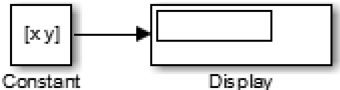
You can now select Kp and Ki for optimization. See, "Specify Design Variables" on page 3-58.

Specify Independent Parameters for Optimization

You can also specify independent parameters that do not appear explicitly in the model as variables for optimization. However, you cannot use this workflow with Simulink fast restart.

Suppose that a model parameter Kint is related to independent parameters x and y such that Kint = x+y. To optimize x and y instead of Kint:

- Create the independent variables x and y by adding them to the model workspace and specifying initial values.
- The software only allows tuning of variables that are used by model blocks. To ensure that the software detects x and y for tuning, add a Constant block to your model, and specify the **Constant value** of the block as [x y]. Connect the block to a Display block.



- Write code in the **InitFcn** callback of the model that defines the relationship between Kint, x, and y. You must first use the get_param function to get the variables x and y from the model workspace before you can use them to define Kint.

```
wks = get_param(gcs,'ModelWorkspace')
x = evalin(wks,'x')
y = evalin(wks,'y')
Kint = x+y;
```

You can now select x and y for optimization. Do not optimize the independent and dependent parameters simultaneously. Doing so can lead to incorrect results. For example, do not optimize Kint, x and y together.

Specify Design Variables

To specify the parameters to be tuned using the **Response Optimizer**:

1. In the **Design Variables Set** list, select **New**.

   A window opens where you specify design variables. All parameters in use by the model are displayed in this window.
2. Select one or more parameter names and click

   to add the selected parameters to a design variables set.

   Note You can add the same parameter to multiple design variable sets.
3. (Optional) Specify design variable settings.

Setting	Description	Default
Variable	The name of the parameter.	Not an editable field
Value	Value of the model parameter. This value is used by the optimization method as the initial value and is modified during optimization.	Current value of the parameter in the model. If you edit this column, click **Update model variable values** to update the values in the model.

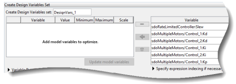
Setting	Description	Default
Minimum	The minimum value or lower bound for the parameter. You can edit this field to provide an alternate minimum value.	`-Inf`
Maximum	The maximum value or upper bound for the parameter. You can edit this field to provide an alternate maximum value.	`Inf`
Scale	During optimization, the design variables are scaled, or normalized, by dividing their current value by a scale value. You can edit this field to provide an alternate scaling factor.	Next power of 2 greater than the current value of the parameter

The check-box indicates whether the parameter is selected as a design variable in the set. Select it if you want this parameter to be tuned during the optimization. Deselect if you do not want this parameter to be tuned during the optimization but you would like to keep it on the list of tuned parameters (for a subsequent optimization).

Expand **Variable Detail** to see the block in the model that contains this parameter.

4 Click **OK** to create a design variable set.

If your model contains referenced models, you can select the referenced variables from the **Create Design Variables Set** dialog box. For example, the first variable in the dialog box, `Slew`, is listed as `sdoRateLimitedController:Slew`. `sdoRateLimitedController` is the name of the referenced model with the variable `Slew`. The `Slew` variable has the same value for all instances of the `sdoRateLimitedController` model. In contrast, the variable `Kd` can have a different value for each instance of the referenced model containing it. For example, the second variable in the dialog box is listed as `sdoMultipleMotors/Control_1:Kd`. The upper-level model `sdoMultipleMotors` has block `Control_1`, which is a referenced model that has variable `Kd`. The value of this variable can be different than `Kd` in block `Control_2`, which is the third variable in the dialog box. To enable instance-specific values, `Kd` is specified as a model argument in the referenced model workspace.



See Also

Related Examples

- “Optimize Parameters for Robustness (GUI)” on page 3-179
- “Update Model with Design Variables Set” on page 3-60
- “Save Design Variable Values for Specific Iteration” on page 3-74

Update Model with Design Variables Set

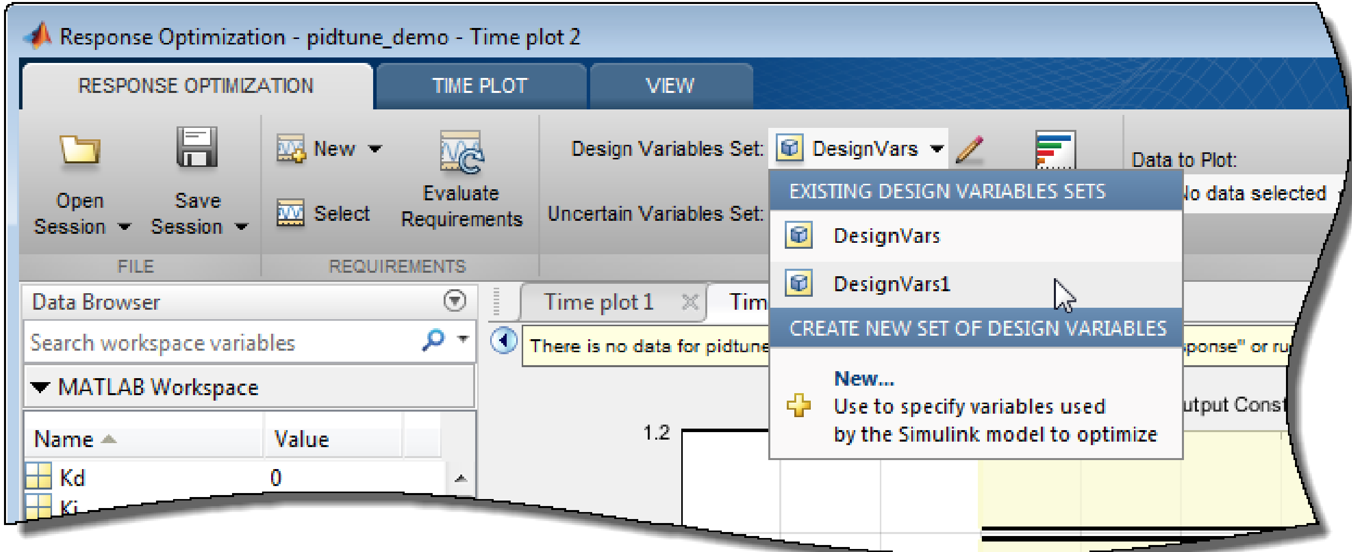
This example shows how to update a model with a set of design variables.

Open the Simulink model and load the pre-configured **Response Optimizer** session.

```
load('pidtune_demo_sdosession_update_dv.mat')
sdotool(SDOSessionData)
```

The **Response Optimizer** opens and loads the preconfigured session. In the **Data** area, `DesignVars1` is a set of tuned design variables.

In the **Design Variables Set** list, select the design variable set, `DesignVars1`.

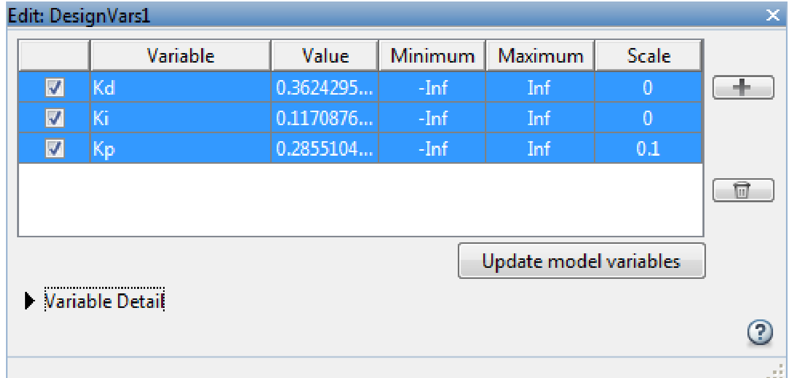


Open the Edit dialog box.

Click for the **Design Variable Set** list.

Select the variables you want to update in the model.

For this example, select `Kd`, `Ki`, and `Kp`.



Click **Update model variables**.

Plot the model response.

In the **Response Optimization** tab, click **Plot Current Response**.

See Also

Related Examples

- "Save Design Variable Values for Specific Iteration" on page 3-74

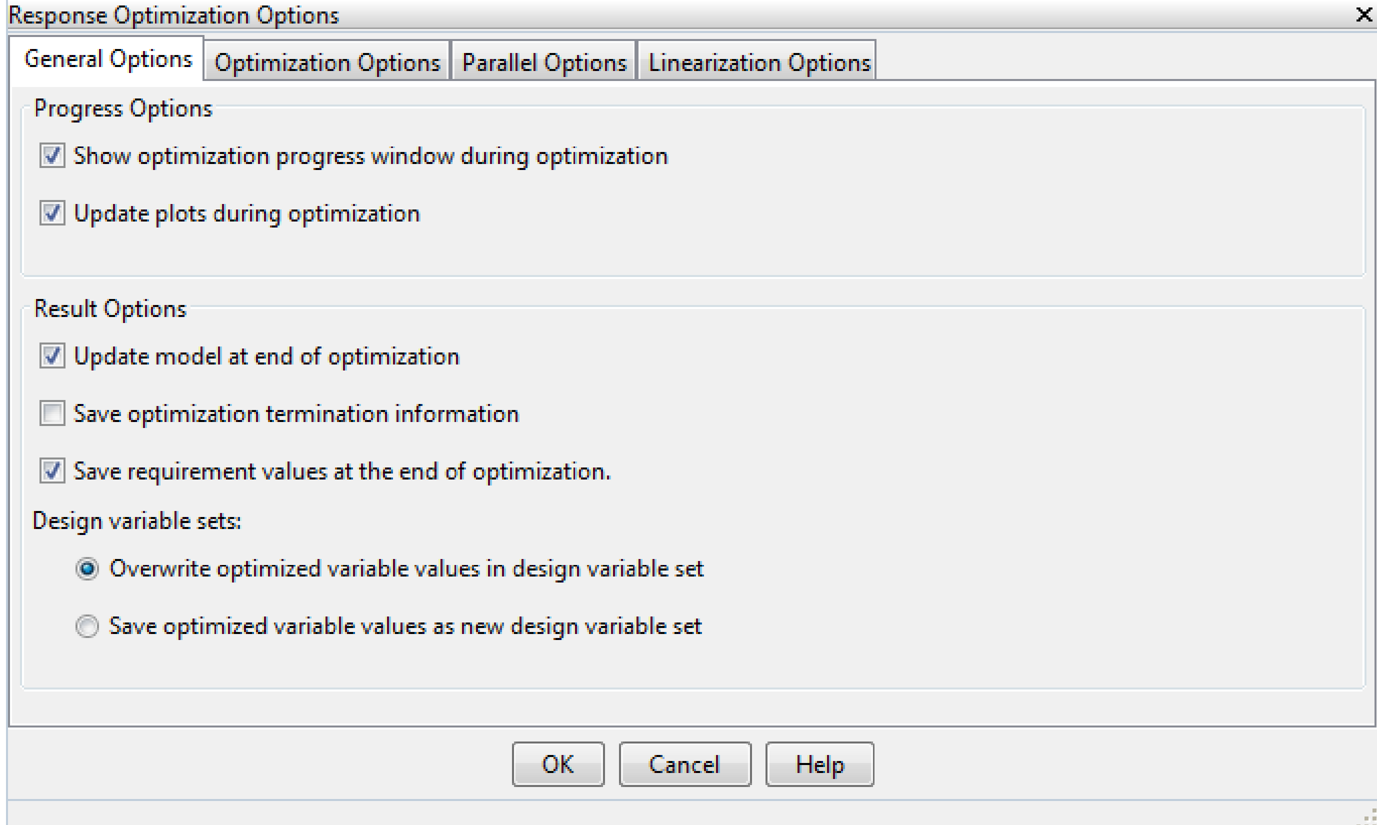
Specify Optimization Options

This topic shows how to specify optimization options in the **Response Optimizer**, after you have configured the design variables and design requirements.

After you have configured the design variables and design requirements, specify the following optimization options:

1. Optimization progress and result options for optimization task

   To specify these options, in the **Response Optimization** tab, click **Options** to open the Response Optimization Options dialog box. In the **General Options** tab, specify the optimization progress and result options. For details about the options, click the **Help** button.



2. Optimization method and termination options

   Specify these options in the **Optimization Options** tab of the Response Optimization Options dialog box.
3. Parallel computing options

   Specify these options in the **Parallel Options** tab of the Response Optimization Options dialog box. For details about the options, see “Optimize Design Using Parallel Computing (GUI)” on page 3-191.
4. Linearization options

Specify these options in the **Linearization Options** tab of the Response Optimization Options dialog box.

See Also

Related Examples

- “Specify Design Variables” on page 3-56
- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43
- “Specify Custom Requirements in the App” on page 3-11

More About

- “How the Optimization Algorithm Formulates Minimization Problems” on page 3-3

Create Linearization I/O Sets

This example shows how to create a linearization input/output set in the **Response Optimizer** or **Sensitivity Analyzer**.

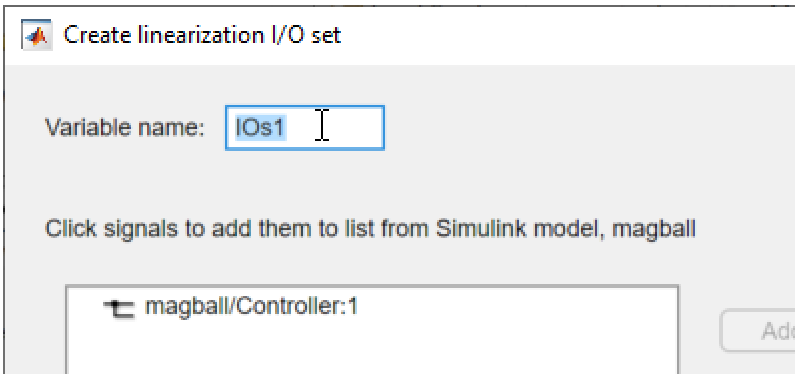
To create a linearization I/O set:

1. Open the Create Linearization I/O Set dialog box using one of the following methods:

   - In a requirement dialog box, in the **Select Systems to Bound** section, click [+].
   - In the **Response Optimizer**, in the **New** drop-down list, select **Linearization I/Os**.

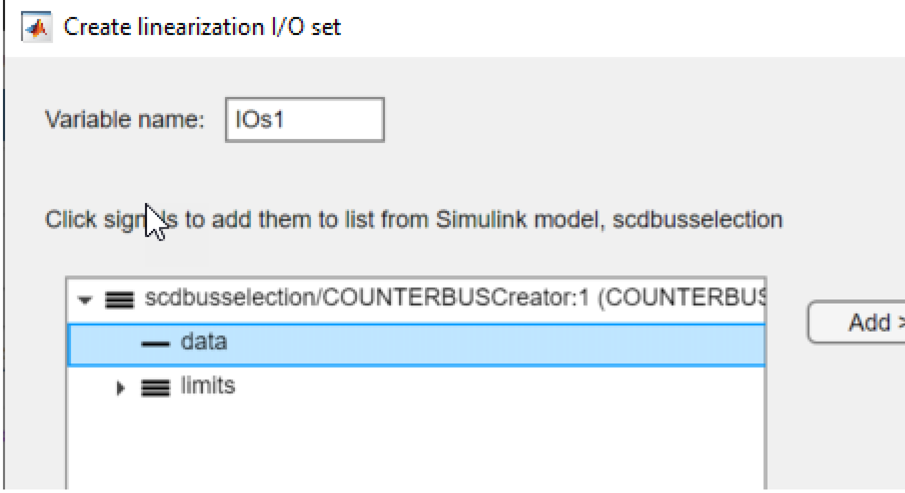
1. In your Simulink model, select one or more signals that you want to define as analysis points.

   The selected signals appear in the Create linearization I/O set dialog box.

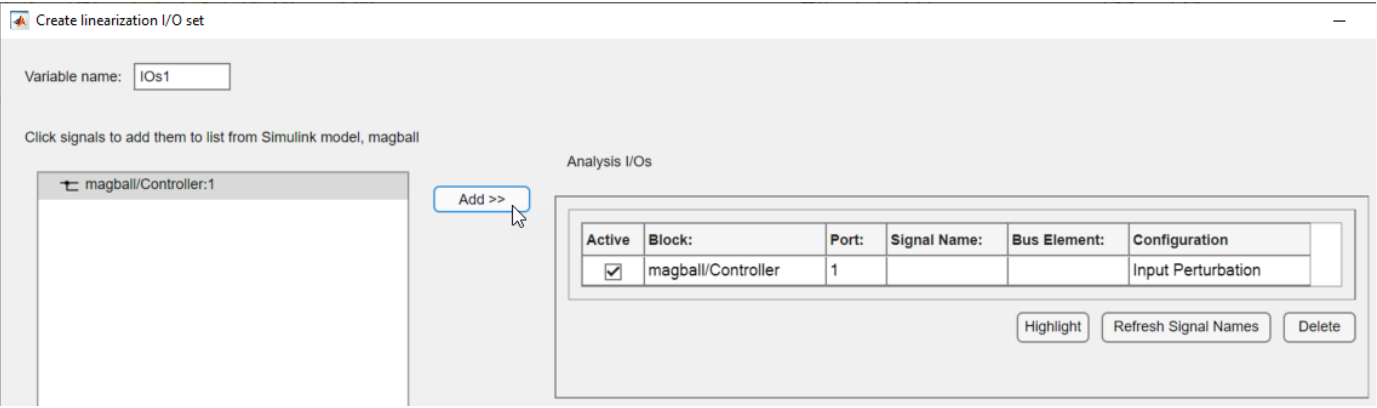


2. In the box displaying currently selected signals, click the signal you want to add. To select multiple signals, hold **Ctrl** and click each signal you want to add.

   To add a signal from within a bus signal, expand the bus and select the signal. For example, select the `data` signal within the `COUNTERBUS` signal.



3. To add the signal to list of **Analysis I/Os**, click **Add**.



4 In the **Configuration** drop-down list for the signal, select the type of analysis point you want to define:

- **Input Perturbation** — Specifies an additive input to a signal.
- **Output Measurement** — Takes a measurement at a signal.
- **Loop Break** — Specifies a loop opening.
- **Open-Loop Input** — Specifies a loop break followed by an input perturbation.
- **Open-Loop Output** — Specifies an output measurement followed by a loop break.
- **Loop Transfer** — Specifies an output measurement before a loop break followed by an input perturbation.
- **Sensitivity** — Specifies an input perturbation followed by an output measurement.
- **Complementary Sensitivity** — Specifies an output measurement followed by an input perturbation.

For more information on the different types of analysis points, see “Specify Portion of Model to Linearize” (Simulink Control Design).

5 Repeat steps 1–4 for any other signals you want to define as analysis points.

Tip To highlight the source block of an analysis point in the Simulink model, in the **Analysis I/Os** list, select the analysis point, and click **Highlight**.

---

6 In the **Variable name** box, enter a name for the I/O set.

7 Click **OK**.

See Also

Related Examples

- “Design Optimization to Meet Frequency-Domain Requirements (GUI)” on page 3-136

More About

- “What Is Linearization?” (Simulink Control Design)

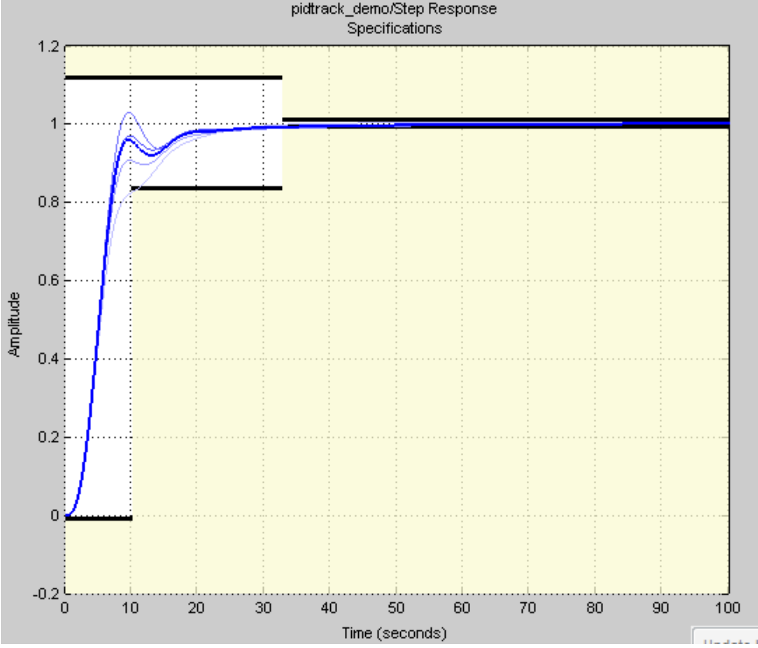
Interact with Plots

This topic shows how to interact with plots in the **Response Optimizer**.

Response Plots

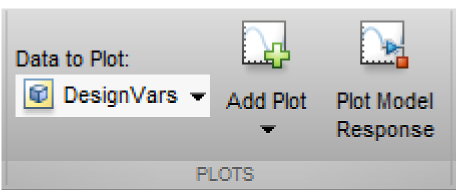
View model signals and the requirements applied to the signal using a response plot. You can also plot the frequency response of a system (requires Simulink Control Design software).

The response plot shows the system response as it varies during optimization. You can also view the uncertain system responses in the plot.



To plot a response plot:

1. In the **Response Optimization** tab of the app, in the **Data to Plot** drop-down list, choose a signal, linear system, or requirement.



2. Select a response plot in the **Add Plot** drop-down list.

   You can add to an existing plot, or create a plot. The drop-down list has entries for the supported plot types for the given plot variable.
3. Display the current model response.

   Click **Plot Model Response**. The current response appears as a thick line on the response plot.

4 Configure the plot display.

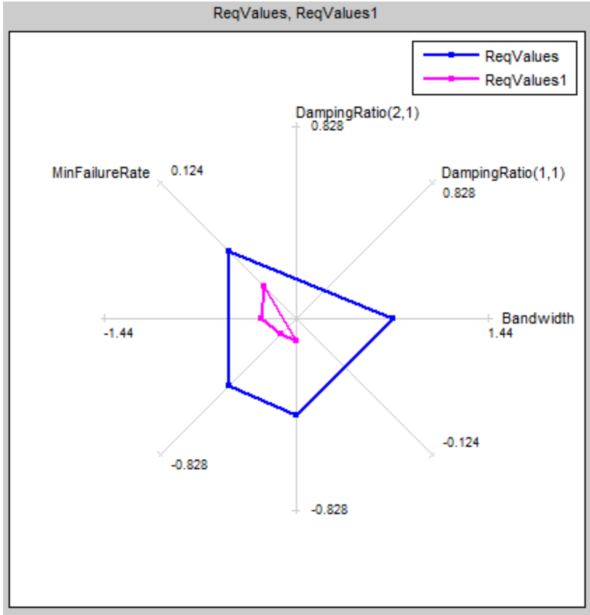
   - To select the signal or systems to display, right-click within the white space in the plot, and choose from **Signals** and **Systems** in the menu.
   - To control whether the response signal displays at intermediate steps during optimization, right-click within the white space in the plot and select **Responses** > **Show Iteration Responses**. The response at an intermediate step is based on parameter values at that intermediate step in the optimization.
   - Modify plot properties.

     You can change plot properties such as plot title, axis labels, axes limits, and units. Right-click the white space in a plot and select **Axes Properties** to open the Property Editor dialog box.

Spider Plots

Compare the values of design variable sets or evaluated requirements using a spider plot.

Spider plots depict multivariate data using a separate axis for each variable. The various axes are arranged clockwise and have a common intersecting point.



To plot a spider plot for a design variable set or evaluated requirements:

1 In the **Response Optimization** tab of the app, in **Data to Plot**, choose design variables, or evaluated requirements.
2 Select a Spider plot in the **Add Plot** drop-down list.

   You can add to an existing plot, or create a new one. The drop-down list has entries for the supported plot types for the given plot variable.
3 Configure the plot display.

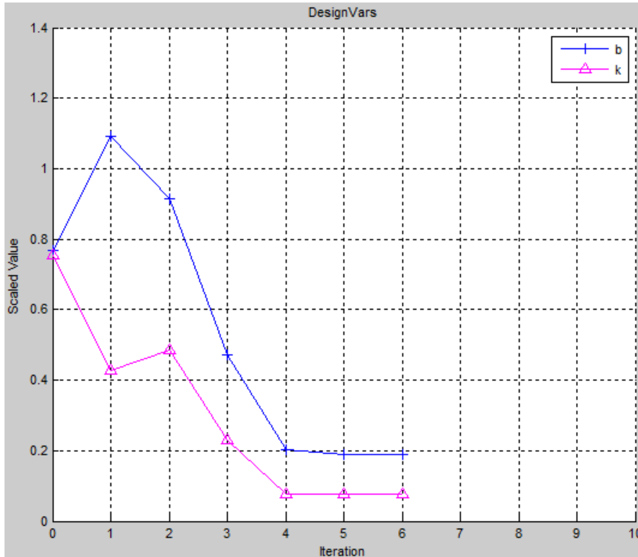
   To view only some of the variables or requirement values in a given plot, right-click the plot, and select the variables or requirements in the **Show** list.

For information on using a spider plot to compare design variables sets or evaluated requirements, see “Compare Requirements and Design Variables Using Spider Plot” on page 3-71

Iteration Plots

Plot the values of design variables and requirements as they vary during optimization using an iteration plot.

Iteration plots depict the value of the plot variables for each iteration. The x-axis represents the iteration number.



To plot an iteration plot for a design variable set or requirements:

1. In the **Response Optimization** tab of the app, in **Data to Plot**, choose design variables or requirements.
2. Select an iteration plot in the **Add Plot** drop-down list.

   You can add to an existing plot, or create a plot. The drop-down list has entries for the supported plot types for the given plot variable.
3. Configure the plot display.

   To view scaled values of the plotted variables, right-click the plot, and select **Show scaled values**.
4. Save design variables and requirements values for a given iteration using the iteration plots.

   For more information, see “Save Design Variable Values for Specific Iteration” on page 3-74.

See Also

Related Examples

- “Save Design Variable Values for Specific Iteration” on page 3-74

- “Compare Requirements and Design Variables Using Spider Plot” on page 3-71

Compare Requirements and Design Variables Using Spider Plot

This example shows how to use a spider plot to compare requirement evaluations before and after optimizing the response. You can use a similar procedure to compare the values of sets of design variables.

Open the Simulink model and load the pre-configured Response Optimizer App session.

For this example, which uses a distillation column model, the step response requirements are preconfigured and loaded in the model workspace.

1 Open the distillation model.

```
sys = 'distillation_demo';
open_system(sys)
```

2 Open the **Response Optimizer**.

   In the Simulink model window, from the **Apps** tab, in the gallery, under **Control Systems** select **Response Optimizer**.

   Alternatively, click the `Response Optimization GUI with preloaded data` block in the model and skip the next step.

3 Load the preconfigured **Response Optimizer** session.

   Click the **Response Optimization** tab. In the **Open Session** drop-down list, select **Open from model workspace**. A window opens where you select the **Response Optimizer** session to load. Select `distillation_optim` and click **OK**.

   The preconfigured step response requirements are loaded in the **Response Optimizer**.

Evaluate the requirement before optimization.

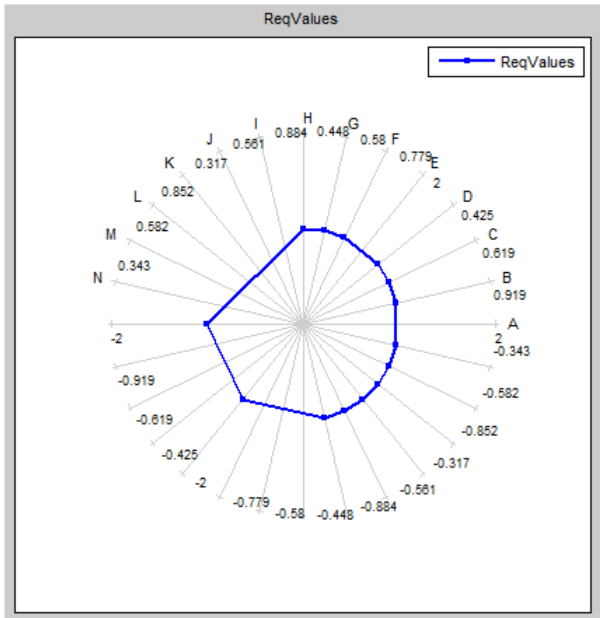
In the **Response Optimization** tab, click **Evaluate Requirements**.

A new variable, `ReqValues`, containing the evaluation of the requirements appears in the **Data** area.

When optimizing the model response, you create a set of requirements that it must satisfy. If the requirements are violated, meaning that they evaluate to non-negative values, the design variables must be optimized. After the optimization, you can compare the original requirement value with the requirement evaluated using the optimized design variable values.

Plot the requirement value before optimization.

1 In the **Data to Plot** list, select `ReqValues`.
2 In the **Add Plot** list, select `Spider plot`.



The plot has an axis for each edge-and-signal combination defined in the `distillation_demo/Desired Step Response` check block. Points on each axis represent the violation for that signal-edge combination and the plot connects these points to form a closed polygon representing the initial design. Note that some points are negative, representing satisfied constraints, and some positive, representing violated constraints.

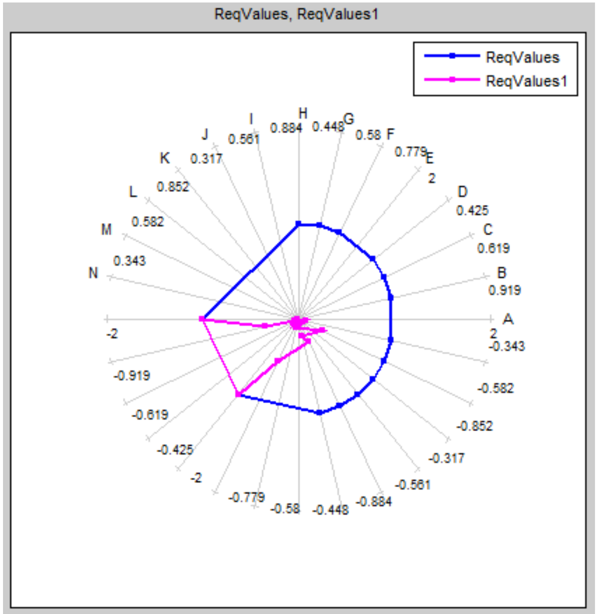
Optimize the model.

Click **Optimize**.

A new variable, `ReqValues1`, containing the evaluation of the requirements using the optimized design variables appears in the **Data** area.

Compare the requirement values before and after optimization.

1 In the **Data to Plot** list, select `ReqValues1`.
2 In the **Add Plot** list, select `Spider plot 1`.



The optimized requirement values, `ReqValues1`, are all negative or zero, indicating that all the constraints are satisfied.

See Also

More About

- "Save Design Variable Values for Specific Iteration" on page 3-74

Save Design Variable Values for Specific Iteration

This example shows how to save the design variable values for specific optimization iterations.

During optimization, the optimization solver simulates the model using a different set of design variables at each iteration. After the optimization completes, you can export the values for an iteration from the iteration plot of the design variable set.

For this example, load a preconfigured **Response Optimizer** session. Optimize the model, and export the design variable set values for the third iteration.

Open the Simulink model and load the preconfigured **Response Optimizer** session.

```
load('distillation_demo_sdosession_export_iter_dv.mat')
sdotool(SDOSessionData)
```

The **Response Optimizer** opens and loads the preconfigured session. **Iteration Plot 1** is configured to plot the values of `DesignVars` for each optimization iteration.

Click **Optimize**.

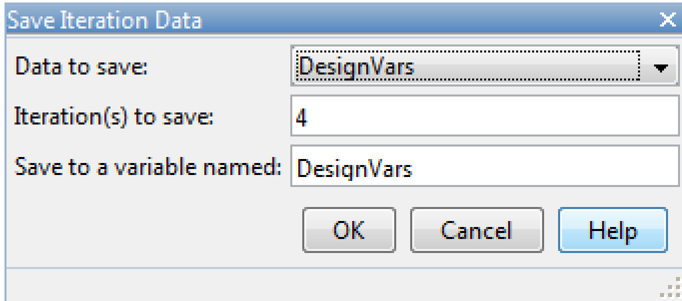
The optimization completes after four iterations.

Select the iteration plot of the design variable set.

Click **Iteration plot 1**.

Open the Save Iteration Data dialog box.

Right-click on the iteration plot, and select **Save Iteration Data**.



You can also access the Save Iteration Data dialog box from the Optimization Progress Report. To do so, in the progress report, click **Save Iteration**.

Specify details about the design variable data to save:

- In the **Data to save** list, select `DesignVars`.
- In **Iteration(s) to save**, enter `3`.

  To specify multiple iterations, use a vector of integers. For example, `[0 2 5]`.
- In **Save to a variable named**, enter `DesignVars_iter`.

Export the design variable values set.

Click **OK**. The exported data variable, `DesignVars_iter_3`, appears in the **Data** area of the app.

Note The iteration number is added as a suffix to the saved data variable name.

See Also

Related Examples

- "Update Model with Design Variables Set" on page 3-60
- "Compare Requirements and Design Variables Using Spider Plot" on page 3-71

More About

- "Interact with Plots" on page 3-67

Design Optimization to Meet Time-Domain and Frequency-Domain Requirements (GUI)

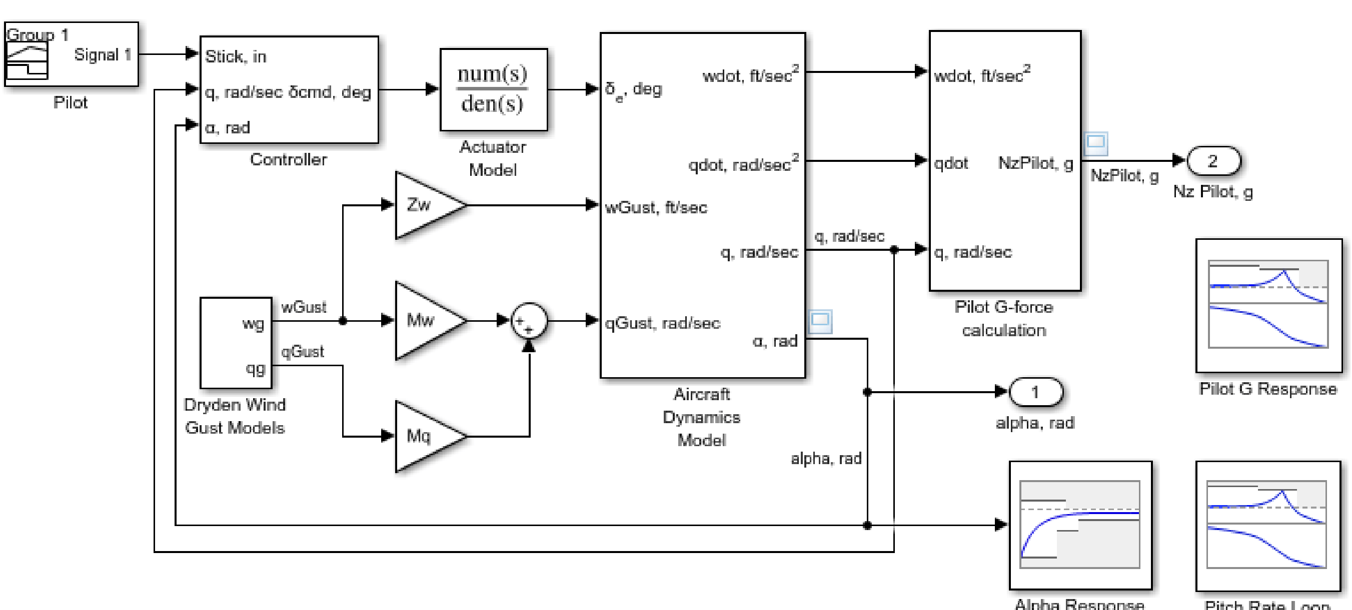
This example shows how to tune a controller to satisfy time-domain and frequency-domain design requirements using the **Response Optimizer**.

The example requires Simulink® Control Design™ software.

Aircraft Longitudinal Flight Control Model

Open the Simulink model.

```
sys = 'sdoAircraft';
open_system(sys);
```



The aircraft model is based on the Simulink `slexAircraftExample` model. The model includes:

- Subsystems to model aircraft dynamics (`Aircraft Dynamics Model`), wind gusts (`Dryden Wind Gust Models`), and pilot G-forces (`Pilot G-force calculation`).
- A step change applied to the aircraft joystick at 1 second into the simulation that causes the aircraft to pitch upward.

Controller Design Problem

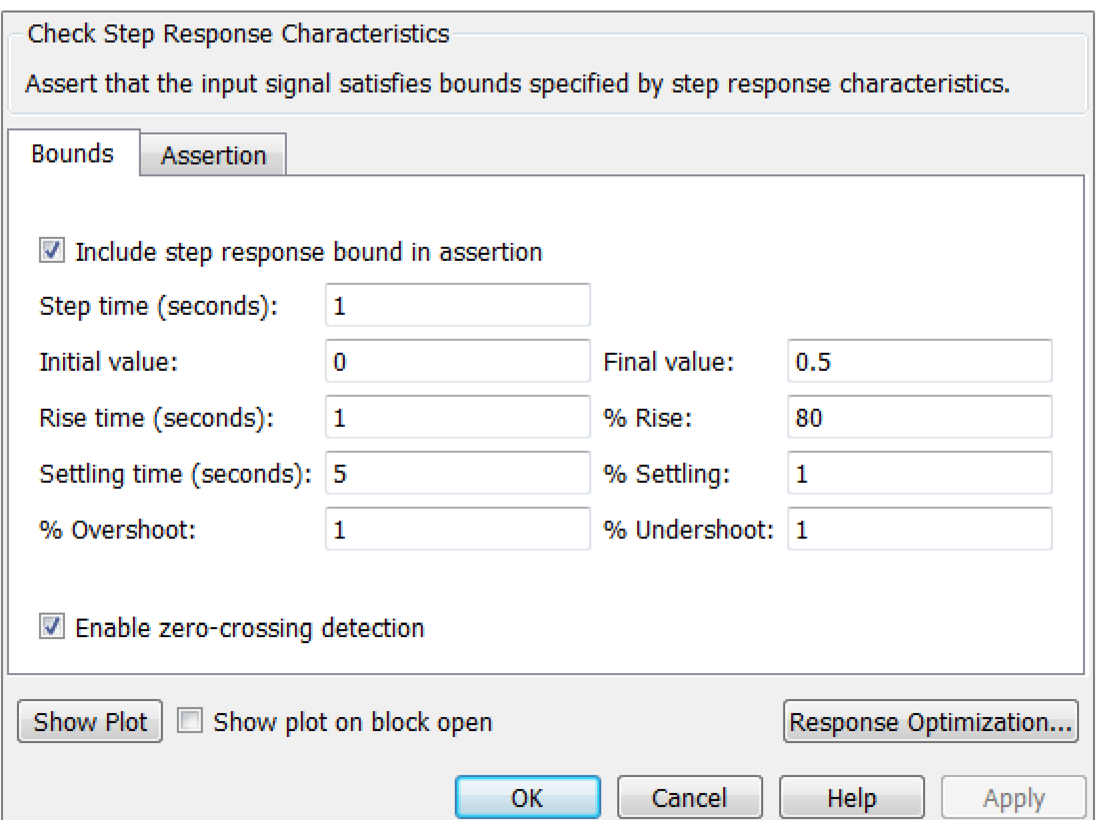
You tune the controller gains to meet the following time-domain and frequency-domain design requirements:

- Angle-of-attack `alpha` response to a step change in the joystick has a rise time of less than 1 second, less than 1% overshoot, and settles to within 1% of steady state within less than 5 seconds
- Pitch-rate control loop has good tracking below 1 rad/s and 20 dB noise rejection above 100 rad/s
- Closed-loop response from joystick to pilot G-Force is below 0 dB above 5 rad/s.

These requirements reduce the high frequency G-forces experienced by the pilot in response to joystick changes while still maintaining flight performance.

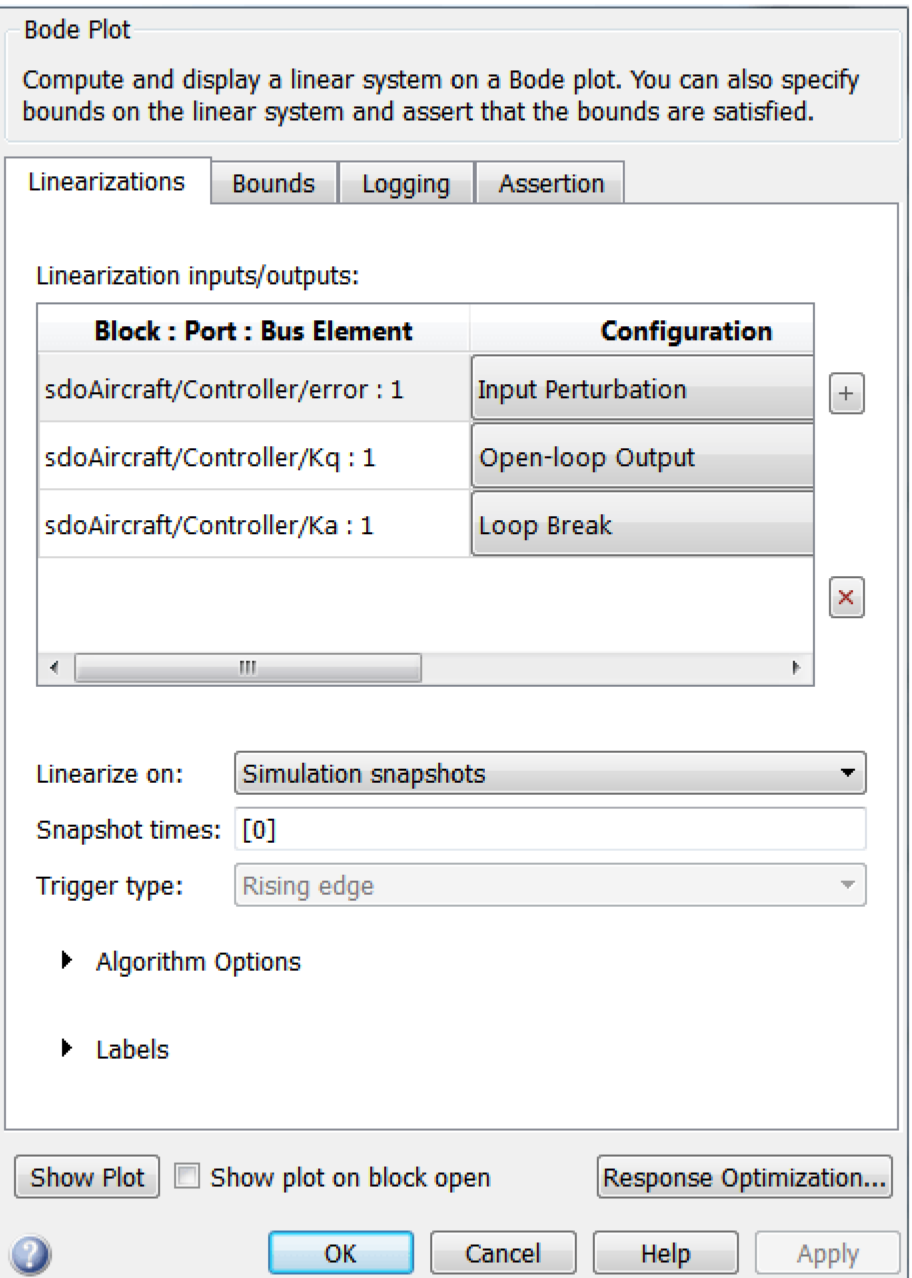
The model includes the following blocks (from Simulink® Design Optimization™ and Simulink Control Design Model Verification libraries):

- `Alpha Response` specifies the alpha step response requirement.



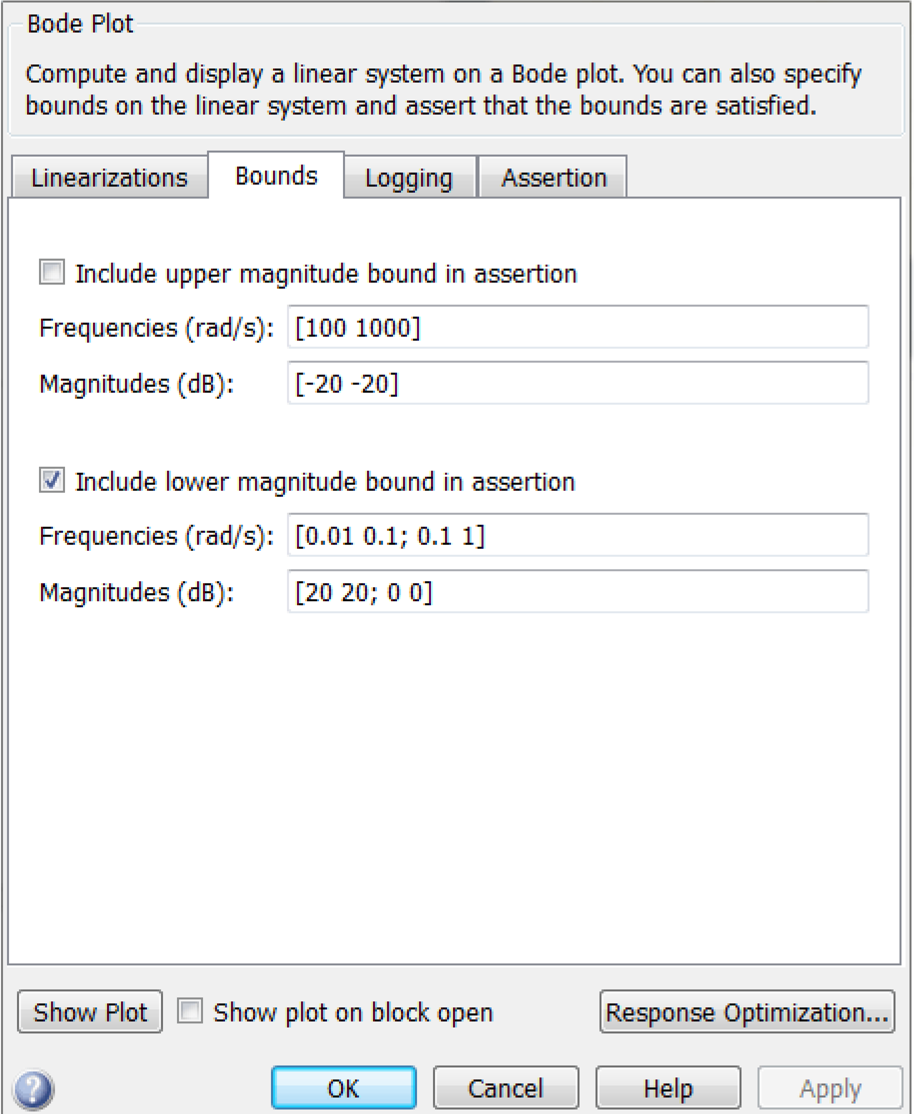
- `Pitch Rate Loop` specifies the pitch-rate performance requirement.

The linearization inputs/outputs are already selected in the **Linearizations** tab. The pitch-rate loop starts from the input of the controller (the controller error signal) and ends at the output of the pitch-rate sensor. The angle-of-attack loop is opened signal so that the block only computes the pitch-rate loop response. The linear system is computed at a simulation time of 0.



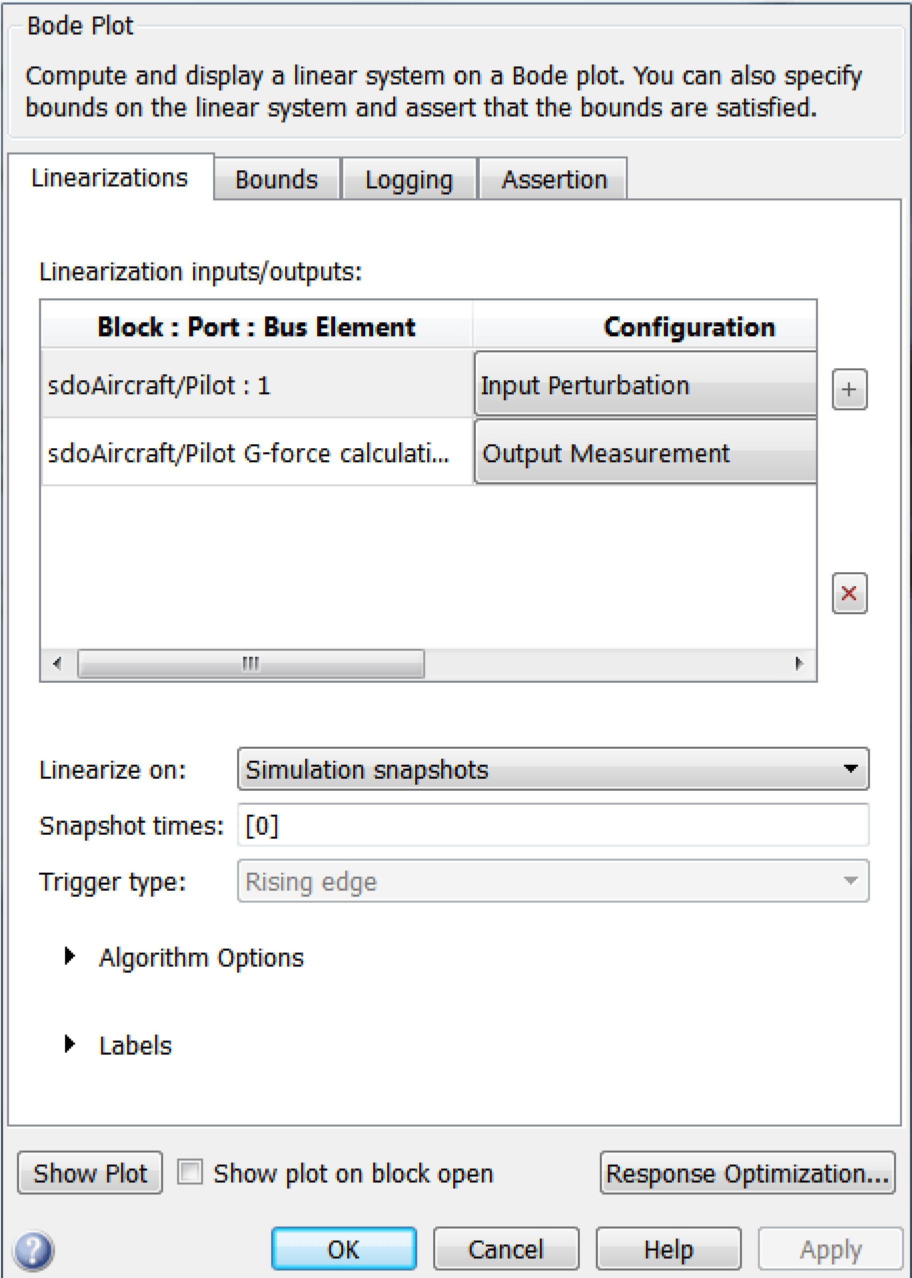
The **Bounds** tab specifies the following pitch-rate loop shape requirements:

- Greater than 20 dB over the range 0.01 rad/s to 0.1 rad/s
- Greater than 0 dB over the range 0.1 rad/s to 1 rad/s
- Less than -20 dB over the range 100 rad/s to 1000 rad/s

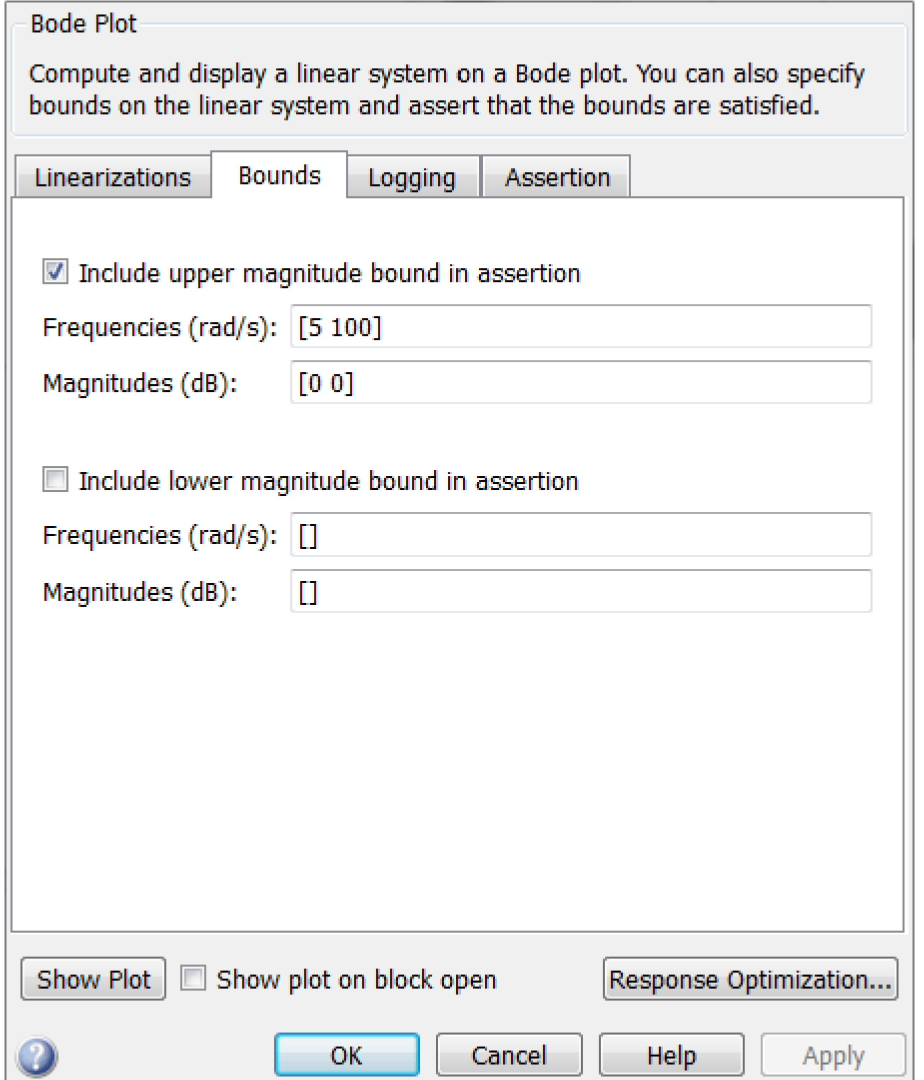


- `Pilot G Response` specifies the G-force requirement.

The linearization inputs/outputs are already selected in the **Linearizations** tab. The linear system is computed at a simulation time of 0.

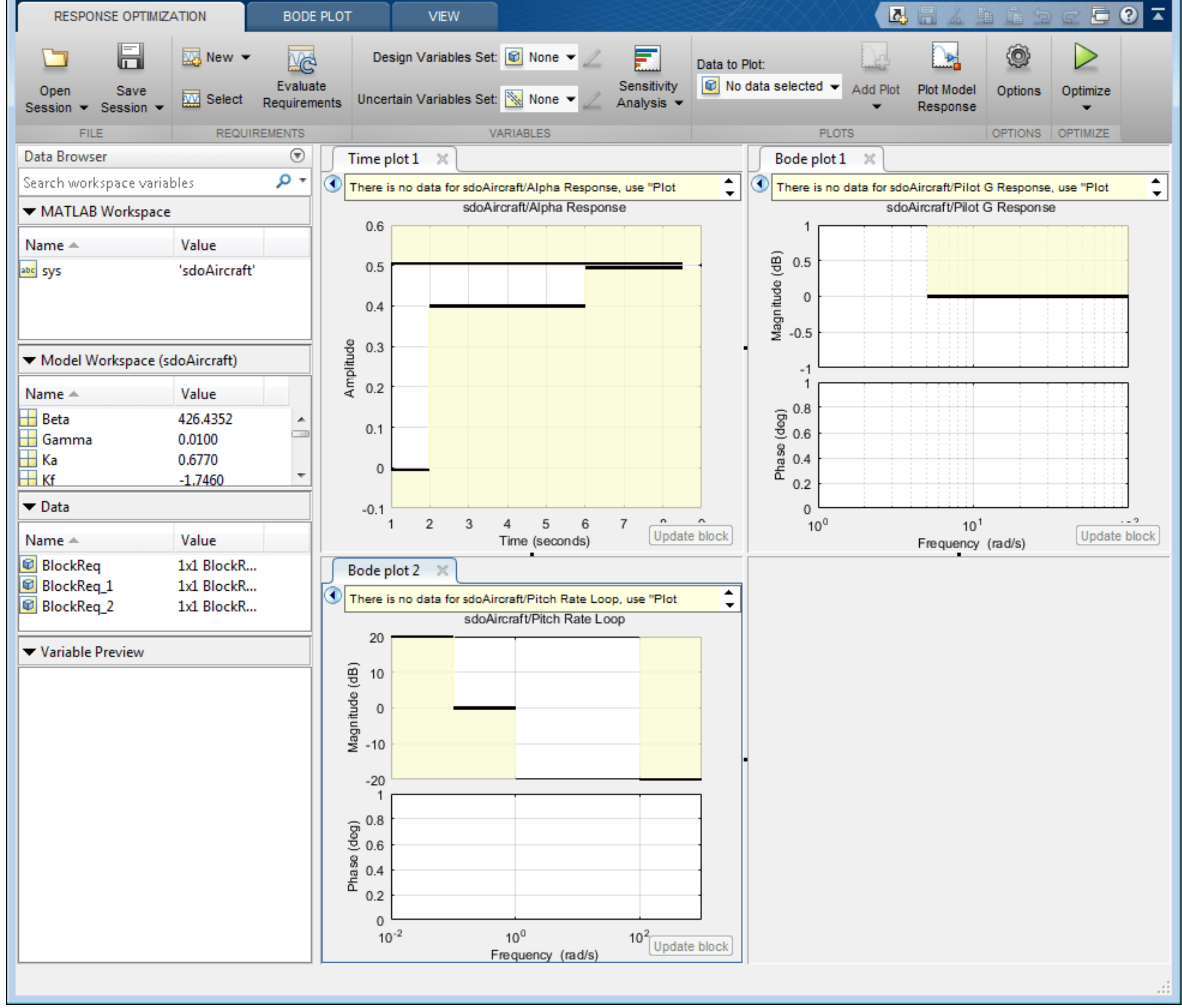


The **Bounds** tab specifies the G-force requirements of less than 0 dB over the range 5 rad/s 100 rad/s.



Open the Response Optimizer

Open the **Response Optimizer** to configure and run design optimization problems interactively. Click **Response Optimization** on the Block Parameters dialog of `Alpha Response`, `Pitch Rate Loop` or `Pilot G Response` block. Alternatively, type `sdotool('sdoAircraft')`. To show multiple requirement plots at the same time, use the **View** tab in the app.



The app detects the requirements specified in the Model Verification blocks and automatically includes them as requirements to satisfy.

Specify Design Variables

Specify the following model parameters as design variables for optimization:

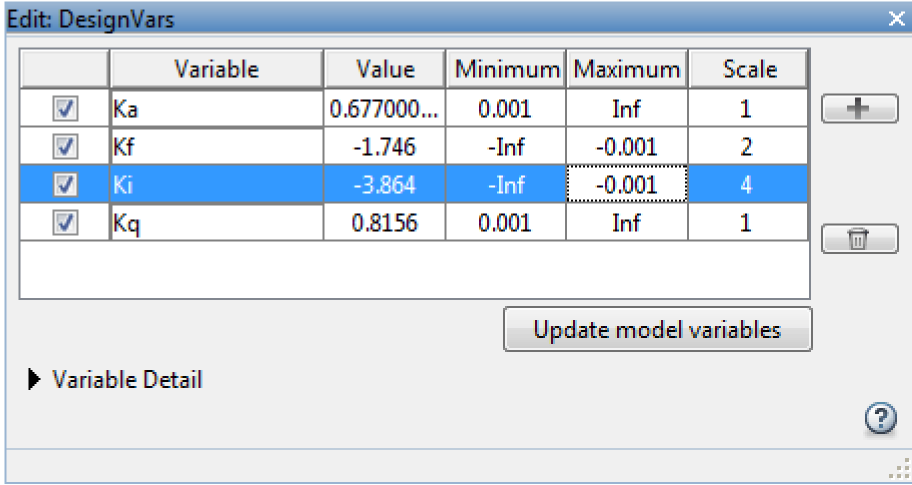
- Controller gains `Ki` and `Kf`
- Pitch-rate sensor gain `Kq`
- Alpha sensor gain `Ka`

In the **Design Variables Set** drop-down list, select **New**. A dialog to select model parameters for optimization opens.

Select `Ki`, `Kf`, `Kq` and `Ka`. Click **<<** to add the selected parameters to the design variables set.

Specify minimum and maximum gain values, the `Ki` and `Kf` values must remain negative while `Ka` and `Kq` must remain positive.

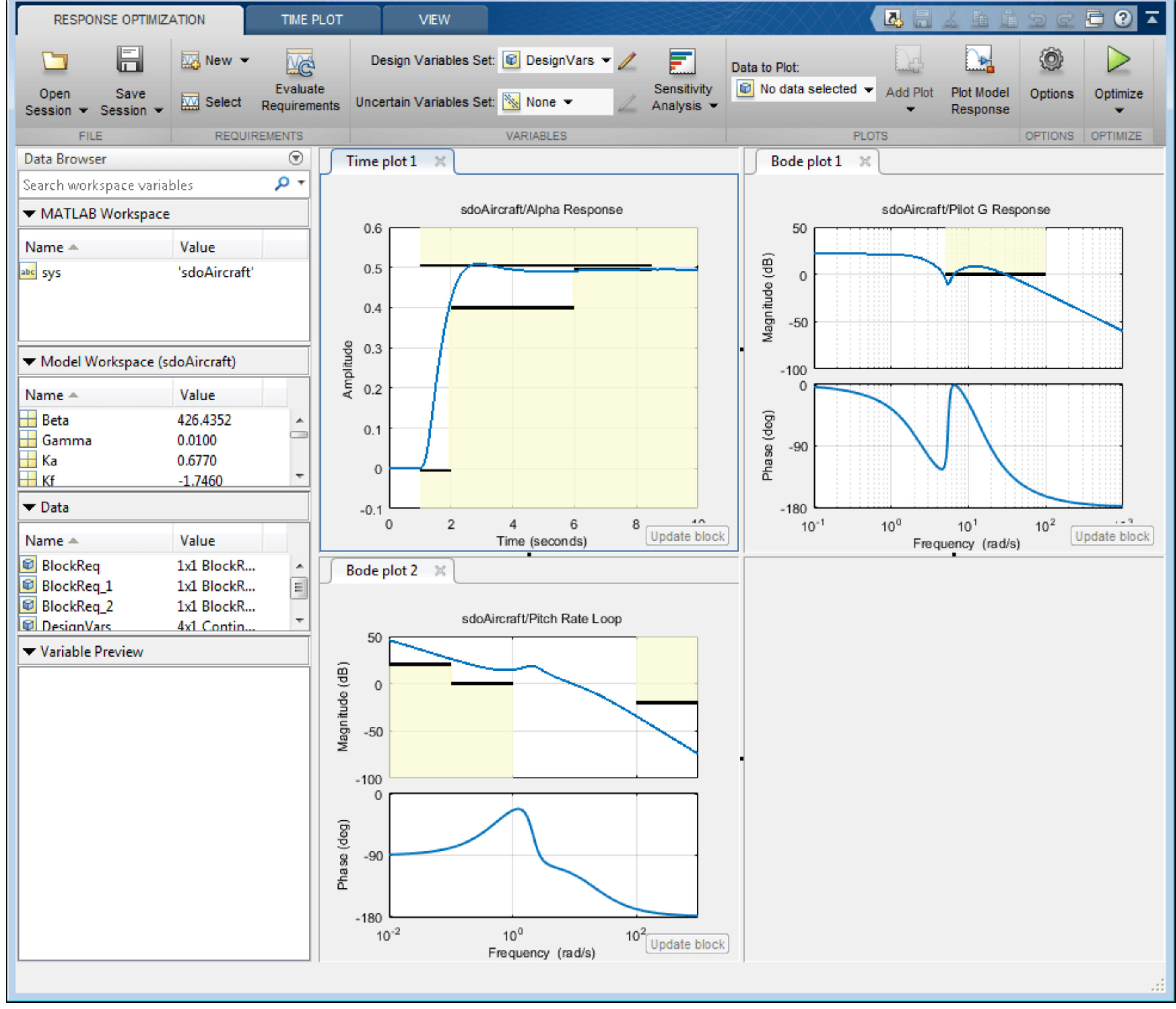
Press **Enter** after you enter the values.



Click **OK**. A new variable `DesignVars` appears in the **Response Optimizer** browser.

Evaluate the Initial Design

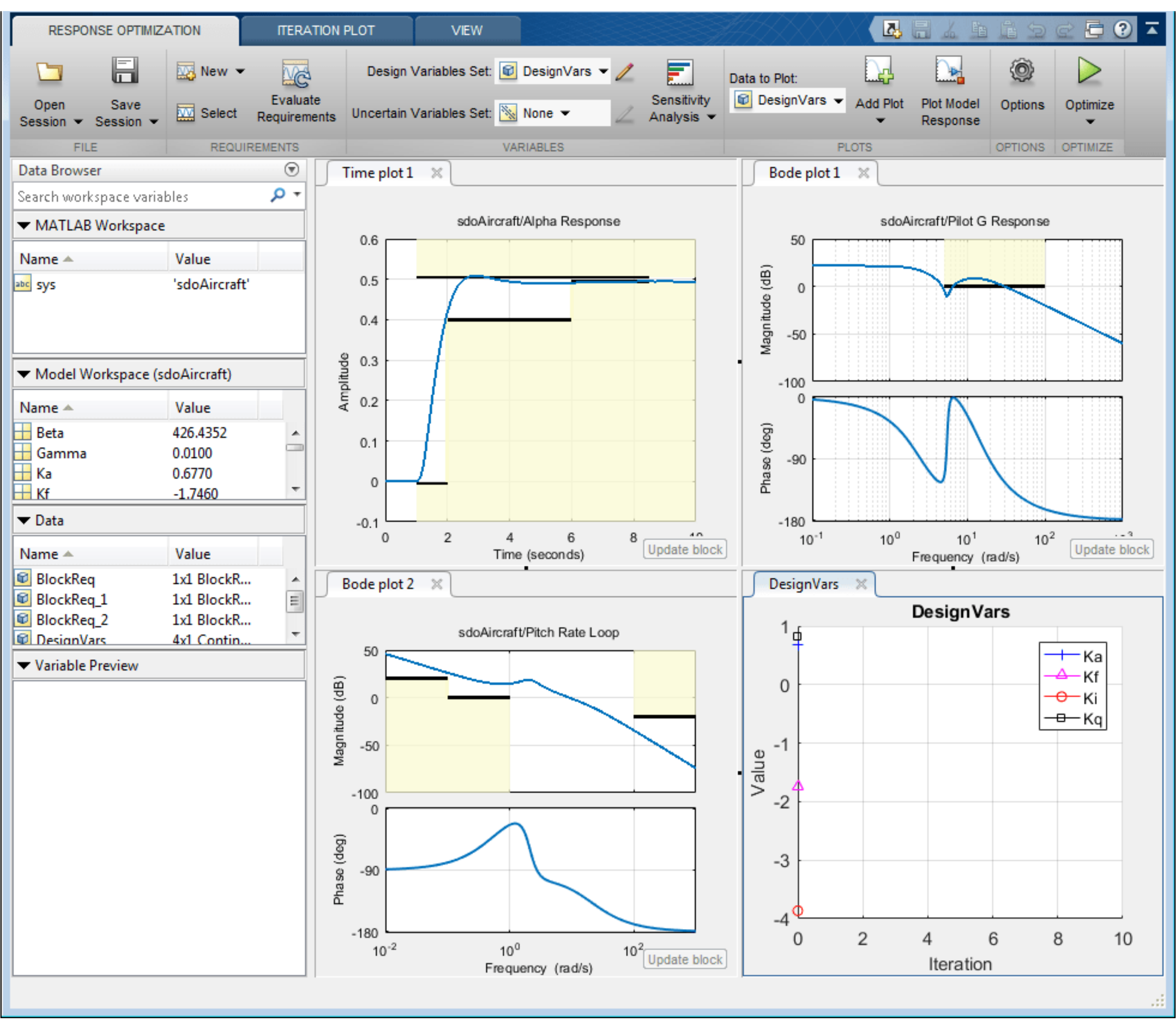
Click **Plot Model Response** to simulate the model and check how well the initial design satisfies the design requirements.



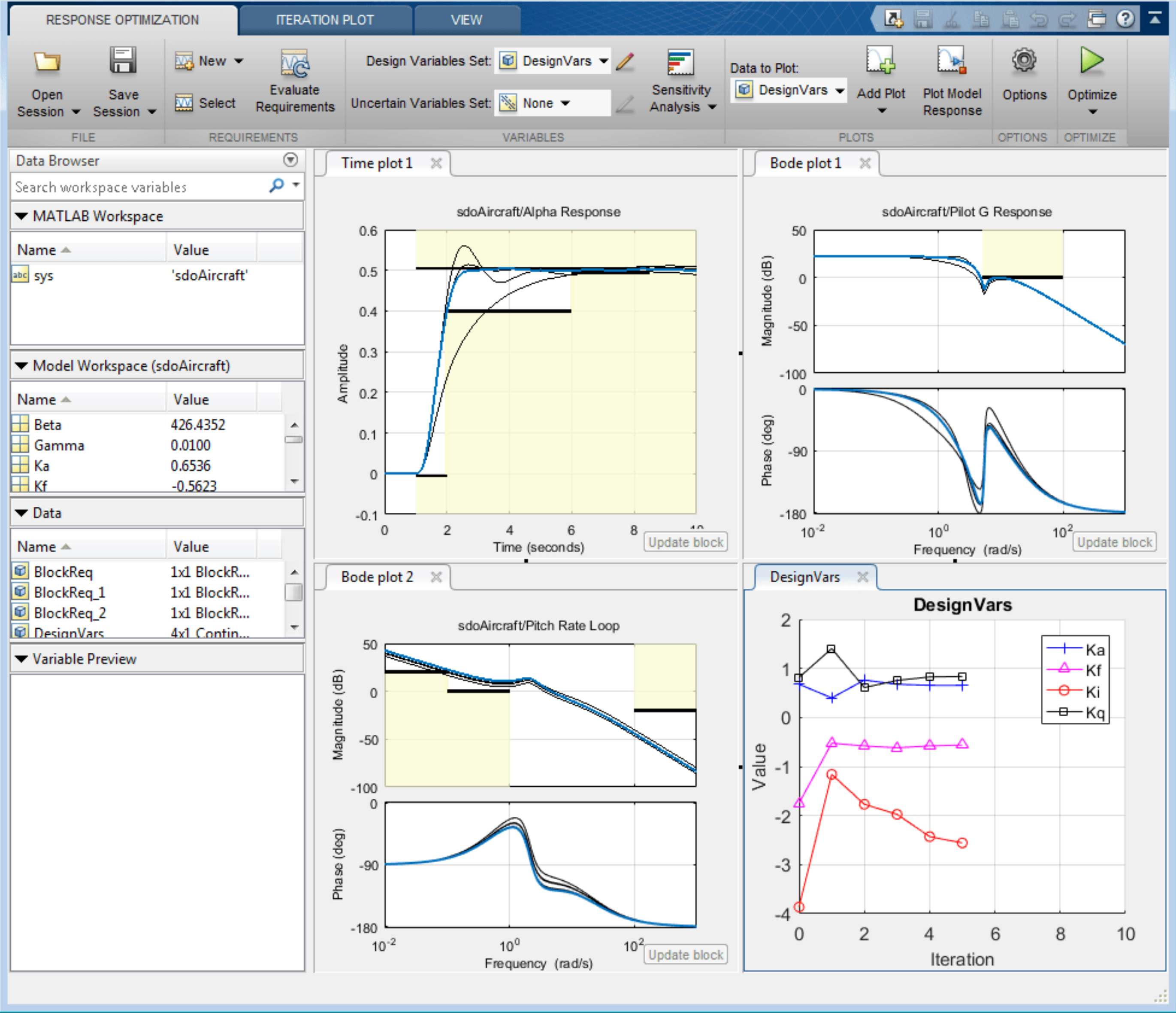
The plots indicate that the current design does not satisfy the pilot G-force requirement and the alpha step response overshoot requirement is violated.

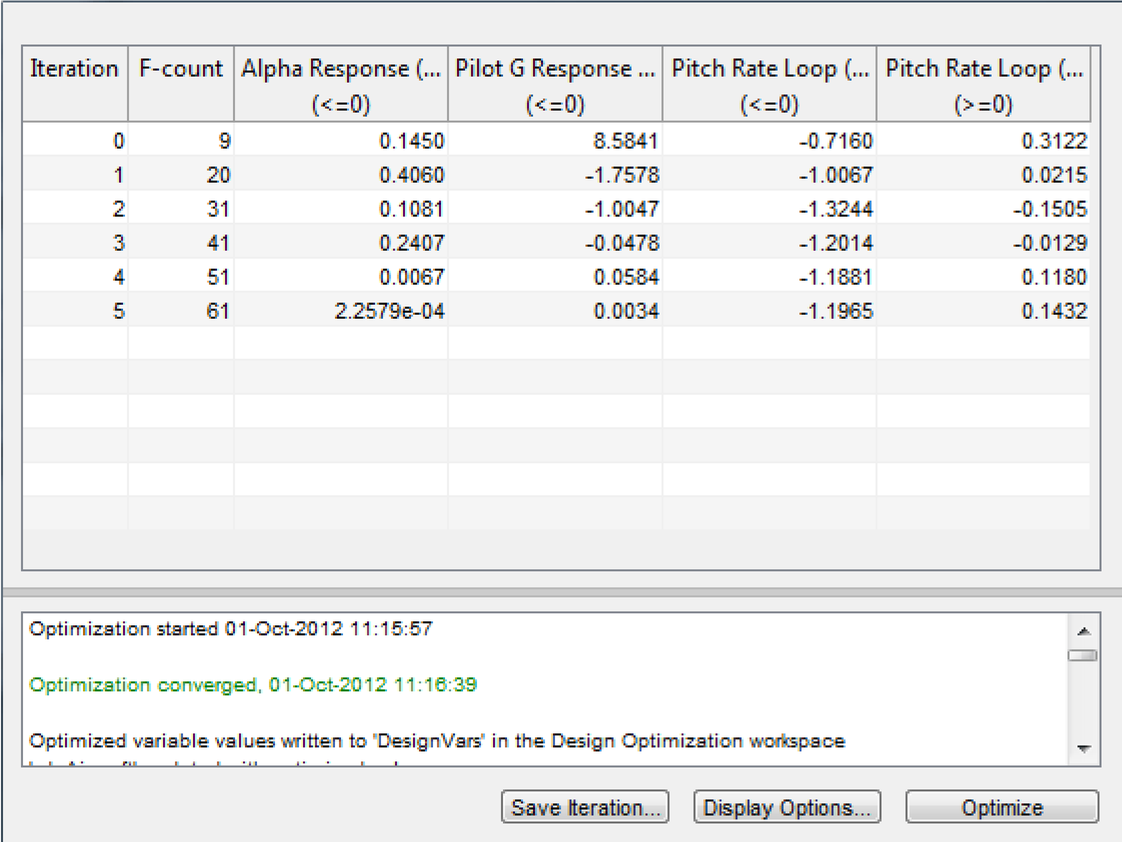
Optimize the Design

Create a plot to display how the controller variables are modified during the optimization. In the **Data To Plot** drop-down list, select **DesignVars**, which contains the optimization design variables `Ki`, `Kf`, `Kq` and `Ka`. In the **Add Plot** drop-down list, select **Iteration plot**.



Click **Optimize**.


RESPONSE OPTIMIZATION
ITERATION PLOT
VIEW
Open Session
Save Session
New
Select
Evaluate Requirements
Design Variables Set: DesignVars
Uncertain Variables Set: None
Sensitivity Analysis
Data to Plot: DesignVars
Add Plot
Plot Model Response
Options
Optimize
FILE
REQUIREMENTS
VARIABLES
PLOTS
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
sys
'sdoAircraft'
Model Workspace (sdoAircraft)
Beta
426.4352
Gamma
0.0100
Ka
0.6536
Kf
-0.5623
Data
BlockReq
BlockReq_1
BlockReq_2
DesignVars
Variable Preview
Time plot 1
sdoAircraft/Alpha Response
Amplitude
Time (seconds)
Update block
Bode plot 1
sdoAircraft/Pilot G Response
Magnitude (dB)
Phase (deg)
Frequency (rad/s)
Bode plot 2
sdoAircraft/Pitch Rate Loop
DesignVars
Value
Iteration
Ka
Kf
Ki
Kq



Iteration	F-count	Alpha Response (... (<=0)	Pilot G Response ... (<=0)	Pitch Rate Loop (... (<=0)	Pitch Rate Loop (... (>=0)
0	9	0.1450	8.5841	-0.7160	0.3122
1	20	0.4060	-1.7578	-1.0067	0.0215
2	31	0.1081	-1.0047	-1.3244	-0.1505
3	41	0.2407	-0.0478	-1.2014	-0.0129
4	51	0.0067	0.0584	-1.1881	0.1180
5	61	2.2579e-04	0.0034	-1.1965	0.1432

To load a pre-configured file and run the optimization, click **Open** in the **Response Optimization** tab and select `sdoAircraft_sdosession.mat`. Alternatively load the project by typing:

>> load sdoAircraft_sdosession

>> sdotool(SDOSessionData)

The optimization progress window updates at each iteration and shows that the optimization converged after 5 iterations.

The `Alpha Response` and `Pilot G Response` plots indicate that the design requirements are satisfied. The `DesignVars` plot shows that the controller gains converged to new values.

To view the optimized design variable values, click `DesignVars` in the **Response Optimizer** browser. The optimized values of the design variables are automatically updated in the Simulink model.

```
% Close the model
bdclose('sdoAircraft')
```

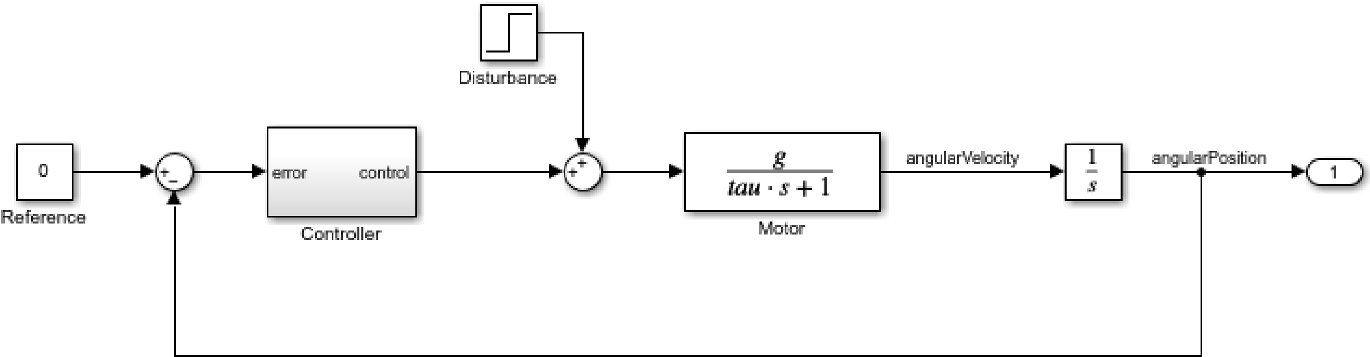
Discrete-Valued Variables in Response Optimization (Code)

This example shows how to use response optimization to tune discrete-valued variables. Discrete-valued variables represent model parameters that are restricted to a finite set of values, instead of continuously varying. To use discrete-valued variables for response optimization or parameter estimation, you must use the `surrogateopt` solver for mixed-integer optimization.

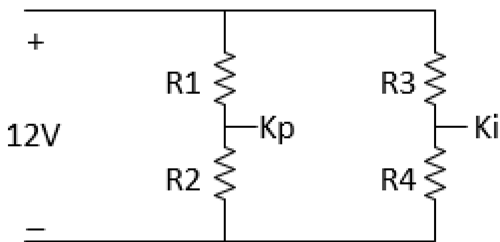
Open the Model

In the `sdoMotorPosition` model, a PI controller enables the angular position of a DC motor to match a desired reference value. The load on the motor is subject to disturbances, and the controller must reject these disturbances.

```
open_system('sdoMotorPosition')
```



Within the `Controller` subsystem, the PI gains are set by a 12 V source divided down by resistors R1, R2, R3, and R4, as shown in the following diagram.



The proportional gain, `Kp`, is given by `12*R2/(R1+R2)` and the integral gain, `Ki`, is given by `12*R4/(R3+R4)`. The initial values of the resistances are R1 = 47 kΩ, R2 = 180 kΩ, R3 = 10 kΩ, and R4 = 10 kΩ.

Specify Discrete Design Variables

Those four resistor values are the model parameters to tune for the optimization. Because resistors are only available in discrete values, use discrete parameters to represent them. To do so, use third input argument to `sdo.getParameterFromModel` to specify discrete parameters.

```
DesignVars = sdo.getParameterFromModel('sdoMotorPosition',[],{'R1','R2','R3','R4'});
```

sdo.getParameterFromModel returns an array of param.Discrete parameter objects that correspond to the model parameters in the order you specified. Set the ValueSet property of each parameter to the set of discrete values allowed for the parameter. Set the Value property to the current value, which must be present in ValueSet.

```
% R1 values
DesignVars(1).ValueSet = [39 43 47 51 56] * 1e3;
DesignVars(1).Value    = 47*1e3;
% R2 values
DesignVars(2).ValueSet = [150 160 180 200 220] * 1e3;
DesignVars(2).Value    = 180*1e3;
% R3 values
DesignVars(3).ValueSet = [8.2 9.1 10 11 12] * 1e3;
DesignVars(3).Value    = 10*1e3;
% R4 values
DesignVars(4).ValueSet = [8.2 9.1 10 11 12] * 1e3;
DesignVars(4).Value    = 10*1e3;
```

Specify Design Requirements and Signals

The model applies a step disturbance at 1 second. With the initial resistance values specified in the model, the disturbance causes the motor to deviate by about 20°. The response then settles back to within ±5° of the reference position by 4 seconds after the disturbance. For this example, find new resistor values to improve this specification by 10%, so that the motor deviates no more than 18°, and settles back to within ±4.5° degrees of the reference position by 4 seconds after the disturbance. First, specify these new design requirements using sdo.requirements.SignalBound.

```
Requirements = struct;
Requirements.UpperBound = sdo.requirements.SignalBound(...
    'BoundMagnitudes', [18 18 ; 4.5 4.5], ...
    'BoundTimes', [1 5 ; 5 15]);
Requirements.LowerBound = sdo.requirements.SignalBound(...
    'BoundMagnitudes', [-4.5 -4.5], ...
    'BoundTimes', [5 15], ...
    'Type', '>=');
```

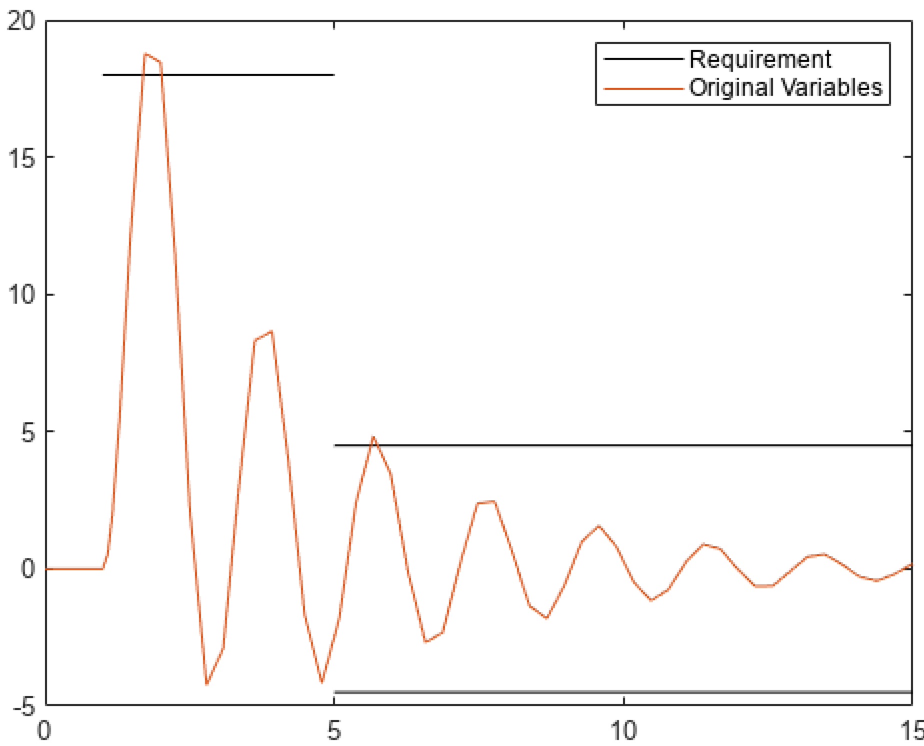
To visualize the initial performance against the requirement, first specify signals to log during simulation. In particular, log the output of the Integrator block, which is the angular position of the model, the signal you want to optimize. To do so, create a simulation scenario with sdo.SimulationTest and configure its LoggingInfo property. Also, to prepare the scenario for later use in the optimization, assign the design variables you created as its Parameters property.

```
Simulator = sdo.SimulationTest('sdoMotorPosition');

Sig_Info = Simulink.SimulationData.SignalLoggingInfo;
Sig_Info.BlockPath = 'sdoMotorPosition/Integrator';
Sig_Info.LoggingInfo.LoggingName = 'Sig';
Sig_Info.LoggingInfo.NameMode = 1;

Simulator.LoggingInfo.Signals = Sig_Info;

Simulator.Parameters = DesignVars;
```

Now create a plot of the disturbance-rejection requirements. Then, simulate the model and add the logged signal to the plot.

```
hRequirement = plot(Requirements.LowerBound.BoundTimes',Requirements.LowerBound.BoundMagnitudes'
hold on
```

```
plot(Requirements.UpperBound.BoundTimes', Requirements.UpperBound.BoundMagnitudes','color','blacl
% Simulator.Parameters = DesignVars;
Simulator = sim(Simulator);
SimLog = find(Simulator.LoggedData,get_param('sdoMotorPosition','SignalLoggingName'));
Sig_Log = find(SimLog,'Sig');
clrs = colororder;
hOriginal = plot(Sig_Log.Values, 'Color', clrs(2,:));
legend([hRequirement hOriginal], 'Requirement','Original Variables');
```



The plot shows that the current resistor values do not quite satisfy the more stringent requirement.

Set up Optimization

The optimization process runs the model many times with different values for the resistor variables. To expedite this, configure the simulator for fast restart.

```
Simulator = fastRestart(Simulator,'on');
```

Optimization requires an objective or cost function that runs the model and determines whether the disturbance rejection requirements are satisfied. For this example, use the function `sdoMotorPosition_optFcn`, which is included at the end of the example. This function is called many times by the optimization solver. To pass the function to the optimizer, use an anonymous function with one argument that calls `sdoMotorPosition_optFcn`.

```
optimfcn = @(P) sdoMotorPosition_optFcn(P,Simulator,Requirements);
```

Specify optimization options. Set the optimization method to `surrogateopt` solver, which is the method that supports tuning of discrete parameters.

```
Options = sdo.OptimizeOptions;
Options.Method = 'surrogateopt';
Options.MethodOptions.MaxFunctionEvaluations = 100;
Options.MethodOptions.ObjectiveLimit = 0.001;
Options.OptimizedModel = Simulator;
```

Optimize the Design

To find resistance values optimized for the requirements, call `sdo.optimize` with the cost function handle, parameters to optimize, and options.

```
rng('default');   % for reproducibility
[Optimized_DesignVars,Info] = sdo.optimize(optimfcn,DesignVars,Options);
```

```
 Optimization started 01-Sep-2022 13:47:59

                                          Current
 F-count     max constraint     max constraint     Trial type
      1           0.0759805          0.0759805     initial
      2           0.0751287          0.0751287     random
      3           0.0751287           0.179179     random
      4           0.0447169          0.0447169     random
      5           0.0317818          0.0317818     random
      6           0.0317818           0.261353     random
      7           0.0257711          0.0257711     random
      8           0.0257711          0.0930365     random
      9           0.0257711          0.0971938     random
     10           0.0257711           0.200359     random
     11           0.0062997          0.0062997     random
     12           0.0062997           0.206374     random
     13           0.0062997          0.0818387     random
     14           0.0062997          0.0585416     random
     15           0.0062997           0.114002     random
     16           0.0062997           0.112485     random
     17           0.0062997          0.0759805     random
     18           0.0062997          0.0709489     random
     19           0.0062997           0.280136     random
     20           0.0062997           0.099985     random
     21         -0.00737024        -0.00737024     adaptive
     22         -0.00737024          0.0691728     random
     23         -0.00737024          0.0347164     random
     24         -0.00737024          0.0977682     random
     25         -0.00737024          0.0589627     random
     26         -0.00737024           0.131778     random
     27         -0.00737024           0.147347     random
     28         -0.00737024           0.104488     random
     29         -0.00737024          0.0534262     random
     30         -0.00737024             0.1643     random
     31         -0.00737024          0.0419731     random
     32         -0.00737024          0.0396579     random
     33         -0.00737024           0.077945     random
     34         -0.00737024          0.0883493     random
     35         -0.00762259        -0.00762259     random
     36         -0.00762259          0.0455853     random
     37         -0.00762259            0.13976     random
     38         -0.00762259           0.140634     random
     39         -0.00762259          0.0662368     random
     40         -0.00762259           0.256738     random
```

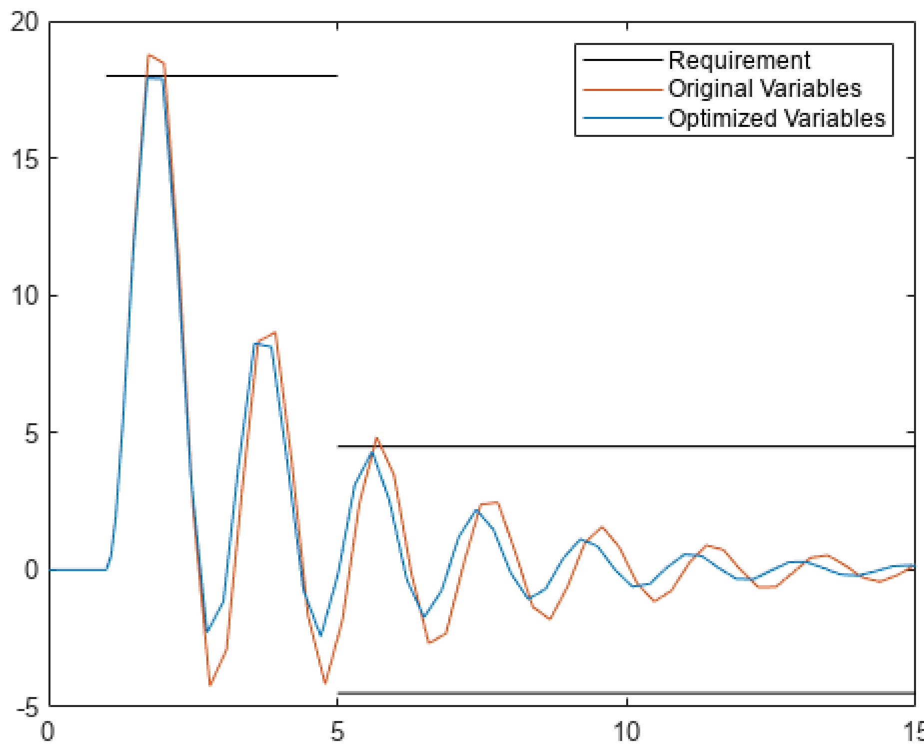
```
      41        -0.00762259         0.0348764     random
      42        -0.00762259           0.18995     random
      43        -0.00762259         0.0615952     random
      44        -0.00762259         0.0597358     random
      45        -0.00762259          0.015983     random
      46        -0.00762259         0.0770592     random
      47        -0.00762259          0.174666     random
      48        -0.00762259          0.081758     random
      49        -0.00762259         0.0240828     random
      50        -0.00762259          0.173292     random

                                      Current
 F-count     max constraint    max constraint     Trial type
      51        -0.00762259          0.116519     random
      52        -0.00762259          0.217099     random
      53        -0.00762259          0.104371     random
      54        -0.00762259         0.0937562     random
      55        -0.00762259          0.104225     random
      56        -0.00762259         0.0380129     random
      57        -0.00762259          0.150819     random
      58        -0.00762259         0.0636666     random
      59        -0.00762259         0.0320499     random
      60        -0.00762259         0.0273158     random
      61        -0.00762259         0.0798937     random
      62        -0.00762259          0.174146     random
      63        -0.00762259         0.0166127     random
      64        -0.00762259        0.00433873     adaptive
      65        -0.00518218       -0.00518218     adaptive
      66        -0.00518218          0.294106     random
      67        -0.00518218         0.0319864     random
      68        -0.00518218          0.266843     random
      69        -0.00518218         0.0342618     random
      70        -0.00518218         0.0982987     random
      71        -0.00518218         0.0419731     random
      72        -0.00518218         0.0396579     random
      73        -0.00518218          0.299815     random
      74        -0.00518218         0.0712971     random
      75        -0.00518218         0.0709489     random
      76        -0.00518218         0.0589627     random
      77        -0.00518218          0.131778     random
      78        -0.00518218        0.00653156     random
      79        -0.00518218          0.211877     random
      80        -0.00518218         0.0967155     random
      81        -0.00518218         0.0689487     random
      82        -0.00518218         0.0257711     random
      83        -0.00518218         0.0930365     random
      84        -0.00518218          0.114002     random
      85        -0.00518218          0.112485     random
      86        -0.00518218           0.06706     random
      87        -0.00495699       -0.00495699     adaptive
      88        -0.00495699         0.0751287     random
      89        -0.00495699         0.0759805     random
      90        -0.00495699           0.10447     random
      91        -0.00495699          0.190644     random
      92        -0.00495699          0.142755     random
      93        -0.00495699          0.104193     random
      94        -0.00495699          0.100237     random
      95        -0.00495699          0.097787     random
```

```
        96        -0.00495699          0.0735855     random
        97        -0.00495699           0.137557     random
        98        -0.00495699          0.0783709     random
        99        -0.00495699          0.0875674     random
       100        -0.00495699          0.0794652     random
       101        -0.00495699        -0.00495699     best value
The current solution is feasible. surrogateopt stopped because it exceeded the function evaluati
If the solution needs to be improved, you could try increasing the function evaluation limit.
```

Evaluate Optimized Design

Plot the model response after optimization.

```
Simulator.Parameters = Optimized_DesignVars;
Simulator = sim(Simulator);
SimLog = find(Simulator.LoggedData,get_param('sdoMotorPosition','SignalLoggingName'));
Sig_Log = find(SimLog,'Sig');
clrs = colororder;
hOptimized = plot(Sig_Log.Values, 'Color', clrs(1,:));
legend([hRequirement hOriginal hOptimized], 'Requirement','Original Variables','Optimized Variab
```



Now the motor position is within the spec of the disturbance rejection requirement.

Update Model with Optimized Parameter Values

`sdo.Optimize` returns tuned versions of the parameters in the array `Optimized_DesignVars`. Each entry in this array is a `param.Discrete` parameter object whose `Value` property is set to the optimized value. For instance, examine the new value of `R2`.

```
Optimized_DesignVars(2).Value
```

```
ans = 220000
```

Update the model with the optimized parameter values.

```
sdo.setValueInModel('sdoMotorPosition',Optimized_DesignVars);
```

Restore the simulator fast restart settings.

```
Simulator = fastRestart(Simulator,'off');
```

Conclusion

In this example you tuned variables to improve the disturbance rejection characteristics of a motor controller. The variables being tuned were electrical component parts that could only take on discrete values, rather than continuous values. You used `sdo.getParameterFromModel` to specify the variables as discrete, and used the `surrogateopt` solver to tune the parameters.

Objective Function

The function `sdoMotorPosition_optFcn` is called at each iteration of the optimization problem with a set of parameter values, `P`. The function returns the objective value and constraint violations, `Vals`, to the optimization solver. See `sdo.optimize` for a more detailed description of the function signature.

```
function Vals = sdoMotorPosition_optFcn(P,Simulator,Requirements)
%SDOMOTORPOSITION_OPTFCN
%

% Simulate the model.
Simulator.Parameters = P;
Simulator = sim(Simulator);

% Retrieve logged signal data.
SimLog = find(Simulator.LoggedData,get_param('sdoMotorPosition','SignalLoggingName'));
Sig_Log = find(SimLog,'Sig');

% Evaluate the design requirements.
Cleq_UpperBound = evalRequirement(Requirements.UpperBound,Sig_Log.Values);
Cleq_LowerBound = evalRequirement(Requirements.LowerBound,Sig_Log.Values);

% Collect the evaluated design requirement values in a structure to
% return to the optimization solver.
Vals.Cleq = [...
    Cleq_UpperBound(:); ...
    Cleq_LowerBound(:)];
end
```

See Also

`sdo.optimize` | `param.Discrete` | `sdo.getParameterFromModel` | `sdo.OptimizeOptions`

Related Examples

- “Design Optimization to Meet Step Response Requirements (Code)”

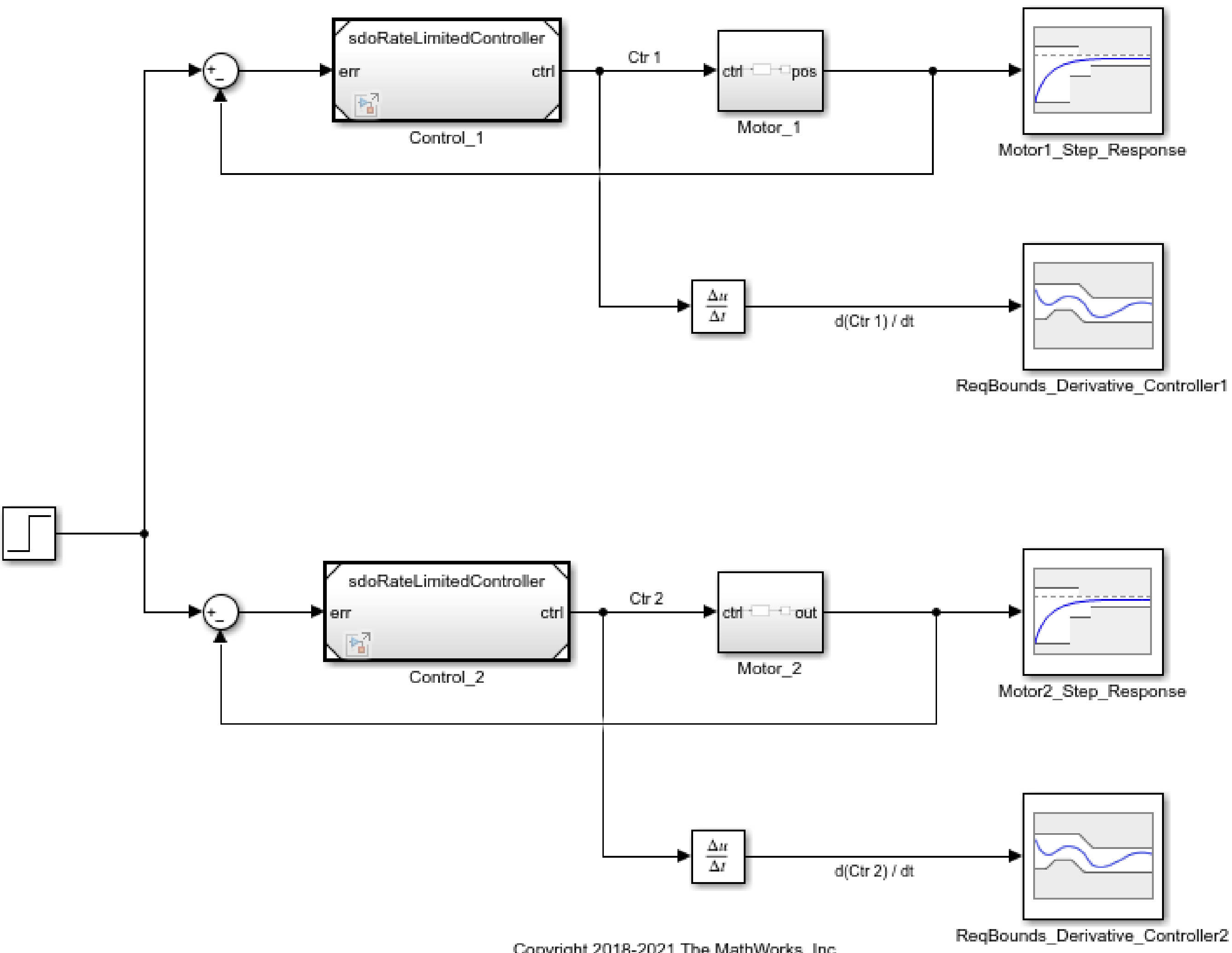
Design Optimization Tuning Parameters in Referenced Models (GUI)

This example shows how to tune parameters in referenced models using the **Response Optimizer** app.

Motor Control Model

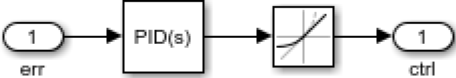
The model shows the control of angular position for two motors. Open the Simulink® model.

```
open_system('sdoMultipleMotors')
```



Model references are used for the two controllers, which are instances of the same model. Open the controller.

```
open_system('sdoRateLimitedController')
```



Each controller has PID gains `Kp`, `Ki`, and `Kd`, and a slew rate, `Slew`. The `Slew` value limits the rate at which the control signal changes, so that currents drawn from the power supply stay within the power supply's limits. The `Slew` value is common to both instances of the controller. In contrast, the PID gains need to be different for each instance of the controller, since the motors being controlled have different characteristics. Therefore, the PID gains are specified as model arguments in the controller's model workspace. The PID gain values are set at the level of the `sdoMultipleMotors` model.

Design Problem

The control reference signal is a step change in position, which occurs at 1 second. Each motor's angular position should follow the reference signal, but the first motor has a smaller moment of inertia and can respond more quickly to changes in the reference signal. The angular position of the first motor must satisfy the following requirements:

- Rise time: 2 seconds
- Settling time: 7 seconds

The second motor has a larger moment of inertia so it can't respond as quickly. The angular position of the second motor must satisfy the following requirements:

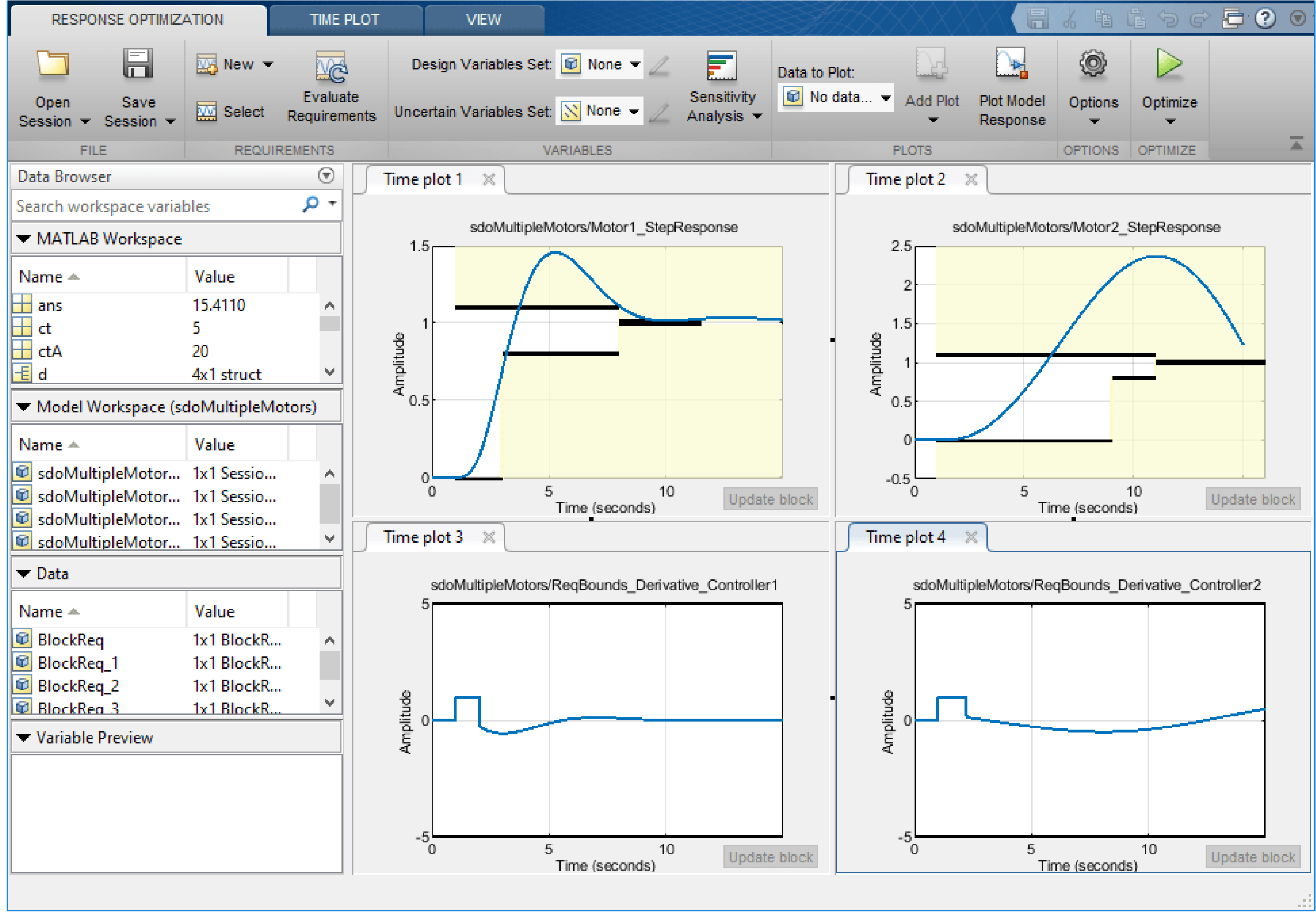
- Rise time: 8 seconds
- Settling time: 10 seconds

Also, the derivative of each controller signal is required to be in the range from -5 to 5, so that currents drawn from the power supply stay within the power supply's limits.

All these requirements are specified using blocks in the Simulink model.

Open the Response Optimizer

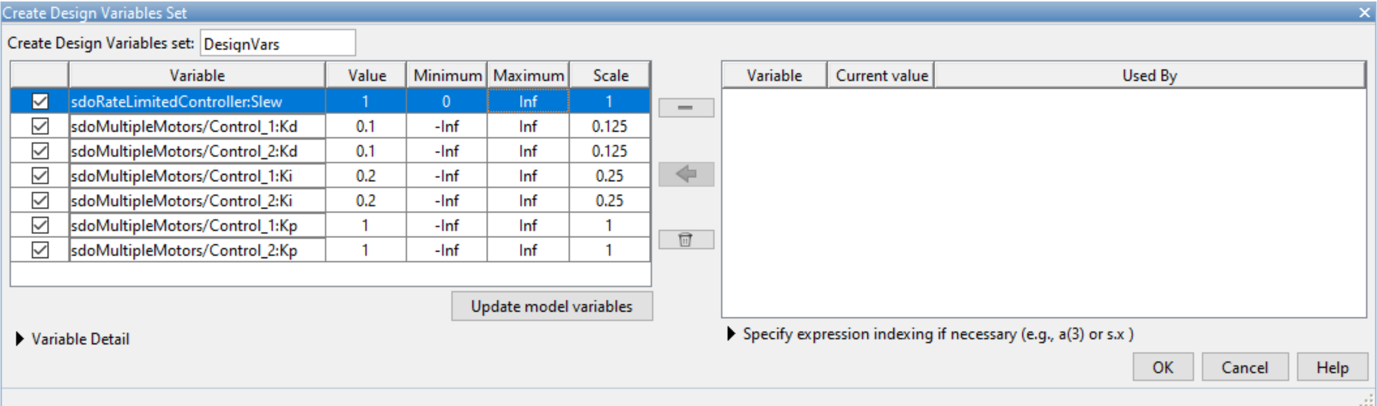
In the Simulink model from the **Apps** tab, click **Response Optimizer** under **Control Systems** to launch the **Response Optimizer** app. With the current settings of the controller variables, observe that neither step response requirement is satisfied.



Specify Design Variables

In the **Design Variables Set** list, select **New**. The dialog shows tunable variables. The `Slew` variable is listed as `sdoRateLimitedController:Slew`, indicating that the variable is set at the level of the `sdoRateLimitedController` model. The colon is a delimiter between the model and variable. The `Slew` variable has the same value for all instances of the controller model. In contrast, the derivative gain for the first controller is listed as `sdoMultipleMotors/Control_1:Kd`, indicating that the variable is set at the level of the `sdoMultipleMotors` model, where it appears in the `Control_1` block. The forward slash is the delimiter for Simulink blockpaths.

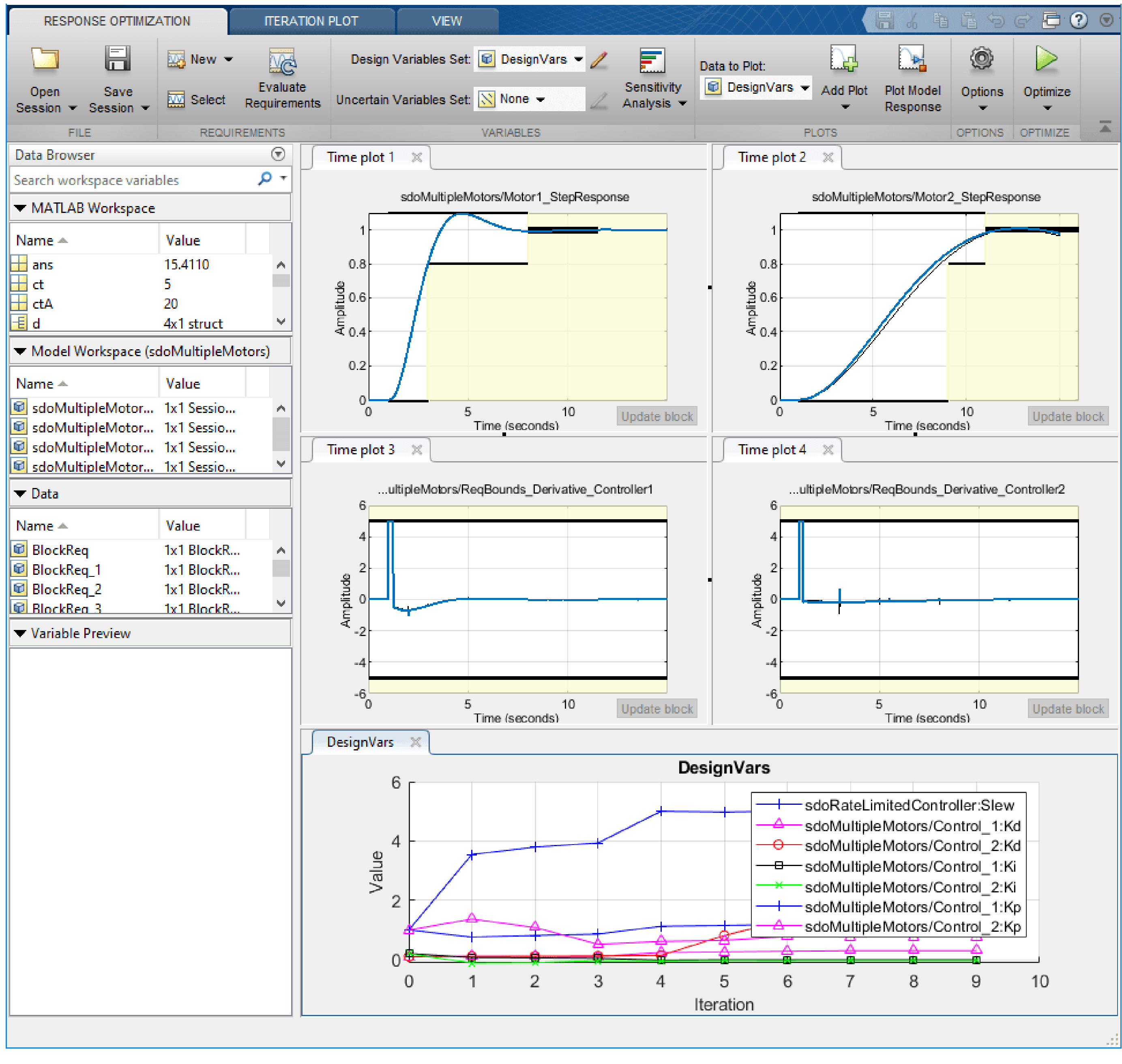
Select the common `Slew` variable, as well as the `Kd`, `Ki`, and `Kp` parameters for each model. Add these variables to the design variable set. Specify the minimum value for the `Slew` variable as 0.

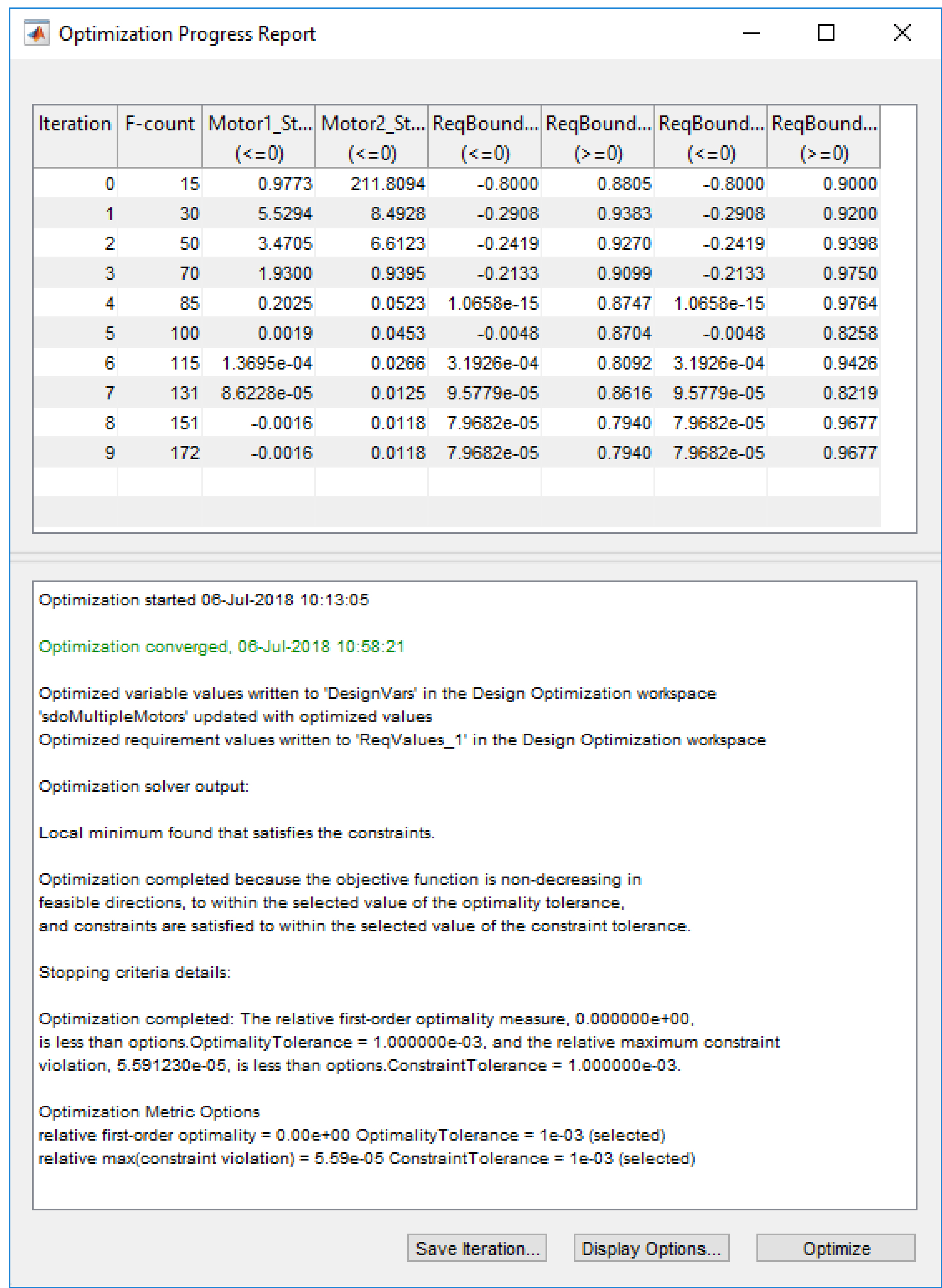


Click **OK**. A new variable, `DesignVars`, appears in the **Response Optimizer** browser. Create a plot of the design variables to see how they evolve during optimization. Under **Data to Plot**, select `DesignVars`. Click **Add Plot** and add an iteration plot. You can use the **View** tab to arrange the plots so they are all visible.

Optimize the Design

To optimize the design, click **Optimize**. The plots are updated during optimization. When optimization is complete, observe that all design requirements are satisfied. The step responses are within the prescribed bounds, as are the controller output signal derivatives.


RESPONSE OPTIMIZATION
ITERATION PLOT
VIEW
Open Session
Save Session
New
Select
Evaluate Requirements
Design Variables Set: DesignVars
Uncertain Variables Set: None
Sensitivity Analysis
Data to Plot: DesignVars
Add Plot
Plot Model Response
Options
Optimize
FILE
REQUIREMENTS
VARIABLES
PLOTS
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
ans 15.4110
ct 5
ctA 20
d 4x1 struct
Model Workspace (sdoMultipleMotors)
sdoMultipleMotor... 1x1 Sessio...
Data
BlockReq 1x1 BlockR...
BlockReq_1 1x1 BlockR...
BlockReq_2 1x1 BlockR...
BlockReq_3 1x1 BlockR...
Variable Preview
Time plot 1
sdoMultipleMotors/Motor1_StepResponse
Time plot 2
sdoMultipleMotors/Motor2_StepResponse
Time plot 3
...ultipleMotors/ReqBounds_Derivative_Controller1
Time plot 4
...ultipleMotors/ReqBounds_Derivative_Controller2
Amplitude
Time (seconds)
Update block
DesignVars
Value
Iteration
sdoRateLimitedController:Slew
sdoMultipleMotors/Control_1:Kd
sdoMultipleMotors/Control_2:Kd
sdoMultipleMotors/Control_1:Ki
sdoMultipleMotors/Control_2:Ki
sdoMultipleMotors/Control_1:Kp
sdoMultipleMotors/Control_2:Kp



Close the models.

```
bdclose('sdoMultipleMotors')
bdclose('sdoRateLimitedController')
```

See Also

More About

- "Design Optimization Tuning Parameters in Referenced Models (Code)" on page 3-102

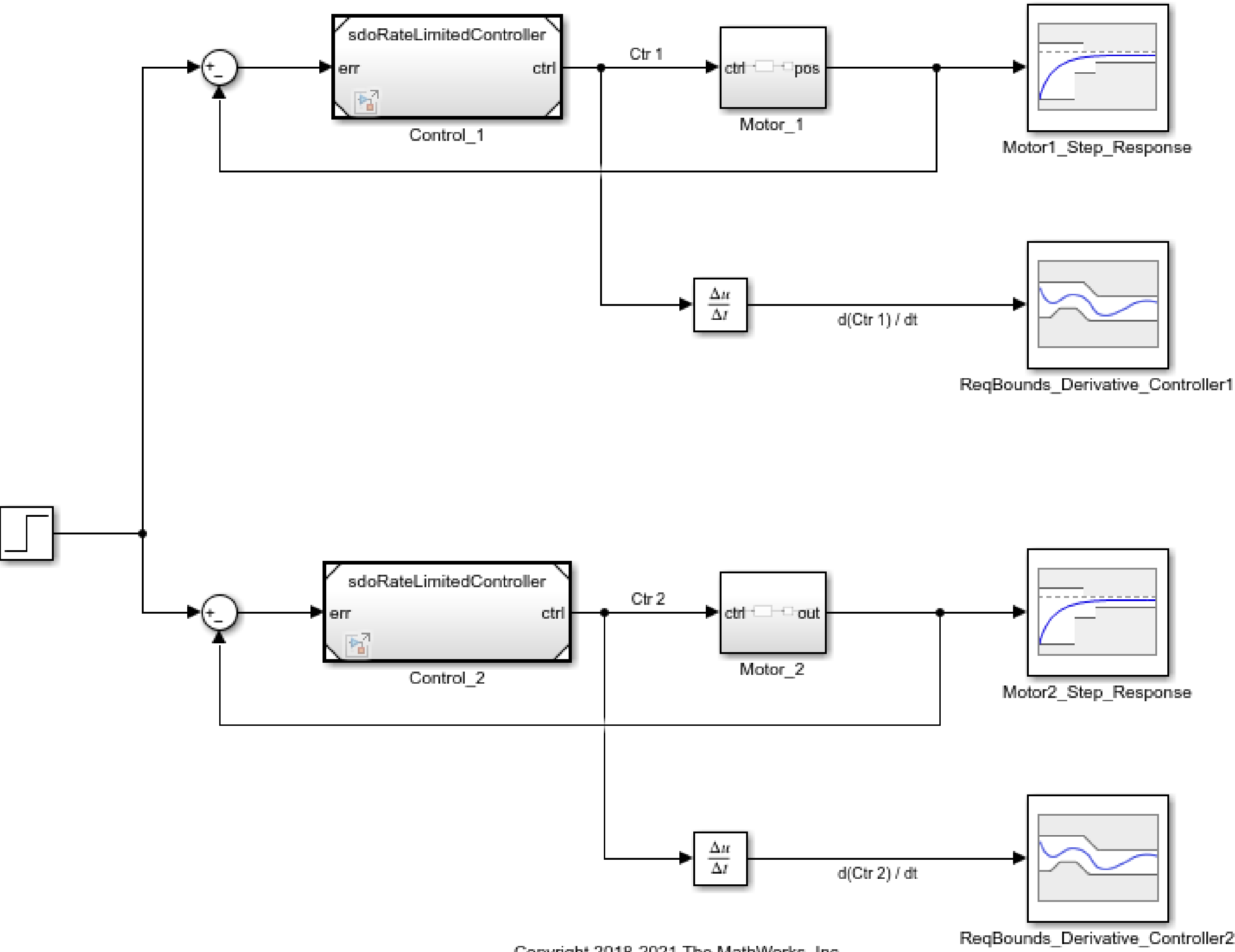
Design Optimization Tuning Parameters in Referenced Models (Code)

This example shows how to tune parameters in referenced models, using the `sdo.optimize` command.

Motor Control Model

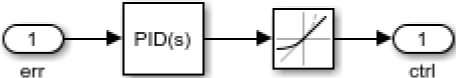
The model shows the control of angular position for two motors. Open the Simulink model.

```
open_system('sdoMultipleMotors')
```



Two motors are controlled. Model references are used for the controllers, which are instances of the same model. Open the controller.

```
open_system('sdoRateLimitedController')
```



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Design Problem

The two motors in the main model have different characteristics, so each controller needs to be tailored to its motor. Each controller has PID gains `Kp`, `Ki`, and `Kd`, and a slew rate, `Slew`. The `Slew` value limits the rate at which the control signal changes. The `Slew` value is common to both instances of the controller. In contrast, the PID gains need to be different for each instance of the controller, since the motors being controlled have different characteristics. Therefore, the PID gains are specified as model arguments in the controller's model workspace. The PID gain values are set at the level of the `sdoMultipleMotors` model.

The control reference signal is a step change in position, which occurs at 1 second. Each motor's angular position should follow the reference signal, but the first motor has a smaller moment of inertia and can respond more quickly to changes in the reference signal. Also, the derivative of each controller signal must be limited, so that currents drawn from the power supply stay within the power supply's limits.

Specify Design Variables

Specify the design variables to be tuned by the optimization routine in order to satisfy the requirements. The `Slew` variable is specified as `sdoRateLimitedController:Slew`, indicating that the variable is set at the level of the `sdoRateLimitedController` model. The colon is a delimiter between the model and variable. The `Slew` variable has the same value for all instances of the controller model. In contrast, the proportional gain for the first controller is specified as `sdoMultipleMotors/Control_1:Kp`, indicating that the variable is set at the level of the `sdoMultipleMotors` model, where it appears in the `Control_1` block. The forward slash is the delimiter for Simulink blockpaths.

Specify that design variables include the gains `Kp`, `Ki`, and `Kd`, for both PID controllers. Also include the slew rate, `Slew`, which is common to both controllers. Finally, specify that the slew rate cannot be negative.

```
DesignVars = sdo.getParameterFromModel('sdoMultipleMotors', ...
    {'sdoRateLimitedController:Slew', ...
    ...
    'sdoMultipleMotors/Control_1:Kp', ...
    'sdoMultipleMotors/Control_1:Ki', ...
    'sdoMultipleMotors/Control_1:Kd', ...
    ...
    'sdoMultipleMotors/Control_2:Kp', ...
    'sdoMultipleMotors/Control_2:Ki', ...
    'sdoMultipleMotors/Control_2:Kd' });
DesignVars(1).Minimum = 0;
```

Specify Design Requirements

Each motor's angular position angle should follow the reference signal, but the first motor has a smaller moment of inertia and can respond more quickly to changes in the reference signal. We want the angular position of the first motor to satisfy the following requirements:

- Rise time: 2 seconds
- Settling time: 7 seconds

This requirement is specified in a step response check block in the Simulink model. We can refer to the block and include the requirement in a variable, to be passed to the optimization objective function.

```
Requirements = struct;
bnds = getbounds('sdoMultipleMotors/Motor1_Step_Response');
Requirements.Motor1_StepResponse = bnds{1};
```

The second motor has a larger moment of inertia, so it can't respond as quickly. We want the angular position of the second motor to satisfy the following requirements:

- Rise time: 8 seconds
- Settling time: 10 seconds

This requirement is also specified in a step response check block in the Simulink model, and we refer to the block to include the requirement in a variable, to be passed to the optimization objective function.

```
bnds = getbounds('sdoMultipleMotors/Motor2_Step_Response');
Requirements.Motor2_StepResponse = bnds{1};
```

Also, the derivative of each controller signal is required to be in the range from -5 to 5, so that currents drawn from the power supply stay within the power supply's limits. These requirements are specified in bound check blocks in the Simulink model, and these requirements should also be collected among requirements to be passed to the optimization objective function.

```
bnds = getbounds('sdoMultipleMotors/ReqBounds_Derivative_Controller1');
Requirements.Controller1_DerivBound1 = bnds{1};
Requirements.Controller1_DerivBound2 = bnds{2};
bnds = getbounds('sdoMultipleMotors/ReqBounds_Derivative_Controller2');
Requirements.Controller2_DerivBound1 = bnds{1};
Requirements.Controller2_DerivBound2 = bnds{2};
```

Prevent check block assertions during optimization.

```
CheckBlockStatus = sdo.setCheckBlockEnabled('sdoMultipleMotors','off');
```

Simulation Definition

The cost function requires a simulation scenario to run the model. Create a simulation scenario and add model signals to log, so their values are available to the cost function.

```
Simulator = sdo.SimulationTest('sdoMultipleMotors');
```

The motor angular positions need to be logged during optimization, to evaluate the requirements on their step responses.

```
Motor1_Position = Simulink.SimulationData.SignalLoggingInfo;
Motor1_Position.BlockPath = 'sdoMultipleMotors/Motor1_Step_Response/u';
Motor1_Position.LoggingInfo.LoggingName = 'Motor1_Position';
Motor1_Position.LoggingInfo.NameMode = 1;

Motor2_Position = Simulink.SimulationData.SignalLoggingInfo;
```

```
Motor2_Position.BlockPath = 'sdoMultipleMotors/Motor2_Step_Response/u';
Motor2_Position.LoggingInfo.LoggingName = 'Motor2_Position';
Motor2_Position.LoggingInfo.NameMode = 1;
```

The controller signal derivatives also need to be logged, to evaluate the bound requirements on them.

```
Controller1_Derivative = Simulink.SimulationData.SignalLoggingInfo;
Controller1_Derivative.BlockPath = 'sdoMultipleMotors/ReqBounds_Derivative_Controller1/u';
Controller1_Derivative.LoggingInfo.LoggingName = 'Controller1_Derivative';
Controller1_Derivative.LoggingInfo.NameMode = 1;

Controller2_Derivative = Simulink.SimulationData.SignalLoggingInfo;
Controller2_Derivative.BlockPath = 'sdoMultipleMotors/ReqBounds_Derivative_Controller2/u';
Controller2_Derivative.LoggingInfo.LoggingName = 'Controller2_Derivative';
Controller2_Derivative.LoggingInfo.NameMode = 1;
```

To log these signals during optimization, collect them into the simulation scenario, `Simulator`.

```
Simulator.LoggingInfo.Signals = [...
    Motor1_Position ; ...
    Motor2_Position ; ...
    Controller1_Derivative ; ...
    Controller2_Derivative ];
```

Create Optimization Objective Function

Create an objective function, which will be called at each optimization iteration, to evaluate the design requirements as the design variables are tuned. This cost function has input arguments for the design variables, simulation scenario, and design requirements.

```
type sdoMultipleMotors_Design
```

```
function Vals = sdoMultipleMotors_Design(P,Simulator,Requirements)
%SDOMULTIPLEMOTORS_DESIGN Objective function for multiple motors
%
% Function called at each iteration of the optimization problem.
%
% The function is called with the model named mdl, a set of parameter
% values, P, a Simulator, and the design Requirements to evaluate.  It
% returns the objective value and constraint violations, Vals, to the
% optimization solver.
%
% See the sdoExampleCostFunction function and sdo.optimize for a more
% detailed description of the function signature.
%
% See also sdoMultipleMotors_cmddemo

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%% Model Evaluation

% Simulate the model.
Simulator.Parameters = P;
Simulator = sim(Simulator);

% Retrieve logged signal data.
SimLog = find(Simulator.LoggedData, get_param('sdoMultipleMotors','SignalLoggingName'));
```

```
Motor1_Position = find(SimLog,'Motor1_Position');
Motor2_Position = find(SimLog,'Motor2_Position');
Controller1_Derivative = find(SimLog,'Controller1_Derivative');
Controller2_Derivative = find(SimLog,'Controller2_Derivative');

% Evaluate the design requirements.
Cleq_Motor1_StepResponse     = evalRequirement(Requirements.Motor1_StepResponse,     Motor1_Posi
Cleq_Motor2_StepResponse     = evalRequirement(Requirements.Motor2_StepResponse,     Motor2_Posi
Cleq_Controller1_DerivBound1 = evalRequirement(Requirements.Controller1_DerivBound1, Controller1_
Cleq_Controller1_DerivBound2 = evalRequirement(Requirements.Controller1_DerivBound2, Controller1_
Cleq_Controller2_DerivBound1 = evalRequirement(Requirements.Controller2_DerivBound1, Controller2_
Cleq_Controller2_DerivBound2 = evalRequirement(Requirements.Controller2_DerivBound2, Controller2_

%% Return Values.
%
% Collect the evaluated design requirement values in a structure to
% return to the optimization solver.
Vals.Cleq = [...
    Cleq_Motor1_StepResponse(:); ...
    Cleq_Motor2_StepResponse(:); ...
    Cleq_Controller1_DerivBound1(:); ...
    Cleq_Controller1_DerivBound2(:); ...
    Cleq_Controller2_DerivBound1(:); ...
    Cleq_Controller2_DerivBound2(:)];

end
```

To optimize, define a handle to the cost function that uses the `Simulator` and `Requirements` defined above. Use an anonymous function that takes one argument (the design variables) and calls the objective function. Finally, call sdo.optimize to optimize the design variables to try to meet the requirements.

```
optimfcn = @(P) sdoMultipleMotors_Design(P, Simulator, Requirements);
[Optimized_DesignVars, Info] = sdo.optimize(optimfcn, DesignVars);
```

```
 Optimization started 01-Sep-2022 13:57:52

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0     15            0        211.8
    1     30            0        8.464         2.92         26.5
    2     50            0        6.531        0.396         15.1
    3     70            0        1.931        0.675         15.7
    4     85            0       0.2419         1.67         41.2
    5    100            0      0.04524        0.271     1.02e+03
    6    110            0      0.04524      0.00399            0
Local minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the value of the optimality tolerance,
and constraints are satisfied to within the value of the constraint tolerance.
```

Restore check block assertions.

```
sdo.setCheckBlockEnabled('sdoMultipleMotors', CheckBlockStatus);
```

Update Model

Update the model with the optimized parameter values.

```
sdo.setValueInModel('sdoMultipleMotors',Optimized_DesignVars);
```

Close the models.

```
bdclose('sdoMultipleMotors')
bdclose('sdoRateLimitedController')
```

See Also

More About

- “Design Optimization Tuning Parameters in Referenced Models (GUI)” on page 3-95
- “Discrete-Valued Variables in Response Optimization (Code)” on page 3-88

Specify Steady-State Operating Point for Response Optimization

What is a Steady-State Operating Point?

An *operating point* of a dynamic system defines the states and root-level input signals of the model at a specific time. For example, in a car engine model, variables such as engine speed, throttle angle, engine temperature, and surrounding atmospheric conditions typically describe the operating point.

A *steady-state operating point* of a model, also called an equilibrium or *trim* condition, includes state variables that do not change with time.

A model can have several steady-state operating points. For example, a hanging damped pendulum has two steady-state operating points at which the pendulum position does not change with time. A *stable steady-state operating point* occurs when a pendulum hangs straight down. When the pendulum position deviates slightly, the pendulum always returns to equilibrium. In other words, small changes in the operating point do not cause the system to leave the region of good approximation around the equilibrium value.

When using optimization search to compute operating points for nonlinear systems, your initial guesses for the states and input levels must be near the desired operating point to ensure convergence.

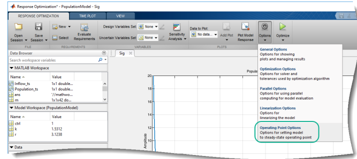
When linearizing a model with multiple steady-state operating points, it is important to have the right operating point. For example, linearizing a pendulum model around the stable steady-state operating point produces a stable linear model, whereas linearizing around the unstable steady-state operating point produces an unstable linear model.

For more information on operating points, see “What Is an Operating Point?” (Simulink Control Design) and “What Is a Steady-State Operating Point?” (Simulink Control Design).

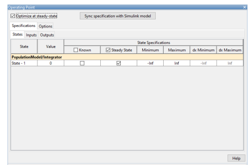
Setting up a Steady-State Operating Point

This topic shows how to setup a steady-state operating point in **Response Optimizer**. To improve the fit between the model and measured data, the model must be set to steady-state before optimization.

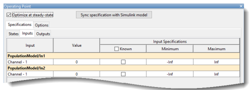
1. Open the **Response Optimizer** and specify your requirements using the steps outlined in “Design Optimization to Meet Frequency-Domain Requirements (GUI)” on page 3-136.
2. In the toolstrip, click **Options** and select `Operating Point Options` from the drop down menu.



3. The following **Operating Point** dialog box opens.

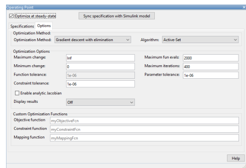


The **Optimize at steady-state** option is checked by default when you open the operating point dialog. Use the **States**, **Inputs** and **Outputs** tabs to specify the known parameters, bounds and deviations. For instance, there is one state in the above figure. Use the operating point dialog to specify that this state should be treated as an unknown, and it should be set to steady state. During response optimization, the operating point computation will vary this state to set it at steady-state.



You can also sync operating point specifications from your Simulink model using the button.

4 The Simulink Design Optimization software uses optimization methods to search for operating points in a model. Use the **Options** tab of the dialog to specify these optimization methods. These options specify the optimization algorithm, tolerances, and stopping conditions. For instance, the option `Gradient descent with projection` is often used to find the operating point for systems that use physical modeling. For more information, click on the button.



5 Having specified the operating point parameters, continue with the optimization workflow as described in “Design Optimization to Meet Frequency-Domain Requirements (GUI)” on page 3-136.

See Also

More About

- “What Is an Operating Point?” (Simulink Control Design)
- “What Is a Steady-State Operating Point?” (Simulink Control Design)
- “Set Model to Steady-State When Estimating Parameters (GUI)” on page 2-118
- “Set Model to Steady-State When Estimating Parameters (Code)” on page 2-97

Design Optimization to Meet a Custom Objective (GUI)

This example shows how to optimize a design to meet a custom objective using the **Response Optimizer** app. You optimize the cylinder parameters to minimize the cylinder geometry and satisfy design requirements.

Hydraulic Cylinder Model

The hydraulic cylinder model is based on the Simulink® model `sldemo_hydcyl`. The model includes:

- `Pump` and `Cylinder Assembly` subsystems. For more information on the subsystems, see “Single Hydraulic Cylinder Simulation”.
- A step change applied to the cylinder control valve orifice area that causes the cylinder piston position to change.

Hydraulic Cylinder Design Problem

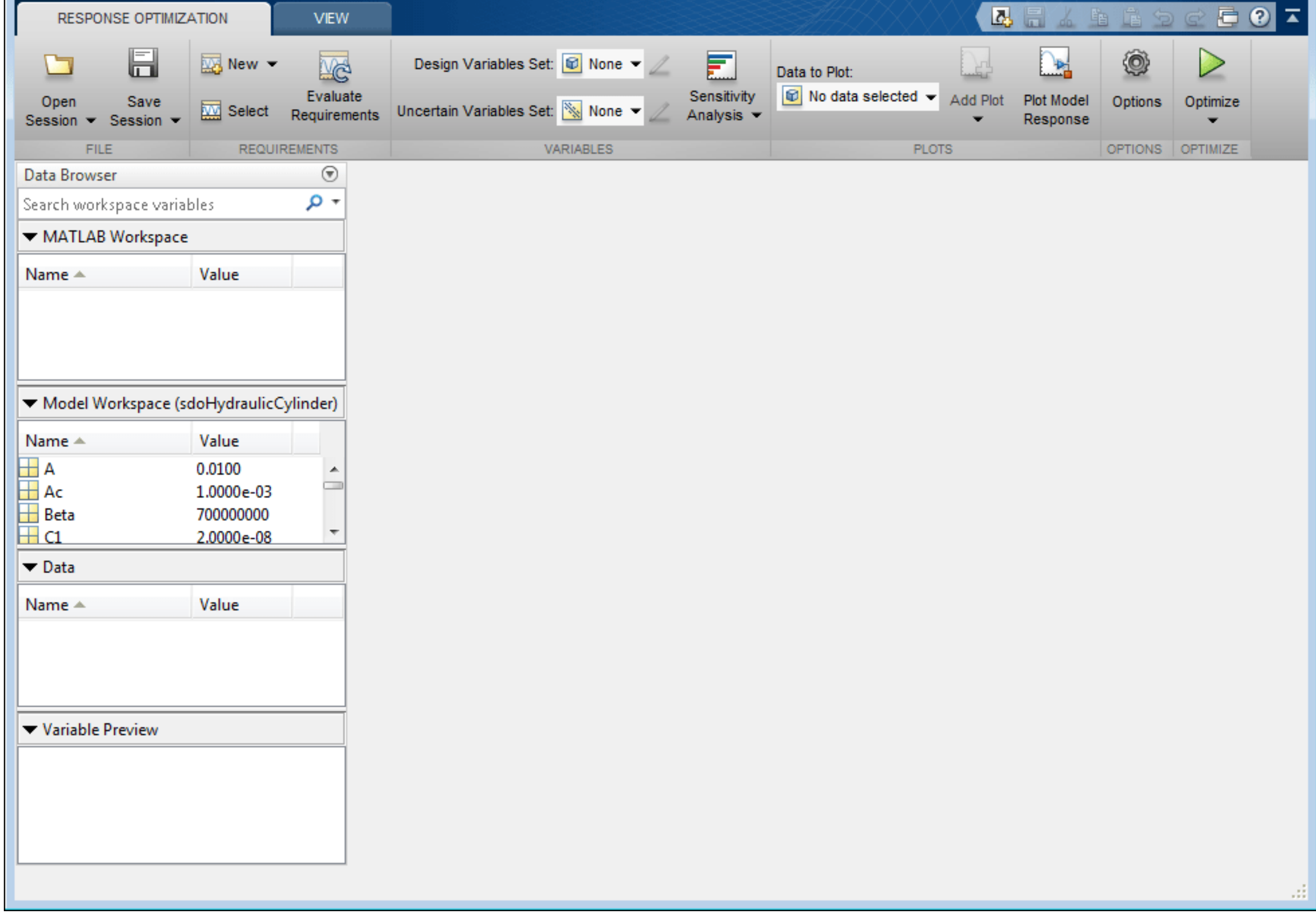
You tune the cylinder cross-sectional area and piston spring constant to meet the following design requirements:

- Ensure that the piston position has a step response rise time of less than 0.04 seconds and setting time of less than 0.05 seconds.
- Limit the maximum cylinder pressures to 1.75e6 N/m.
- Minimize the cylinder cross-sectional area.

Open the Response Optimizer

Open the **Response Optimizer** to configure and run design optimization problems interactively using the following command.

```
sdotool('sdoHydraulicCylinder')
```

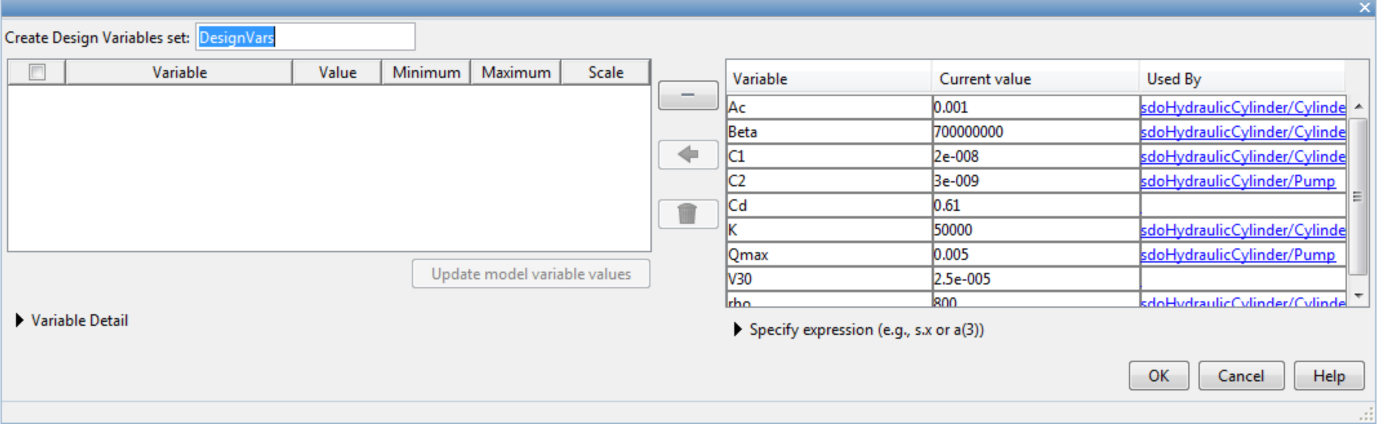


Specify Design Variables

Specify the following model parameters as design variables for optimization:

- Cylinder cross-sectional area Ac
- Piston spring constant K

In the **Design Variables Set** drop-down list, select **New**. A dialog to select model parameters for optimization opens.

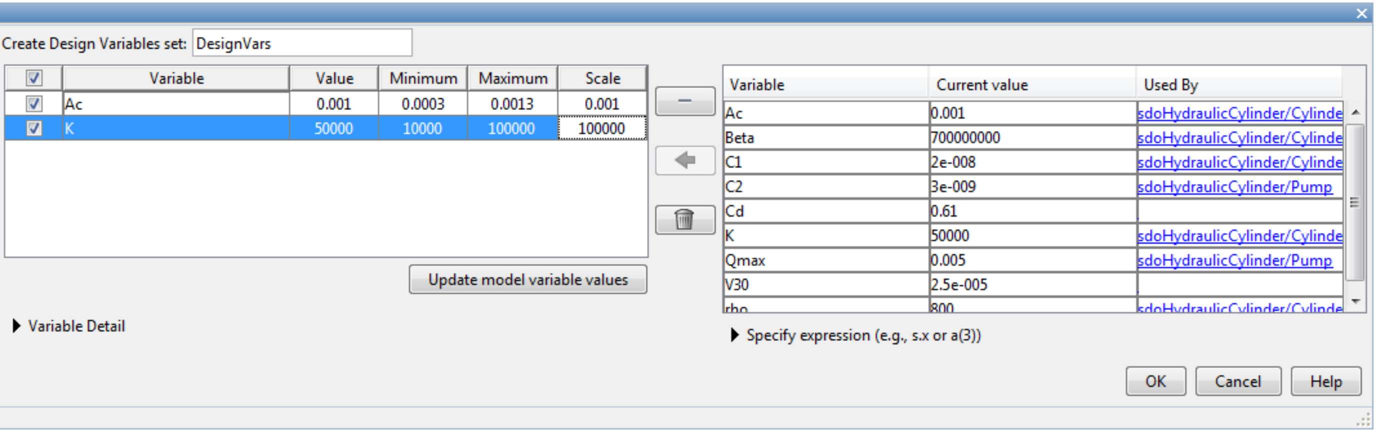


Select Ac and K. Click ⇦ to add the selected parameters to the design variables set.

Limit the cylinder cross-sectional area to circular area with radius between 1 and 2 centimeters and the piston spring constant to a range of 1e4 to 10e4 N/m. To do so, specify the maximum and minimum for the corresponding variable in the **Maximum** and **Minimum** columns.

Because the variable values are different orders of magnitude, scale Ac by 1e-3 and K by 1e5.

Press **Enter** after you specify the values.



Click **OK**. A new variable DesignVars appears in the **Response Optimizer** browser.

Specify Design Requirements

The design requirements require logged model signals. During optimization, the model is simulated using the current value of the design variables and the logged signal is used to evaluate the design requirements.

Log the cylinder pressures, which is the first output port of the Cylinder Assembly block.

In the **New** drop-down list, select **Signal**. A dialog to select model signals to log opens.

RESPONSE OPTIMIZATION VIEW

Open Session Save Session FILE

New

Design Variables Set: DesignVars

Sensitivity Analysis

Data to Plot: No data selected

Add Plot Plot Model Response PLOTS

Options OPTIONS

Optimize OPTIMIZE

Data Browser

Search workspace variab

MATLAB Workspace

Name

ans

Model Workspace (sd

Name

A

Ac

Beta

C1

Data

Name

DesignVars

Variable Preview

Damping Ratio
Specify a bound on the damping ratio of the poles of a linear system.

Natural Frequency
Specify a bound on the natural frequency of the poles of a linear system.

Settling Time
Specify an upper bound on the approximate settling time of a linear system.

Singular Value
Specify a piecewise linear bound on the singular values of a linear system.

Step Response Envelope
Specify bounds on the step response of a linear system.

Custom Requirement
Create a custom requirement.

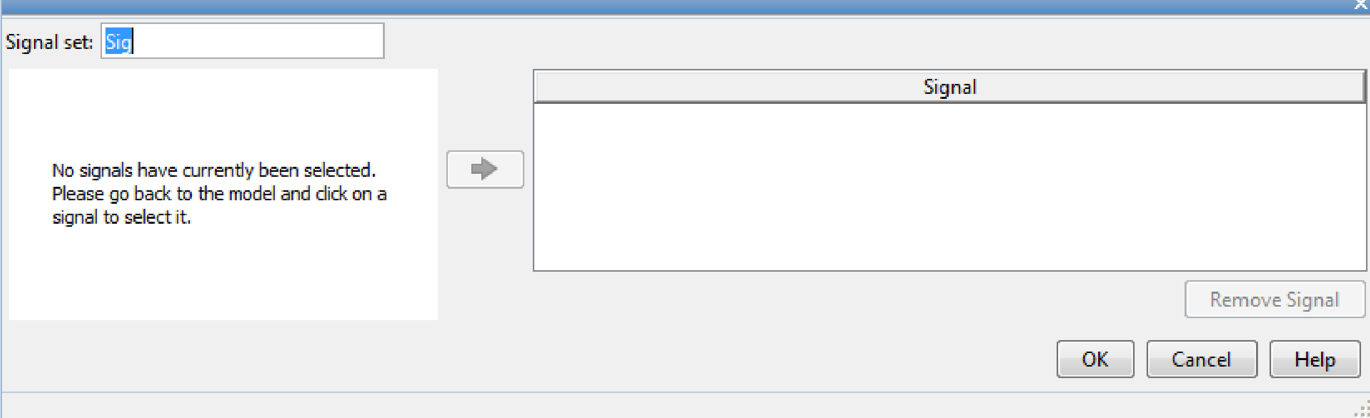
NEW REQUIREMENT SOURCE

Signal
Specify Simulink Signals to log so they can be used in design requirements.

Linearization I/Os
Specify Linearization I/Os so they can be used in design requirements.

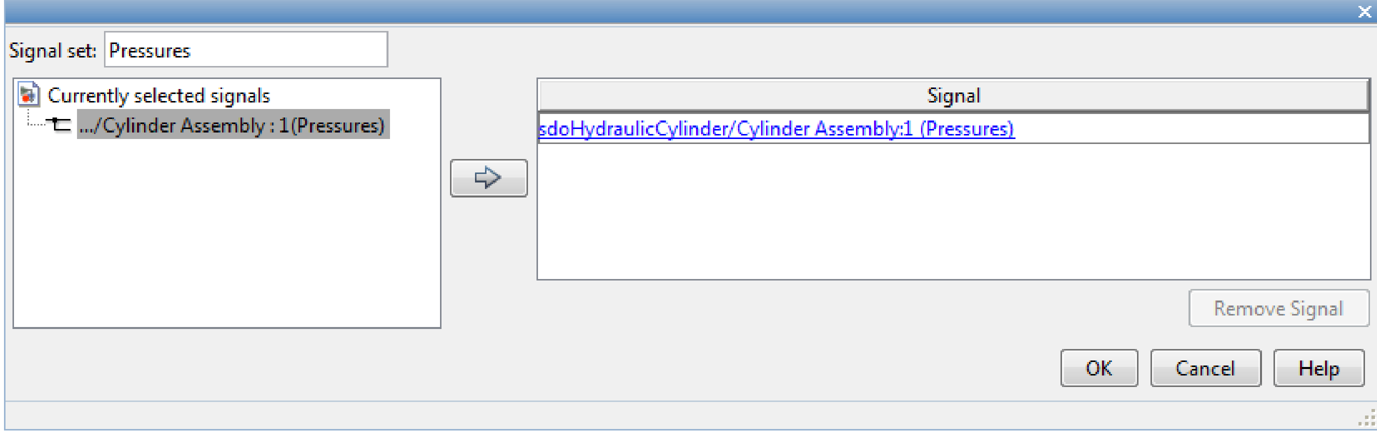
NEW REQUIREMENT USING MODEL BLOCKS

Time Domain Check Blocks
Open the Simulink Design Optimization library and add time domain check blocks to a Simulink model.



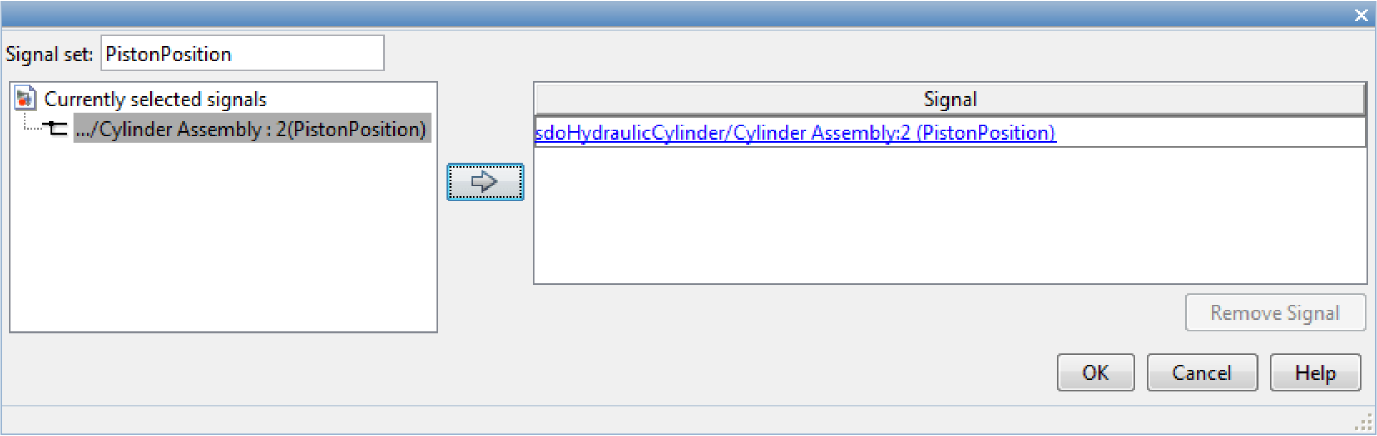
Enter `Pressures` as the signal name in the **Signal set** field. Then, in the Simulink model, click the first output port of the `Cylinder Assembly` block named `Pressure`. The dialog updates to display the selected signal.

Select the signal in the dialog and click ⇨ to add it to the signal set.



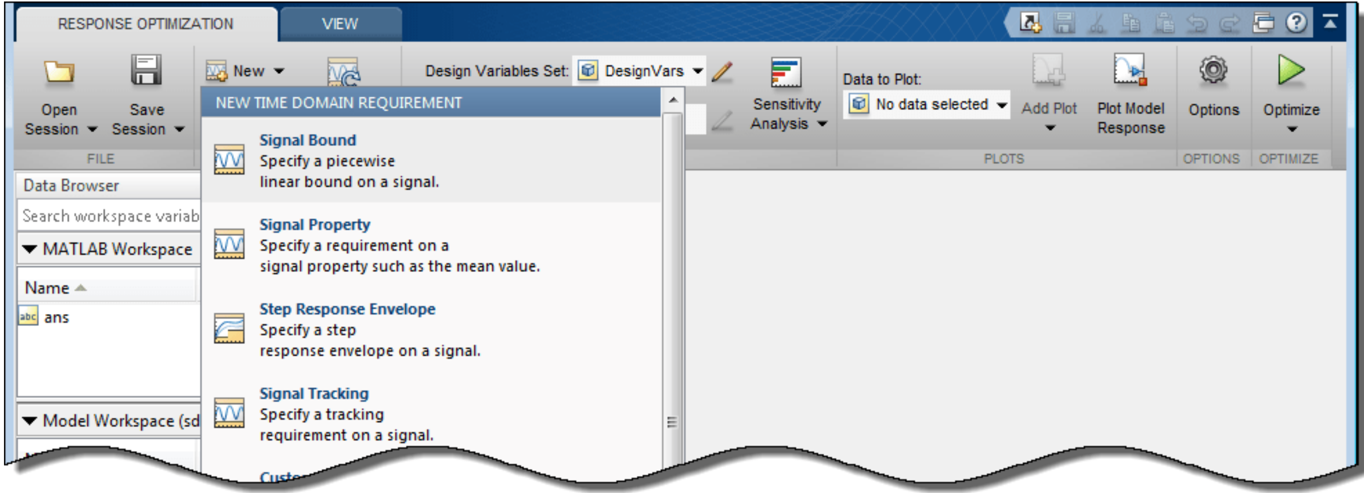
Click **OK**. A new variable **Pressures** appears in the **Response Optimizer** browser.

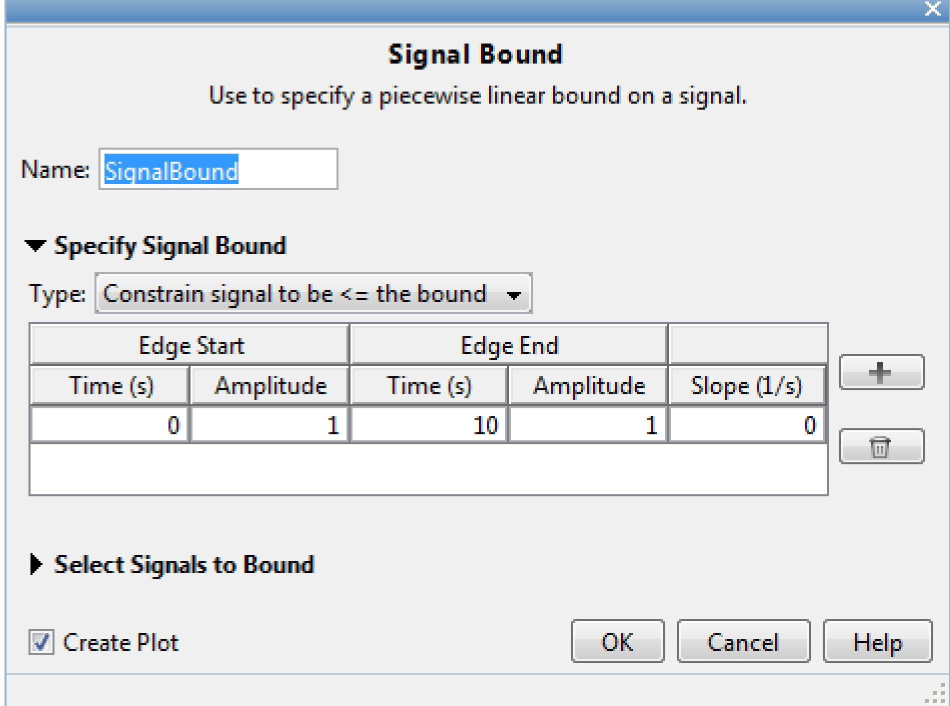
Similarly, log the piston position, which is the second output of the `Cylinder Assembly` block, in a variable named `PistonPosition`.



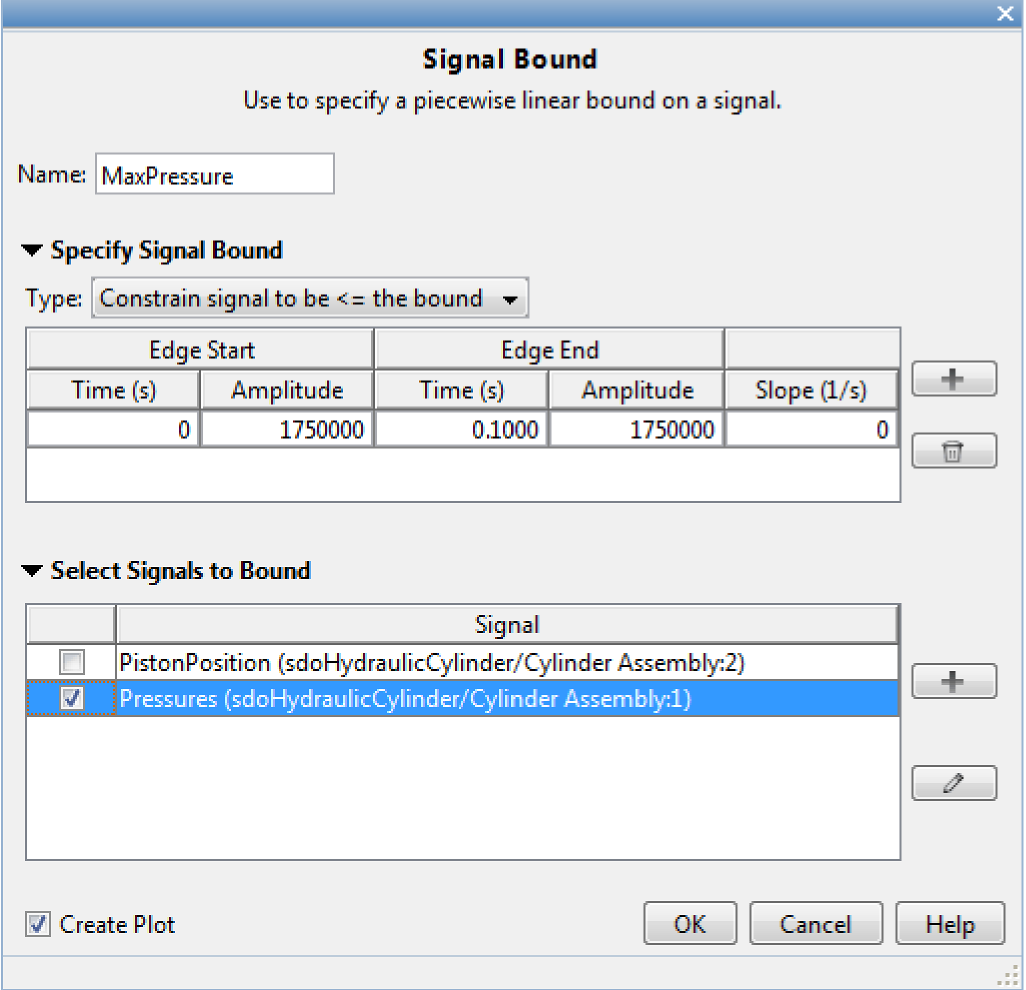
Specify the maximum cylinder pressure requirement of less than 1.75e6 N/m.

In the **New** drop-down list, select **Signal Bound**. A dialog to create a signal bound requirement opens.



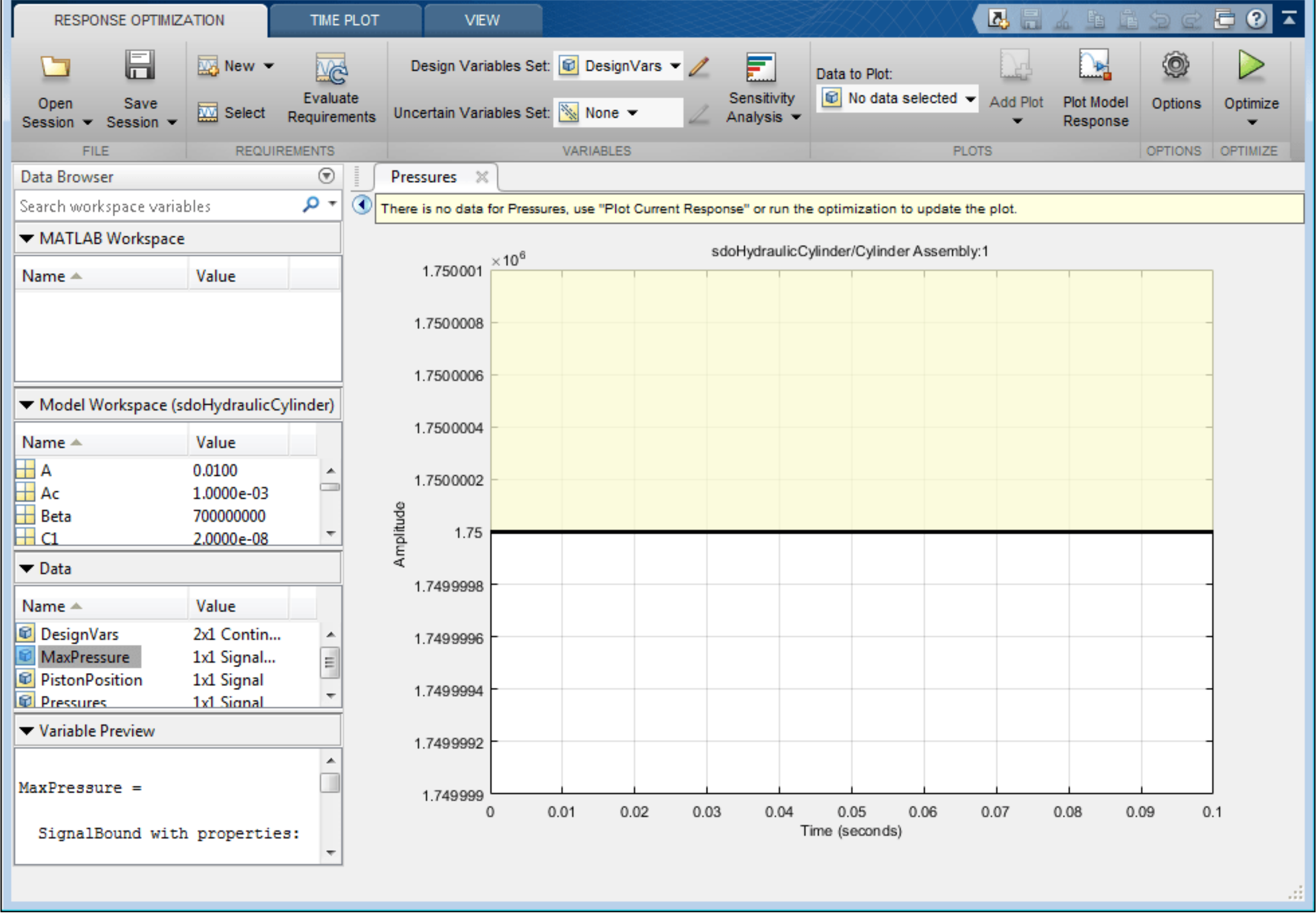


Designate the **Requirement Name** as `MaxPressure`. In both the start and end **Amplitude** columns, enter the maximum pressure requirement of 1.75e6 N/m, and set the **Edge End Time** to 0.1 s. In the **Select Signals to Bound** area, select `Pressures`, the signal on which this requirement applies.



Click **OK**.

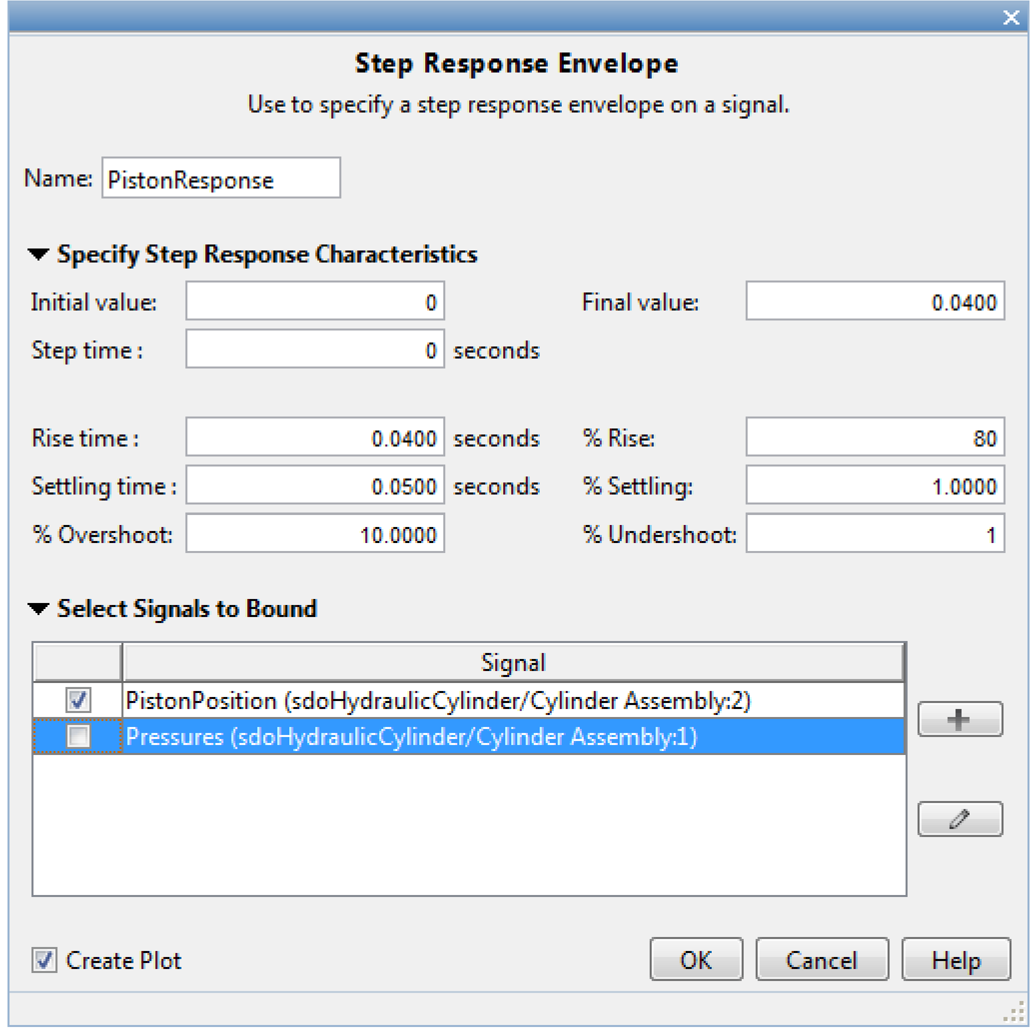
- A new `MaxPressure` variable appears in the **Response Optimizer** browser.
- A graphical view of the maximum pressure requirement is automatically created.



Specify the piston position step response requirement of rise time of less than 0.04 seconds and a settling time of less than 0.05 seconds.

In the **New** drop-down list of the **Response Optimization** tab, select **Step Response Envelope**. A dialog to create a step response requirement opens.

Specify a requirement named `PistonResponse`, and the required rise and settling time bounds. Select `PistonPosition` as the signal to apply the step response requirement to.

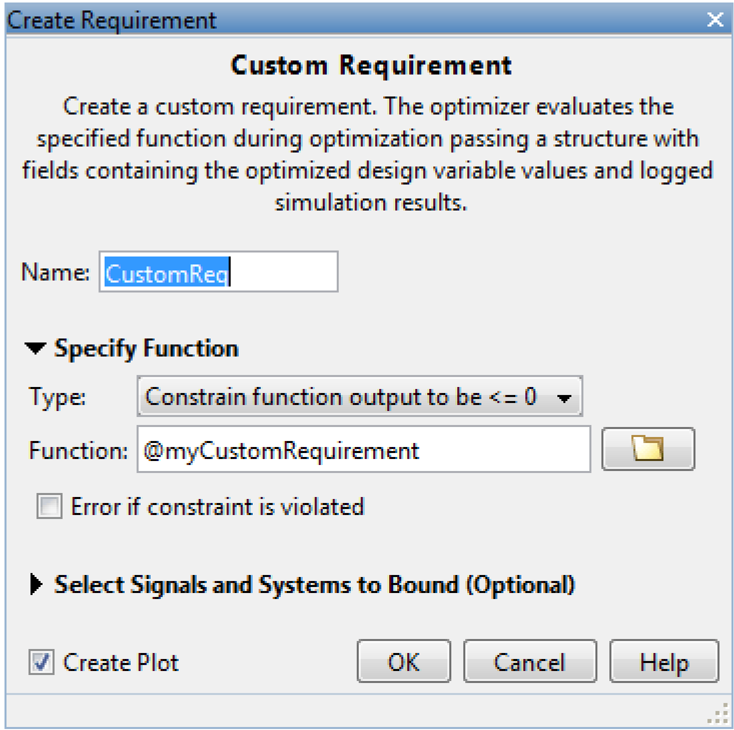


Click **OK**.

Specify Custom Objective

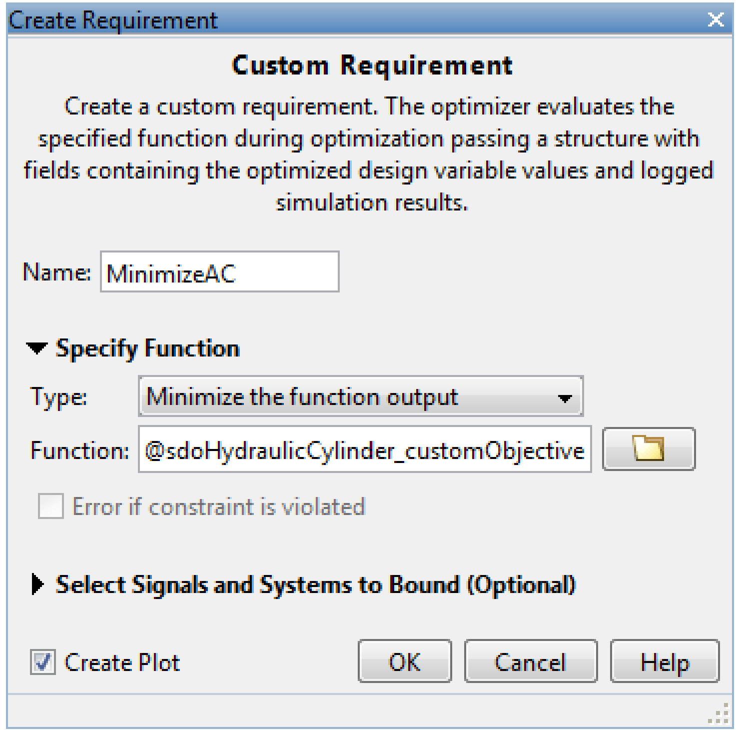
The custom objective is to minimize the cylinder cross-sectional area.

In the **New** drop-down list, select **Custom Requirement**. A dialog to create a custom requirement opens.



Specify a function to call during optimization in the **Requirement Function** field. At each optimization iteration, the software calls the function and passes the current design variable values. You can also optionally pass logged signals to the custom requirement. Here, you use `sdoHydraulicCylinder_customObjective` as the custom requirement function, which returns the value of the cylinder cross-sectional area.

In the **Requirement Type** drop-down list, specify whether the requirement is an objective to minimize (`min`), an inequality constraint (`<=`), or an equality constraint (`==`).




```
type sdoHydraulicCylinder_customObjective
```

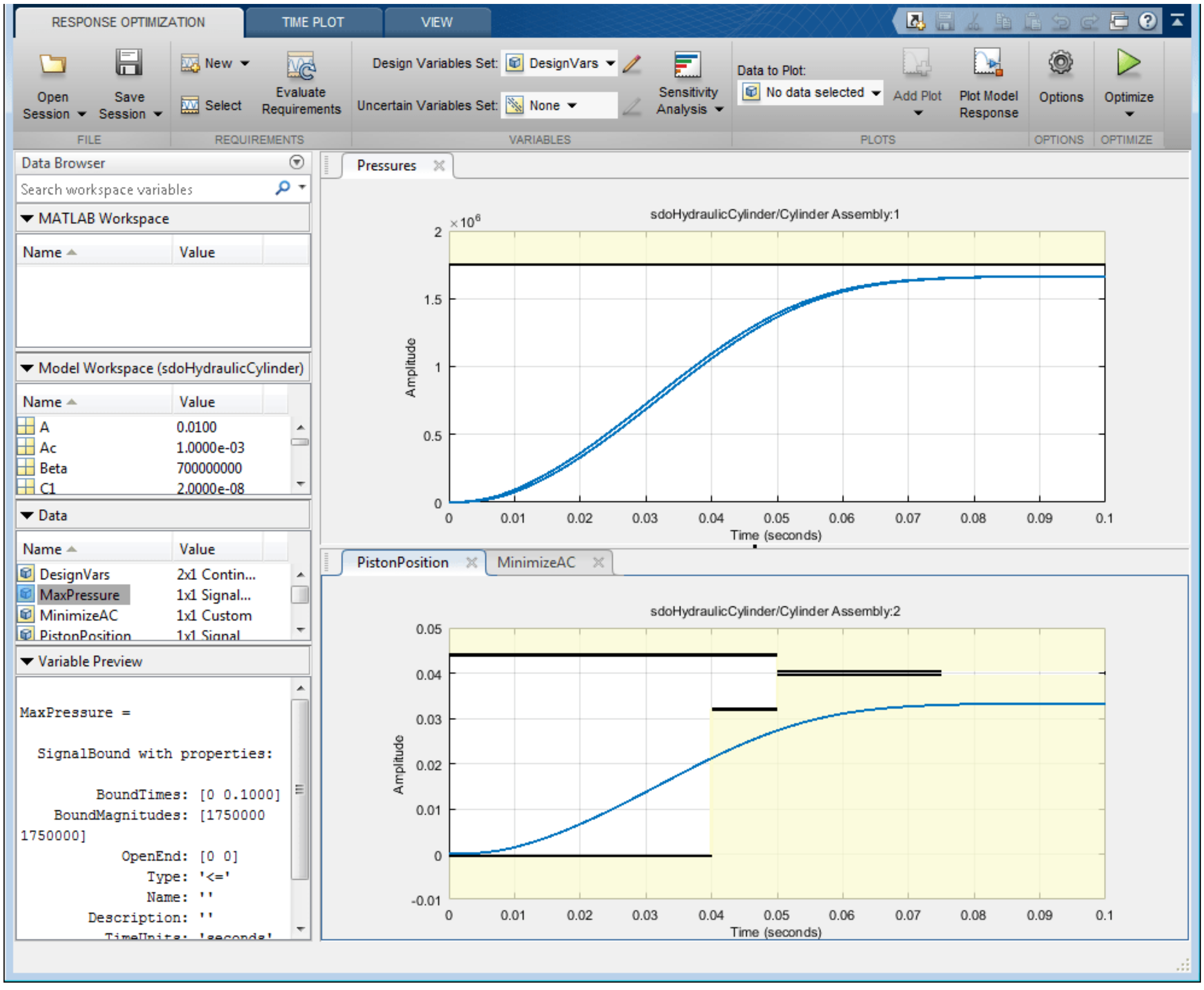
```
function objective = sdoHydraulicCylinder_customObjective(data)
%SDOHYDRAULICCYLINDER_CUSTOMOBJECTIVE
%
% The sdoHydraulicCylinder_customObjective function is used to define a
% custom requirement that can be used in the graphical SDTOOL environment.
%
% The |data| input argument is a structure with fields containing the
% design variable values chosen by the optimizer.
%
% The |objective| return argument is the objective value to be minimized by
% the SDOTOOL optimization solver.
%

% Copyright 2011 The MathWorks, Inc.

%For the cylinder design problem we want to minimize the cylinder
%cross-sectional area so return the cylinder cross-sectional area as an
%objective value.
Ac = data.DesignVars(1);
objective = Ac.Value;
end
```

Evaluate the Initial Design

Click **Plot Model Response** to simulate the model and check how well the initial design satisfies the design requirements. To show both requirement plots at the same time, use the plot layout widgets in the **View** tab.

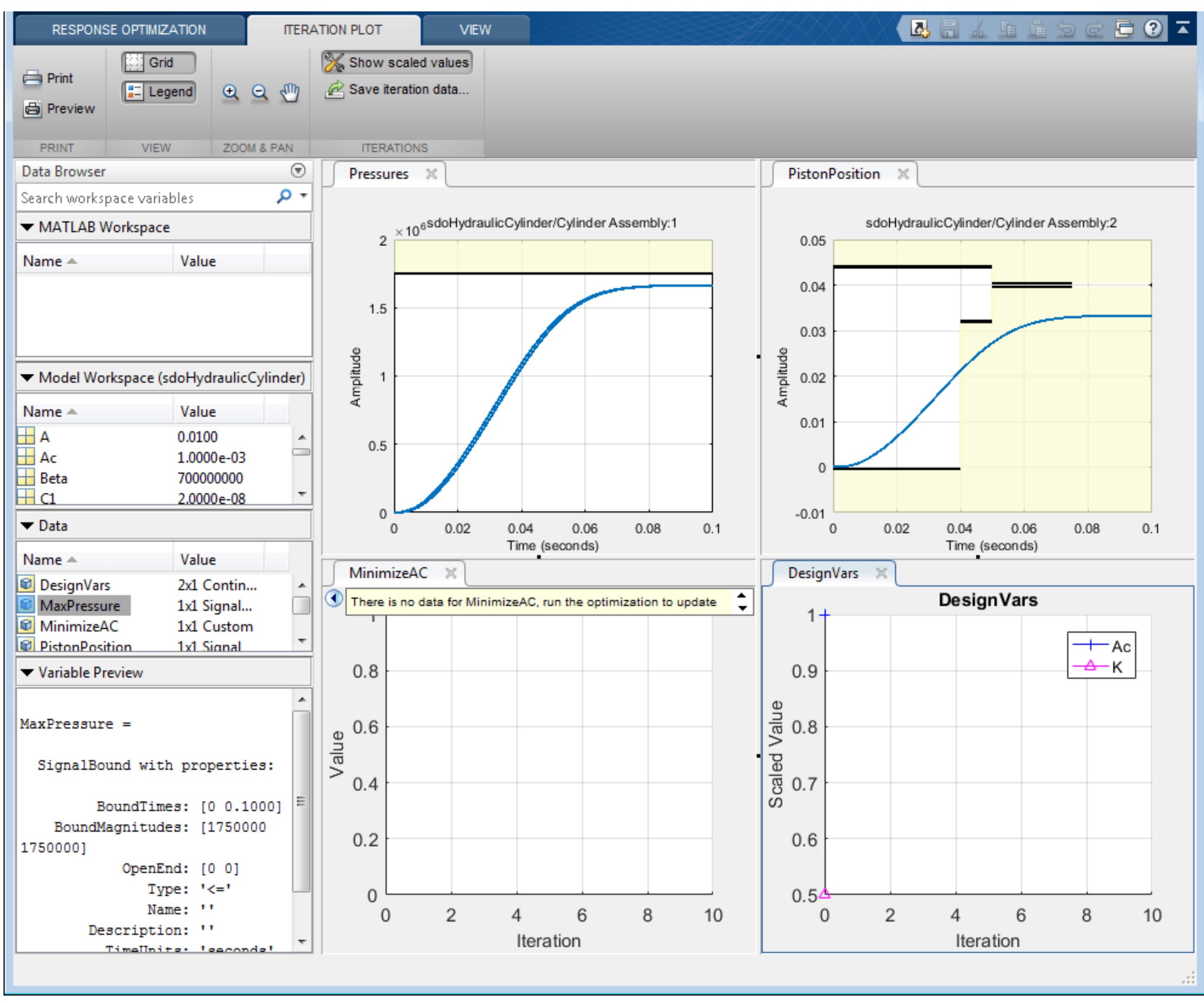


From the plots, see that the maximum pressure requirement is satisfied but the piston position step response requirement is not satisfied.

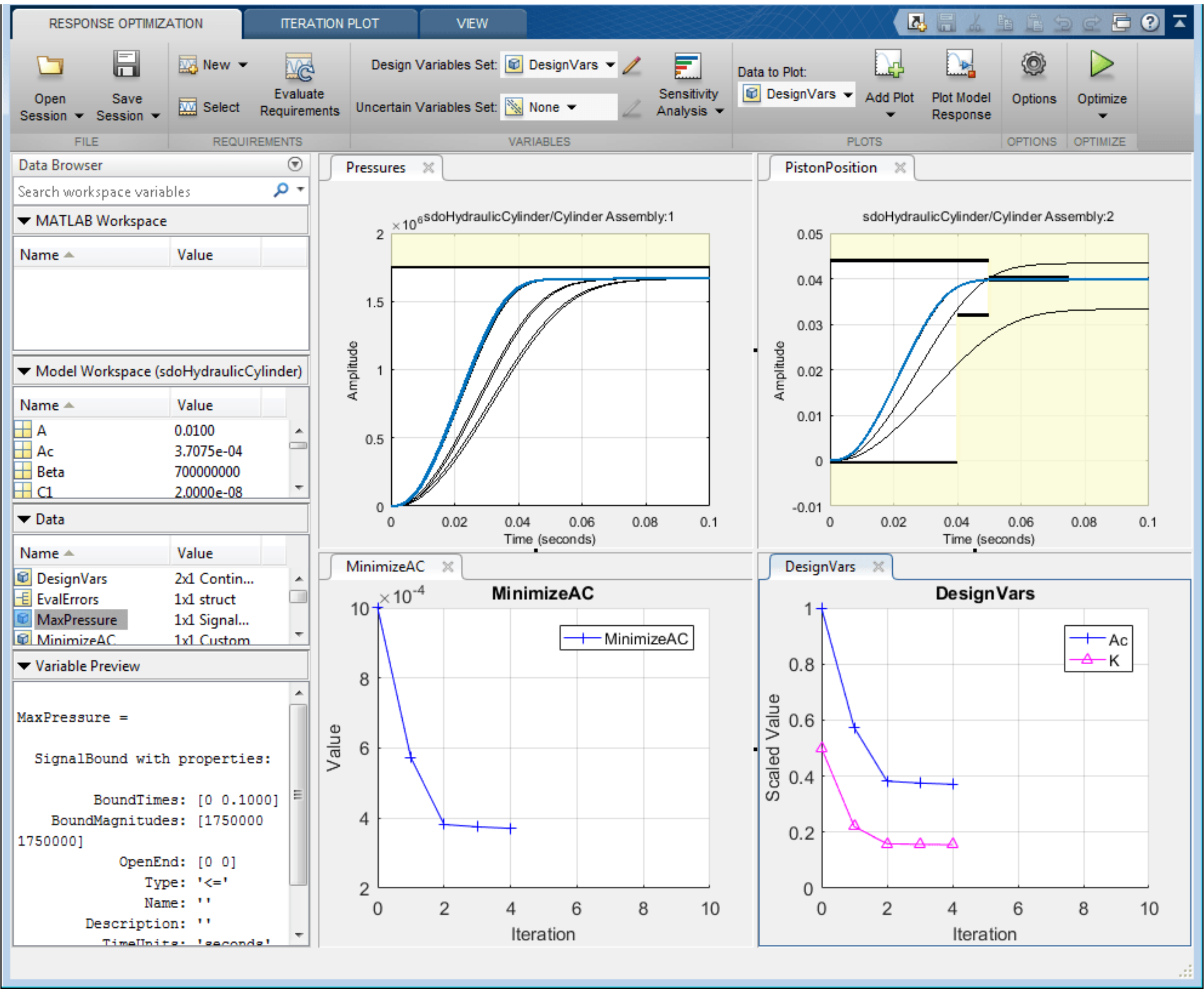
Optimize the Design

Create a plot to display how the cylinder cross-sectional area and piston spring constant are modified during optimization.

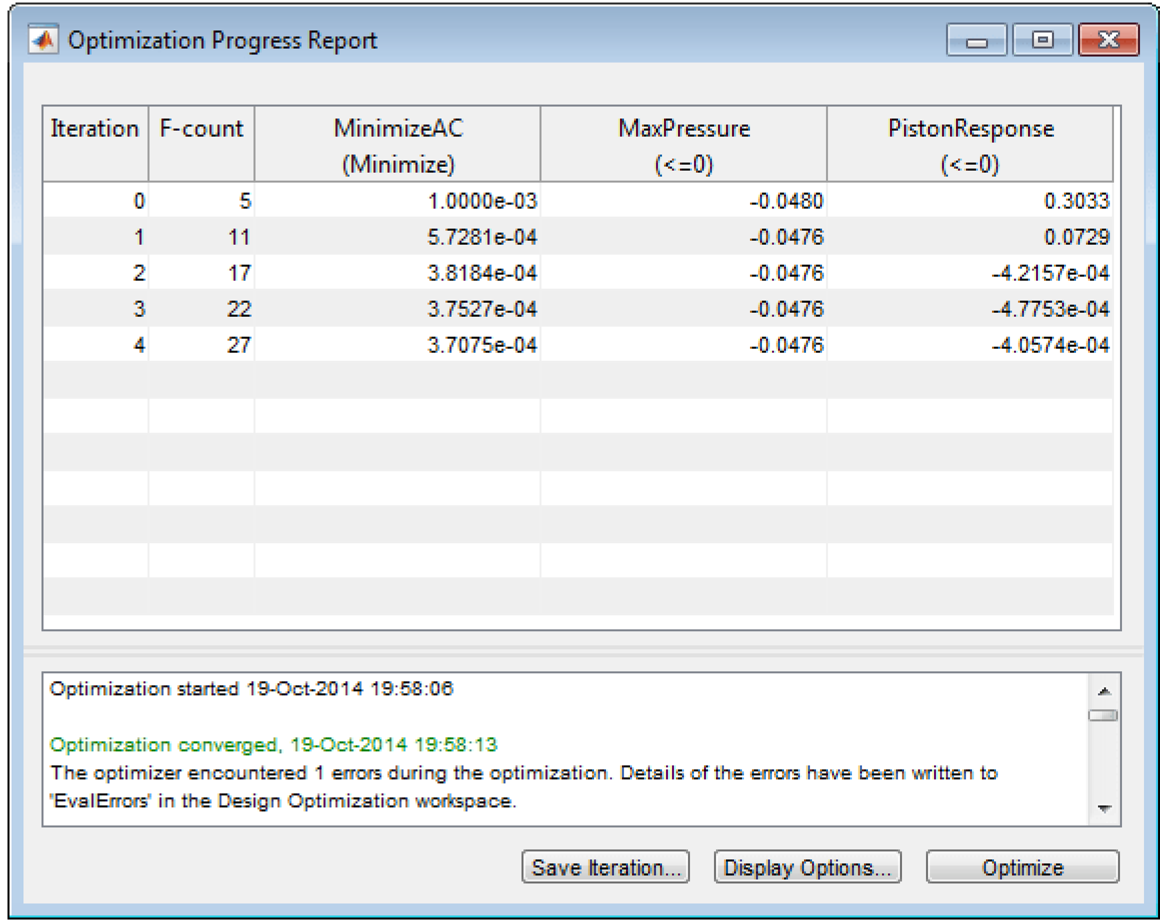
In the **Data to Plot** drop-down list, select **DesignVars**, which contains the optimization design variables Ac and K. In the **Add Plot** drop-down, create a new iteration plot to show the design variable trajectories. For this new plot, click **Show scaled values** in the **Iteration Plot** tab, to facilitate viewing the two trajectories on the same axes.



Click **Optimize** in the **Response Optimization** tab.



RESPONSE OPTIMIZATION
ITERATION PLOT
VIEW
Open Session
Save Session
New
Select
Evaluate Requirements
Design Variables Set: DesignVars
Uncertain Variables Set: None
Sensitivity Analysis
Data to Plot: DesignVars
Add Plot
Plot Model Response
Options
Optimize
FILE
REQUIREMENTS
VARIABLES
PLOTS
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
Model Workspace (sdoHydraulicCylinder)
A 0.0100
Ac 3.7075e-04
Beta 700000000
C1 2.0000e-08
Data
DesignVars 2x1 Contin...
EvalErrors 1x1 struct
MaxPressure 1x1 Signal...
MinimizeAC 1x1 Custom
Variable Preview
MaxPressure =
SignalBound with properties:
BoundTimes: [0 0.1000]
BoundMagnitudes: [1750000 1750000]
OpenEnd: [0 0]
Type: '<='
Name: ''
Description: ''
Pressures
sdoHydraulicCylinder/Cylinder Assembly:1
Amplitude
Time (seconds)
PistonPosition
sdoHydraulicCylinder/Cylinder Assembly:2
MinimizeAC
Value
Iteration
DesignVars
Scaled Value
Ac
K



The optimization progress window updates at each iteration and shows that the optimization converged after 4 iterations.

The `Pressures` and `PistonPosition` plots indicate that the design requirements are satisfied. The `MinimizeAC` plot shows that the cylinder cross-sectional area `Ac` is minimized.

To view the optimized design variable values, click the variable name in the **Response Optimizer** browser. The optimized values of the design variables are automatically updated in the Simulink model.

Related Examples

To learn how to optimize the cylinder design using the `sdo.optimize` command, see “Design Optimization to Meet a Custom Objective (Code)” on page 3-125.

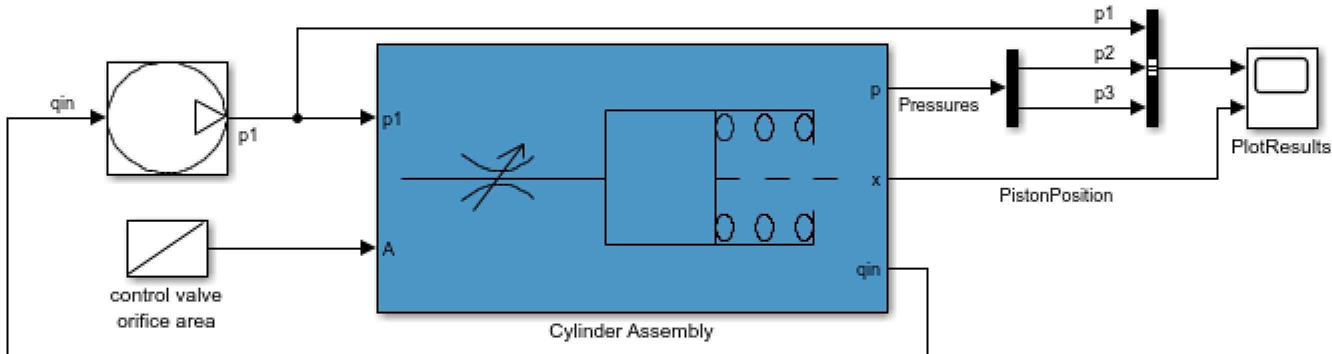
Design Optimization to Meet a Custom Objective (Code)

This example shows how to optimize a design to meet a custom objective using `sdo.optimize`. You optimize the cylinder parameters to minimize the cylinder geometry and satisfy design requirements.

Hydraulic Cylinder Model

Open the Simulink® model.

```
sys = 'sdoHydraulicCylinder';
open_system(sys);
```



The hydraulic cylinder model is based on the Simulink model `sldemo_hydcyl`. The model includes:

- `Pump` and `Cylinder Assembly` subsystems. For more information on the subsystems, see "Single Hydraulic Cylinder Simulation".
- A step change applied to the cylinder control valve orifice area that causes the cylinder piston position to change.

Hydraulic Cylinder Design Problem

You tune the cylinder cross-sectional area and piston spring constant to meet the following design requirements:

- Ensure that the piston position has a step response rise time of less than 0.04 seconds and setting time of less than 0.05 seconds.
- Limit the maximum cylinder pressures to 1.75e6 N/m.
- Minimize the cylinder cross-sectional area.

Specify Design Variables

Select the following model parameters as design variables for optimization:

- Cylinder cross-sectional area `Ac`
- Piston spring constant `K`

```
Ac = sdo.getParameterFromModel('sdoHydraulicCylinder','Ac');
K  = sdo.getParameterFromModel('sdoHydraulicCylinder','K');
```

Limit the cylinder cross-sectional area to a circular area with radius between 1 and 2 centimeters.

```
Ac.Minimum = pi*1e-2^2; % m^2
Ac.Maximum = pi*2e-2^2; % m^2
```

Limit the piston spring constant to a range of 1e4 to 10e4 N/m.

```
K.Minimum  = 1e4;       % N/m
K.Maximum  = 10e4;      % N/m
```

Specify Design Requirements

The design requirements require logged model signals. During optimization, the model is simulated using the current value of the design variables and the logged signal is used to evaluate the design requirements.

Log the following signals:

- Cylinder pressures, available at the first output port of the `Cylinder Assembly` block

```
Pressures = Simulink.SimulationData.SignalLoggingInfo;
Pressures.BlockPath       = 'sdoHydraulicCylinder/Cylinder Assembly';
Pressures.OutputPortIndex = 1;
```

- Piston position, available at the second output port of the `Cylinder Assembly` block

```
PistonPosition = Simulink.SimulationData.SignalLoggingInfo;
PistonPosition.BlockPath       = 'sdoHydraulicCylinder/Cylinder Assembly';
PistonPosition.OutputPortIndex = 2;
```

Create an object to store the logging information and use later to simulate the model

```
simulator = sdo.SimulationTest('sdoHydraulicCylinder');
simulator.LoggingInfo.Signals = [PistonPosition,Pressures];
```

Specify the piston position step response requirement of rise time of less than 0.04 seconds and settling time less than of 0.05 seconds.

```
PistonResponse = sdo.requirements.StepResponseEnvelope;
set(PistonResponse, ...
    'RiseTime',        0.04, ...
    'FinalValue',      0.04, ...
    'SettlingTime',    0.05, ...
    'PercentSettling', 1);
```

Specify the maximum cylinder pressure requirement of less than 1.75e6 N/m.

```
MaxPressure = sdo.requirements.SignalBound;
set(MaxPressure, ...
    'BoundTimes',      [0 0.1], ...
    'BoundMagnitudes', [1.75e6 1.75e6], ...
    'Type',            '<=');
```

For convenience, collect the performance requirements into a single structure to use later.

```
requirements = struct(...
    'PistonResponse', PistonResponse, ...
    'MaxPressure',    MaxPressure);
```

Create Objective/Constraint Function

To optimize the cylinder cross-sectional area and piston spring constant, create a function to evaluate the cylinder design. This function is called at each optimization iteration.

Here, use an anonymous function with one argument that calls the `sdoHydraulicCylinder_design` function.

```
evalDesign = @(p) sdoHydraulicCylinder_design(p,simulator,requirements);
```

The function:

- Has one input argument that specifies the cylinder cross-sectional area and piston spring constant values.
- Returns the optimization objective value and optimization constraint violation values.

The optimization solver minimizes the objective value and attempts to keep the optimization constraint violation values negative. Type `help sdoExampleCostFunction` for more details on how to write the objective/constraint function.

The `sdoHydraulicCylinder_design` function uses the `simulator` and `requirements` objects to evaluate the design. Type `edit sdoHydraulicCylinder_design` to examine the function in more detail.

```
type sdoHydraulicCylinder_design
```

```
function design = sdoHydraulicCylinder_design(p,simulator,requirements)
%SDOHYDRAULICCYLINDER_DESIGN
%
% The sdoHydraulicCylinder_design function is used to evaluate a cylinder
% design.
%
% The |p| input argument is the vector of cylinder design parameters.
%
% The |simulator| input argument is a sdo.SimulinkTest object used to
% simulate the |sdoHydraulicCylinder| model and log simulation signals
%
% The |requirements| input argument contains the design requirements used
% to evaluate the cylinder design
%
% The |design| return argument contains information about the design
% evaluation that can be used by the |sdo.optimize| function to optimize
% the design.
%
% see also sdo.optimize, sdoExampleCostFunction

% Copyright 2011 The MathWorks, Inc.

%% Simulate the model
%
```

```
% Use the simulator input argument to simulate the model and log model
% signals.
%
% First ensure that we simulate the model with the parameter values chosen
% by the optimizer.
%
simulator.Parameters = p;
% Simulate the model and log signals.
%
simulator = sim(simulator);
% Get the simulation signal log, the simulation log name is defined by the
% model |SignalLoggingName| property
%
logName = get_param('sdoHydraulicCylinder','SignalLoggingName');
simLog = get(simulator.LoggedData,logName);

%% Evaluate the design requirements
%
% Use the requirements input argument to evaluate the design requirements
%
% Check the PistonPosition signal against the stepresponse requirement
%
PistonPosition = get(simLog,'PistonPosition');
cPiston = evalRequirement(requirements.PistonResponse,PistonPosition.Values);
% Check the Pressure signals against the maximum requirement
%
Pressures = find(simLog,'Pressures');
cPressure = evalRequirement(requirements.MaxPressure,Pressures.Values);
% Use the PistonResponse and MaxPressure requirements as non-linear
% constraints for optimization.
design.Cleq = [cPiston(:);cPressure(:)];
% Add design objective to minimize the Cylinder cross-sectional area
Ac = p(1);          %Since we called sdo.optimize(evalDesign,[Ac;K])
design.F = Ac.Value;
end
```

Evaluate the Initial Design

Call the objective function with the initial cylinder cross-sectional area and initial piston spring constant.

```
initDesign = evalDesign([Ac;K]);
```

The function simulates the model and evaluates the design requirements. The scope shows that the maximum pressure requirement is satisfied but the piston position step response requirement is not satisfied.

`initDesign` is a structure with the following fields:

- `Cleq` shows that some of the inequality constraints are positive indicating they are not satisfied by the initial design.

```
initDesign.Cleq
```

```
ans =

   -0.3839
```

```
   -0.1861
   -0.1836
   -1.0000
    0.3033
    0.2909
    0.1671
    0.2326
   -0.0480
   -0.0480
```

- F shows the optimization objective value (in this case the cylinder cross-sectional area). The initial design cross-sectional area, as expected, has the same value as the initial cross-sectional area parameter Ac.

```
initDesign.F
```

```
ans =

   1.0000e-03
```

Optimize the Design

Pass the objective function, initial cross-sectional area and piston spring constant values to sdo.optimize.

```
[pOpt,optInfo] = sdo.optimize(evalDesign,[Ac;K]);
```

```
 Optimization started 01-Sep-2022 13:53:02

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      5        0.001       0.3033
    1     11   0.00057281      0.07293         0.48         85.4
    2     17  0.000391755            0        0.128           28
    3     22  0.000387625            0      0.00291      0.00459
    4     27  0.000382932            0      0.00331      0.00187
    5     32  0.000378204            0      0.00331     0.000219
Local minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the value of the optimality tolerance,
and constraints are satisfied to within the value of the constraint tolerance.
```

The optimization repeatedly evaluates the cylinder design by adjusting the cross-sectional area and piston spring constant to meet the design requirements. From the scope, see that the maximum pressure and piston response requirements are met.

The sdo.optimize function returns:

- pOpt shows the optimized cross-sectional area and piston spring constant values.

```
pOpt
```

```
pOpt(1,1) =
```

```
       Name: 'Ac'
      Value: 3.7820e-04
    Minimum: 3.1416e-04
    Maximum: 0.0013
       Free: 1
      Scale: 0.0020
       Info: [1x1 struct]


pOpt(2,1) =

       Name: 'K'
      Value: 1.5809e+04
    Minimum: 10000
    Maximum: 100000
       Free: 1
      Scale: 65536
       Info: [1x1 struct]


2x1 param.Continuous
```

- `optInfo` is a structure that contains optimization termination information such as number of optimization iterations and the optimized design.

```
optInfo
```

```
optInfo =

  struct with fields:

            Cleq: [10x1 double]
               F: 3.7820e-04
       Gradients: [1x1 struct]
        exitflag: 1
      iterations: 5
    SolverOutput: [1x1 struct]
           Stats: [1x1 struct]
```

For example, the `Cleq` field shows the optimized non-linear inequality constraints are all non-positive to within optimization tolerances, indicating that the maximum pressure and piston response requirements are satisfied.

```
optInfo.Cleq
```

```
ans =

   -0.0972
   -0.0131
   -0.0131
   -1.0000
   -0.2064
   -0.0047
```

```
   -0.0069
   -0.0004
   -0.0476
   -0.0476
```

The `F` field contains the optimized cross-sectional area. The optimized cross-sectional area value is nearly 50% less that the initial value.

```
optInfo.F
```

```
ans =

   3.7820e-04
```

Update the Model Variable Values

By default, the model variables `Ac` and `K` are not updated at the end of optimization. Use the `setValueInModel` command to update the model variable values.

```
sdo.setValueInModel('sdoHydraulicCylinder',pOpt)
```

Related Examples

To learn how to optimize the cylinder design using the **Response Optimizer**, see “Design Optimization to Meet a Custom Objective (GUI)” on page 3-110.

```
% Close the model
bdclose('sdoHydraulicCylinder')
```

See Also

`sdo.optimize` | `sdo.getValueFromModel` | `sdo.getParameterFromModel`

Related Examples

- “Discrete-Valued Variables in Response Optimization (Code)” on page 3-88

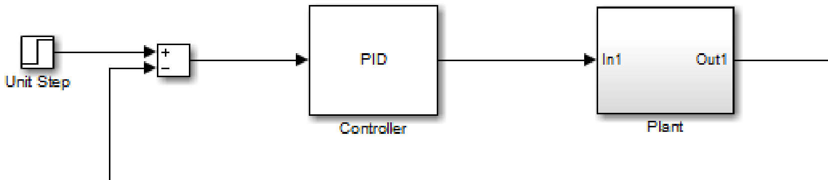
Design Optimization to Meet Custom Signal Requirements (GUI)

This example shows how to optimize a design to meet a custom signal requirement. You optimize the controller parameters to minimize the plant actuation signal energy while satisfying step response requirements.

1 Load a saved **Response Optimizer** session.

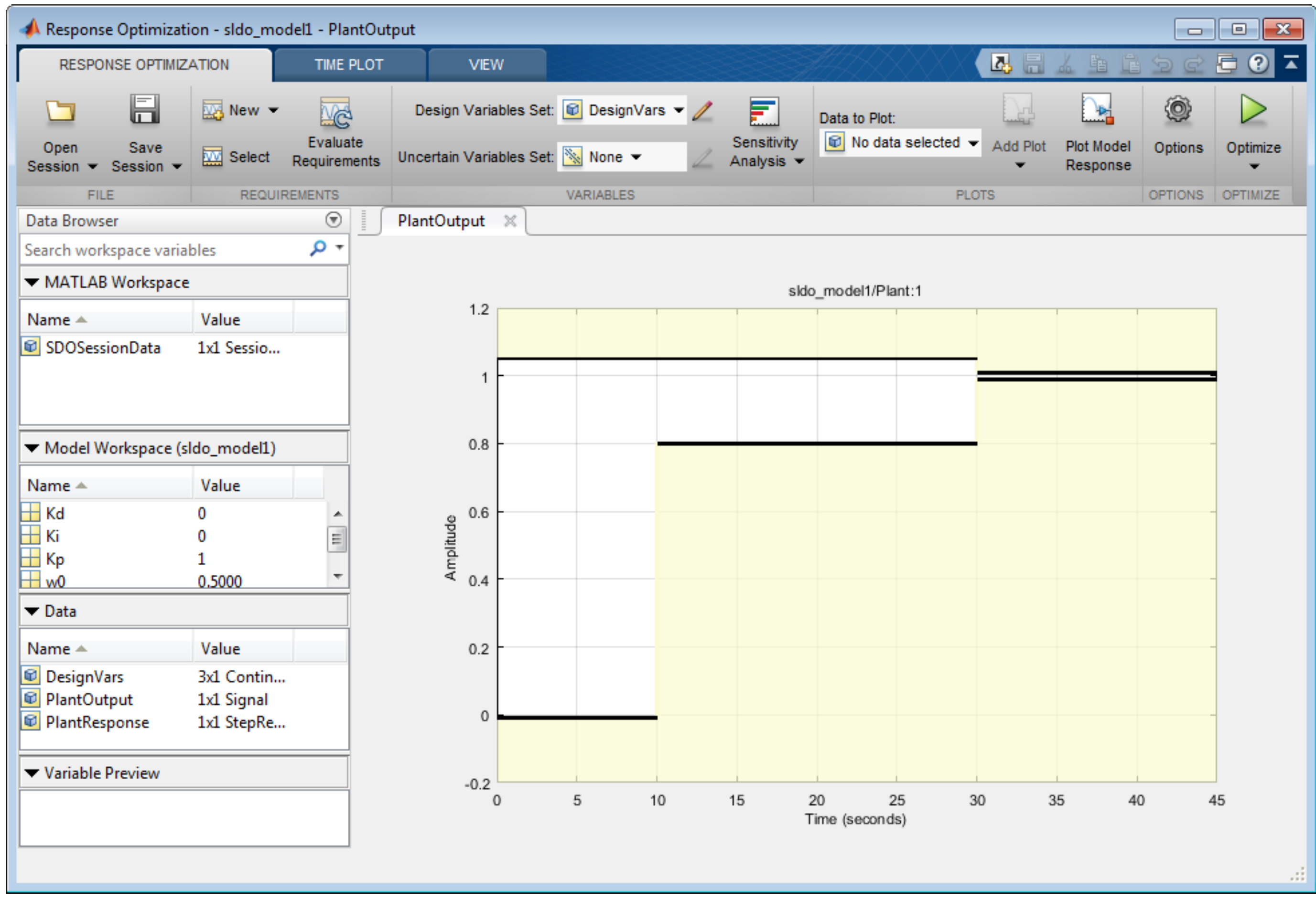
```
load sldo_model1_custom_signal_session
sdotool(SDOSessionData);
```

The following Simulink model opens.



The **Response Optimizer**, configured with the following settings, also opens:

- Step response characteristics, specified on the output of the `Plant` block, that the model output must satisfy:
  - Maximum overshoot of 5%
  - Maximum rise time of 10 seconds
  - Maximum settling time of 30 seconds
- Design variable set with the controller parameters `Kp`, `Ki` and `Kd`. These parameters have a minimum value of 0.
- The variables for step requirements (`PlantResponse`), logged signal (`PlantOutput`) and design variables (`DesignVars`) which appear in the **Data** area.



2 Specify a signal to log. You apply the custom requirement on this logged signal.

a Select **New** > **Signal**.

A window opens where you select a signal to log.

b In the Simulink model window, click the output of the `Controller` block.

The window updates to display the selected signal.

c Select the signal and click [button] to add it to the signal set.

d In **Signal set**, enter `PlantActuator`.

Click **OK**. A new variable `PlantActuator` appears in the **Data** area.

3 Specify the custom requirement to apply to the signal.

The custom requirement calls the objective function `sldo_model1_minimize_energy` which returns the energy in the `PlantActuator` signal. The signal energy is minimized. This function accepts:

- An input argument `data` which is a structure with fields for the design variables in the **Data** area. Signals are logged for the nominal and uncertain parameter values if there are any.
- Returns the objective value to be minimized.

Tip To see the contents of this function, type `edit sldo_model1_minimize_energy`.

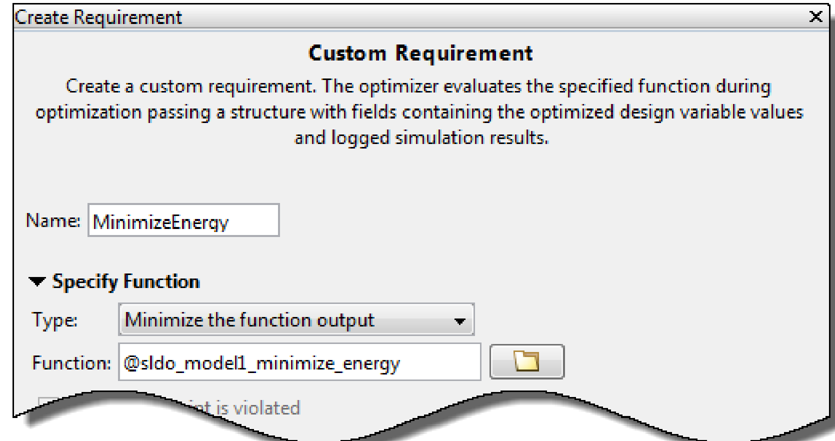
a. Select **New** > **Custom Requirement**.

   A window opens where you specify the custom requirement.

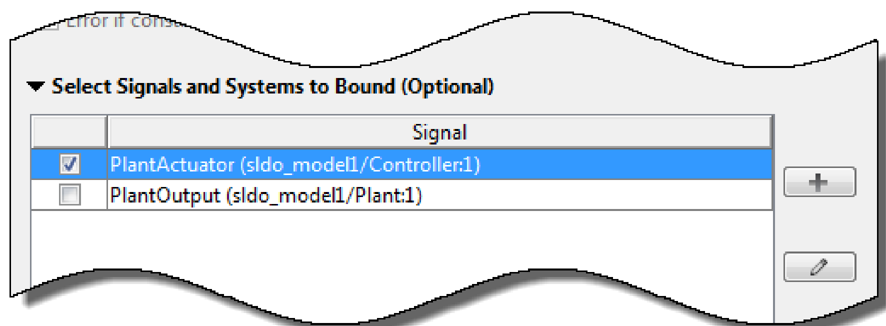
b. Specify `MinimizeEnergy` as the **Name**.

c. Specify `@sldo_model1_minimize_energy` as the **Function**.

d. Select `Minimize the function output` as the **Type**.

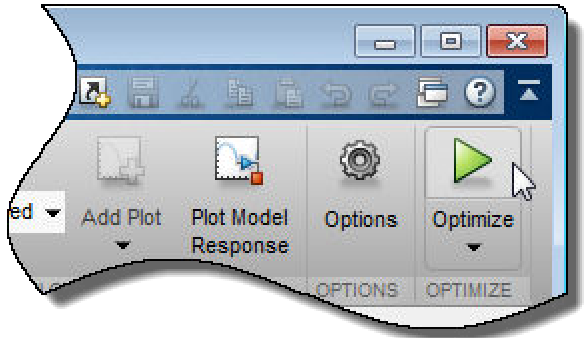


4. In the **Select Signals and Systems to Bound** area, select the `PlantActuator` check box to associate the custom requirement with that signal.

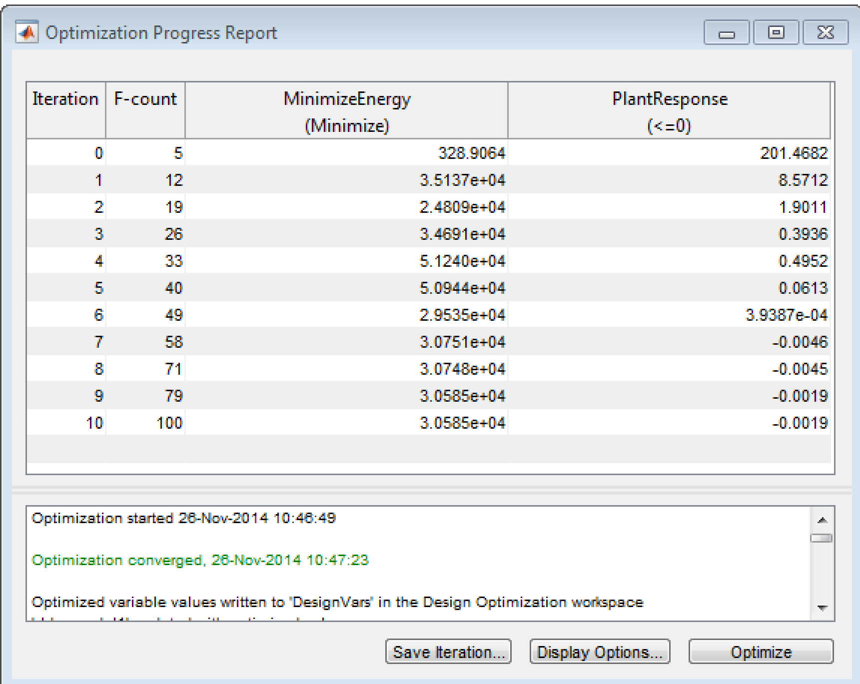


   Click **OK**. A new variable appears in the **Data** area of the app. The window also updates to graphically display the custom signal requirement.

5. Click **Optimize**.



After a few iterations, the optimization converges to meet both the custom signal and step response requirements.



Iteration	F-count	MinimizeEnergy (Minimize)	PlantResponse (<=0)
0	5	328.9064	201.4682
1	12	3.5137e+04	8.5712
2	19	2.4809e+04	1.9011
3	26	3.4691e+04	0.3936
4	33	5.1240e+04	0.4952
5	40	5.0944e+04	0.0613
6	49	2.9535e+04	3.9387e-04
7	58	3.0751e+04	-0.0046
8	71	3.0748e+04	-0.0045
9	79	3.0585e+04	-0.0019
10	100	3.0585e+04	-0.0019

6 Close the model.

```
setOption(sdotool('sldo_model1'),'NoPromptClose',true)
bdclose('sldo_model1')
```

See Also

Related Examples

- “Design Optimization Using Frequency-Domain Check Blocks (GUI)”

Design Optimization to Meet Frequency-Domain Requirements (GUI)

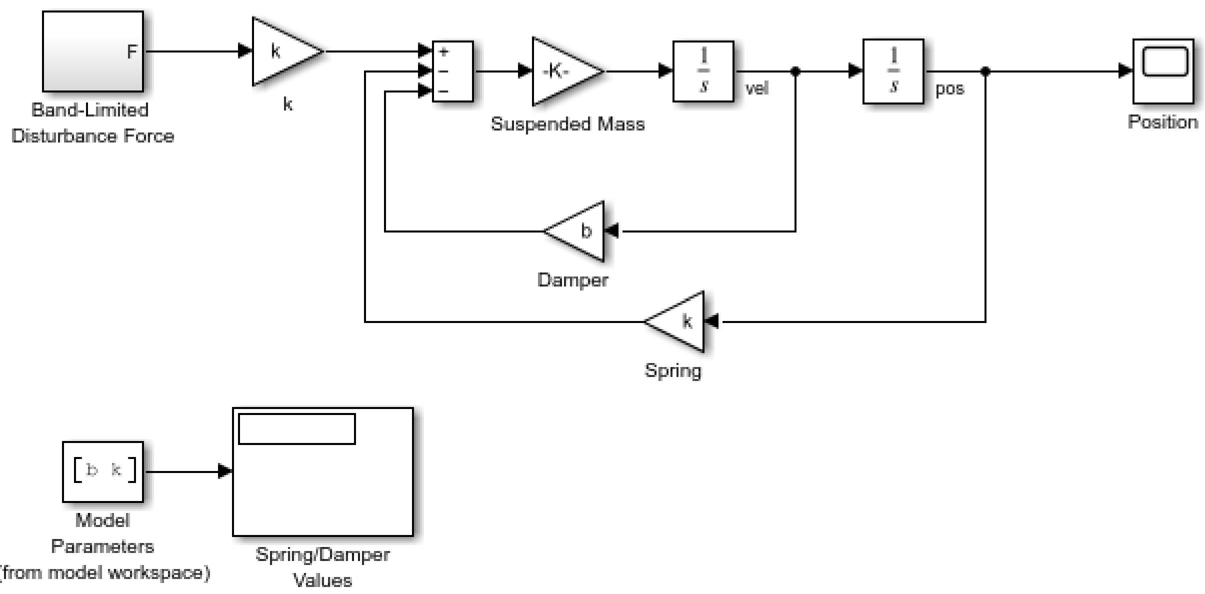
This example shows how to tune model parameters to meet frequency-domain requirements using the **Response Optimizer** app.

This example requires Simulink® Control Design™.

Suspension Model

Open the Simulink model.

```
open_system('sdoSimpleSuspension')
```

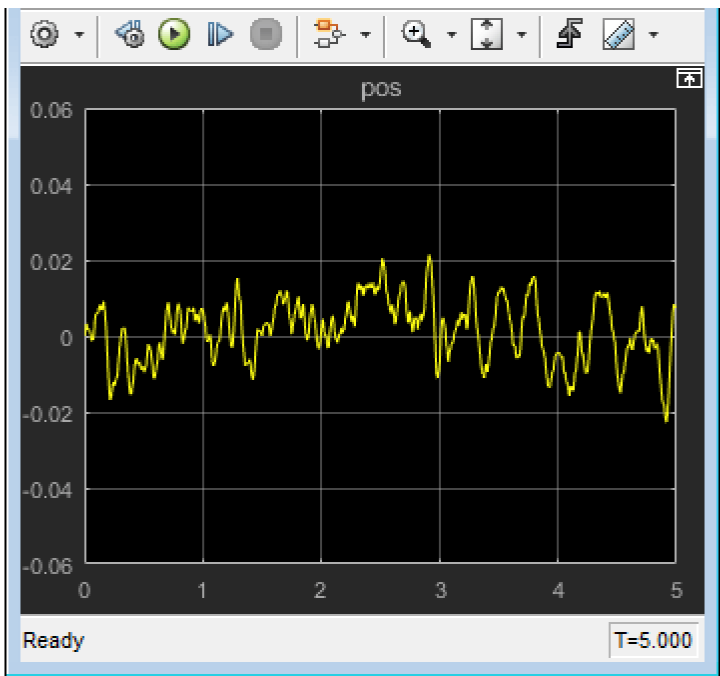


Mass-spring-damper models represent simple suspension systems and for this example you tune the system to meet typical suspension requirements. The model implements the second order system representing a mass-spring-damper using Simulink blocks and includes:

- a `Mass` gain block parameterized by the total suspended mass, `m0+mLoad`. The total mass is the sum of a nominal mass,|m0|, and a variable load mass, `mLoad`.
- a `Damper` gain block parameterized by the damping coefficient, `b`.
- a `Spring` gain block parameterized by the spring constant, `k`.
- two integrator blocks to compute the mass velocity and position.

- a `Band-Limited Disturbance Force` block applying a disturbance force to the mass. The disturbance force is assumed to be band-limited white noise.

Simulate the model to view the system response to the applied disturbance force.



Design Problem

The initial system has a bandwidth that is too high. This can be seen from the spiky position signal. You tune the spring and damper values to meet the following requirements:

- The -3dB system bandwidth must not exceed 10 rad/s.
- The damping ratio of the system must be less than 1/sqrt(2). This ensures that no frequencies in pass band are amplified by the system.
- Minimize the expected failure rate of the system. The expected failure rate is described by a Weibull distribution dependent on the mass, spring, and damper values.
- These requirements must all be satisfied as the load mass ranges from 0 to 20.

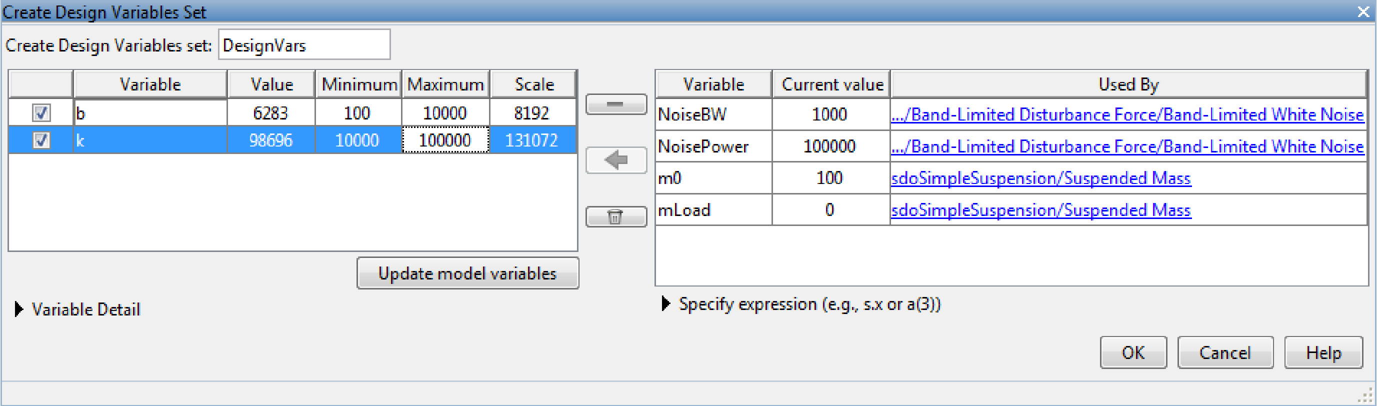
Open the Response Optimizer

In the **Apps** tab, click **Response Optimizer** under **Control Systems**.

Specify Design Variables

In the **Design Variables Set** list, select **New**. Add the `b` and `k` model variables to the design variable set.

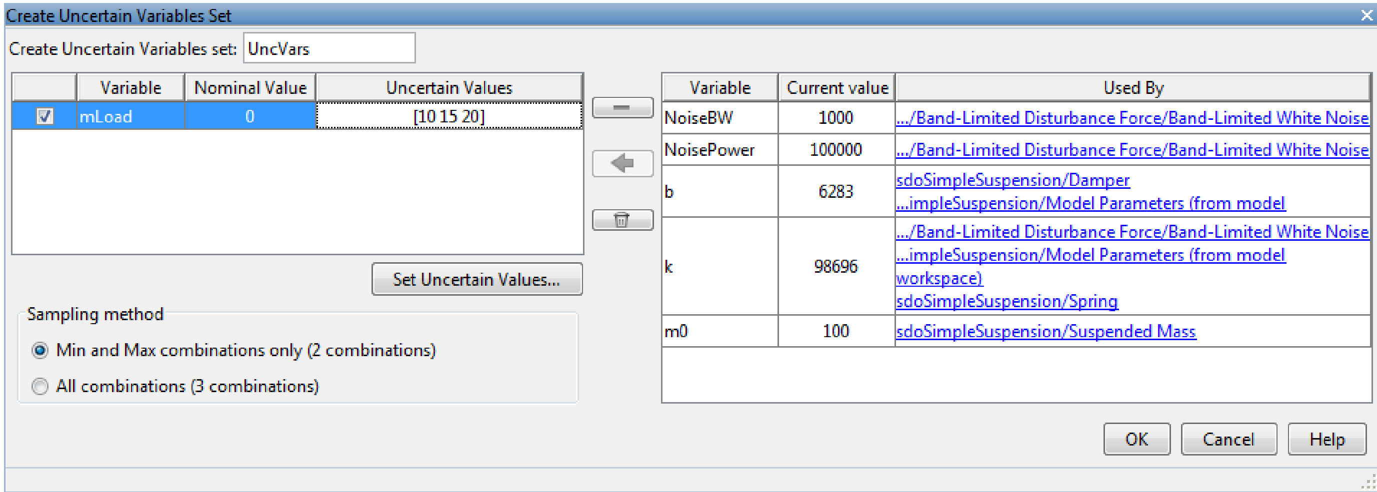
- Specify the `Minimum` and `Maximum` values for the `b` variable as 100 and 10000 respectively.
- Specify the `Minimum` and `Maximum` values for the `k` variable as 10000 and 100000 respectively.



Click **OK**. A new variable, `DesignVars`, appears in the **Response Optimizer** browser.

In the **Uncertain Variables Set** list, select **New**. Add the `mLoad` variable to the uncertain variables set.

- Specify the `Uncertain Values` value for the `mLoad` variable as [10 15 20]



Click **OK**. A new variable, `UncVars`, appears in the **Response Optimizer** browser.

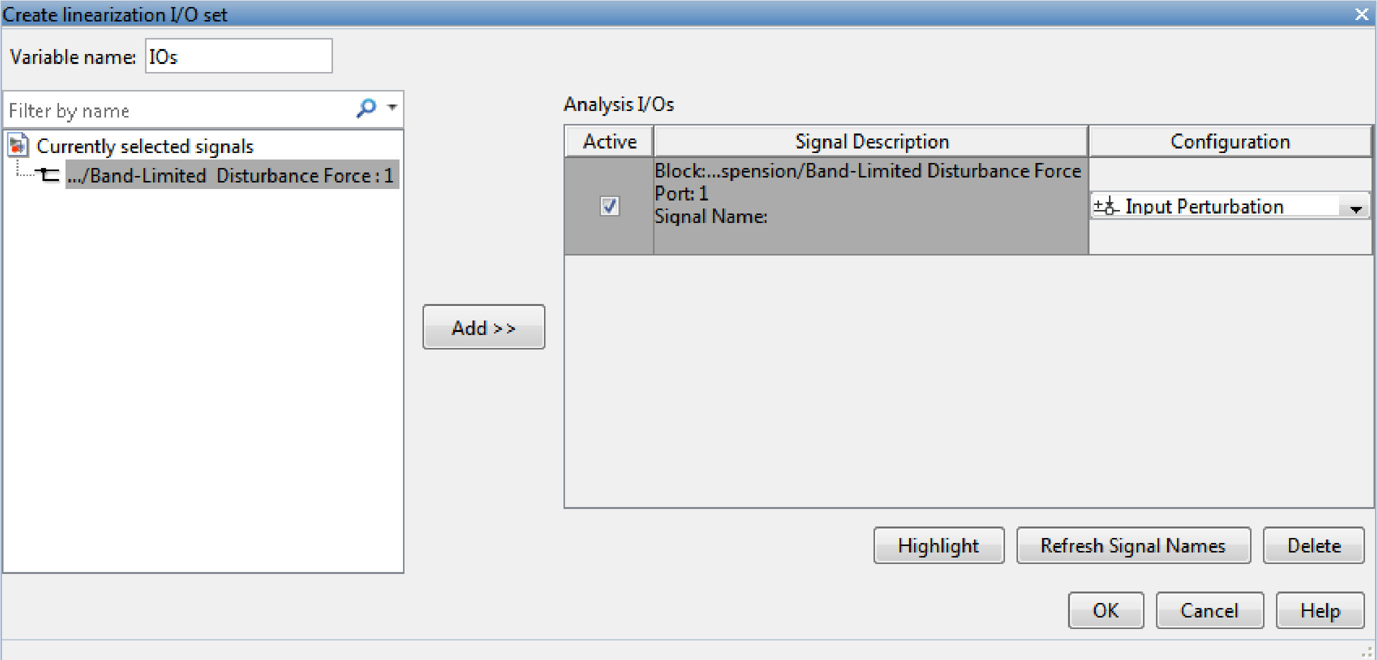
Specify Linear Analysis Input/Output Points

Specify the input/output points defining the linear system used to compute the bandwidth and damping ratio.

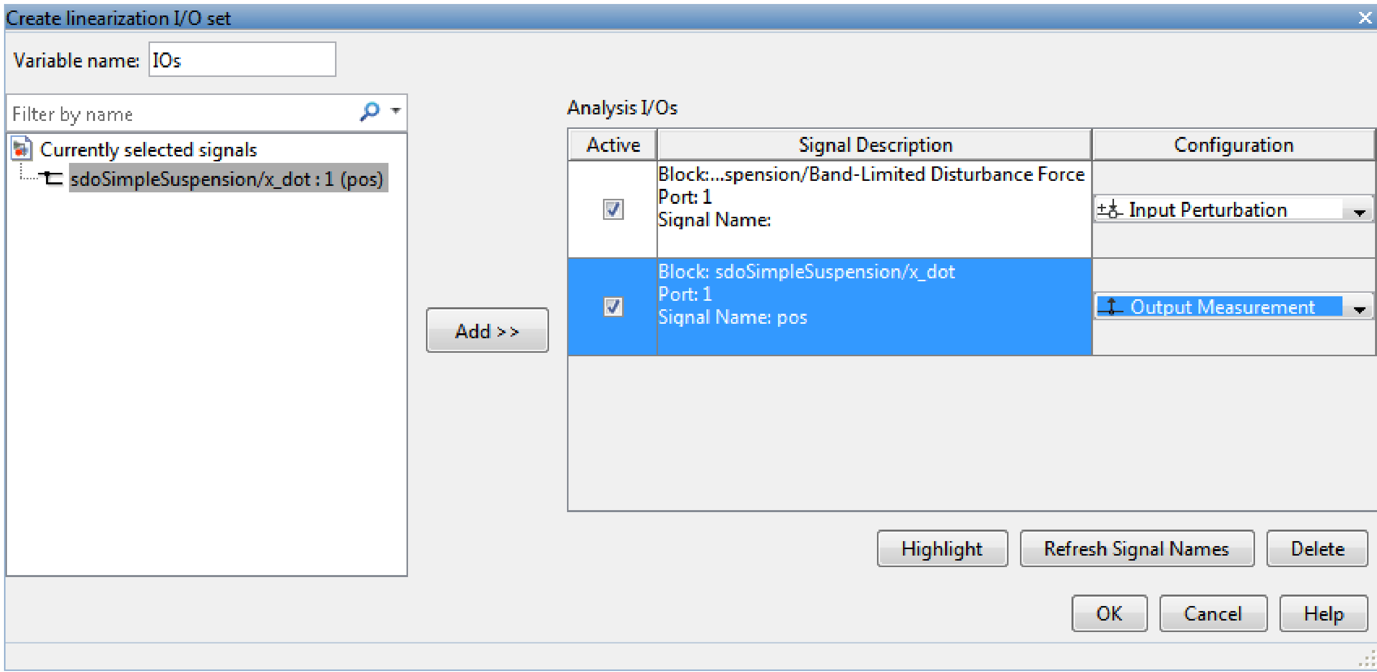
To specify the input/output points:

- In the **New** list, select **Linearization I/Os**.
- In the Simulink model, click the signal at the output of the `Band-Limited Disturbance Force` block. The **Create linearization I/O set** dialog box is updated and the chosen signal appears in it.
- In the **Create linearization I/O** dialog box, select the signal and click **Add**.

- In the **Configuration** list for the selected signal, choose **Input Perturbation** to specify it as an input signal.



- Similarly, add the **pos** signal from the Simulink model. Specify this signal as an output. In the **Configuration** list, select **Output Measurement**.



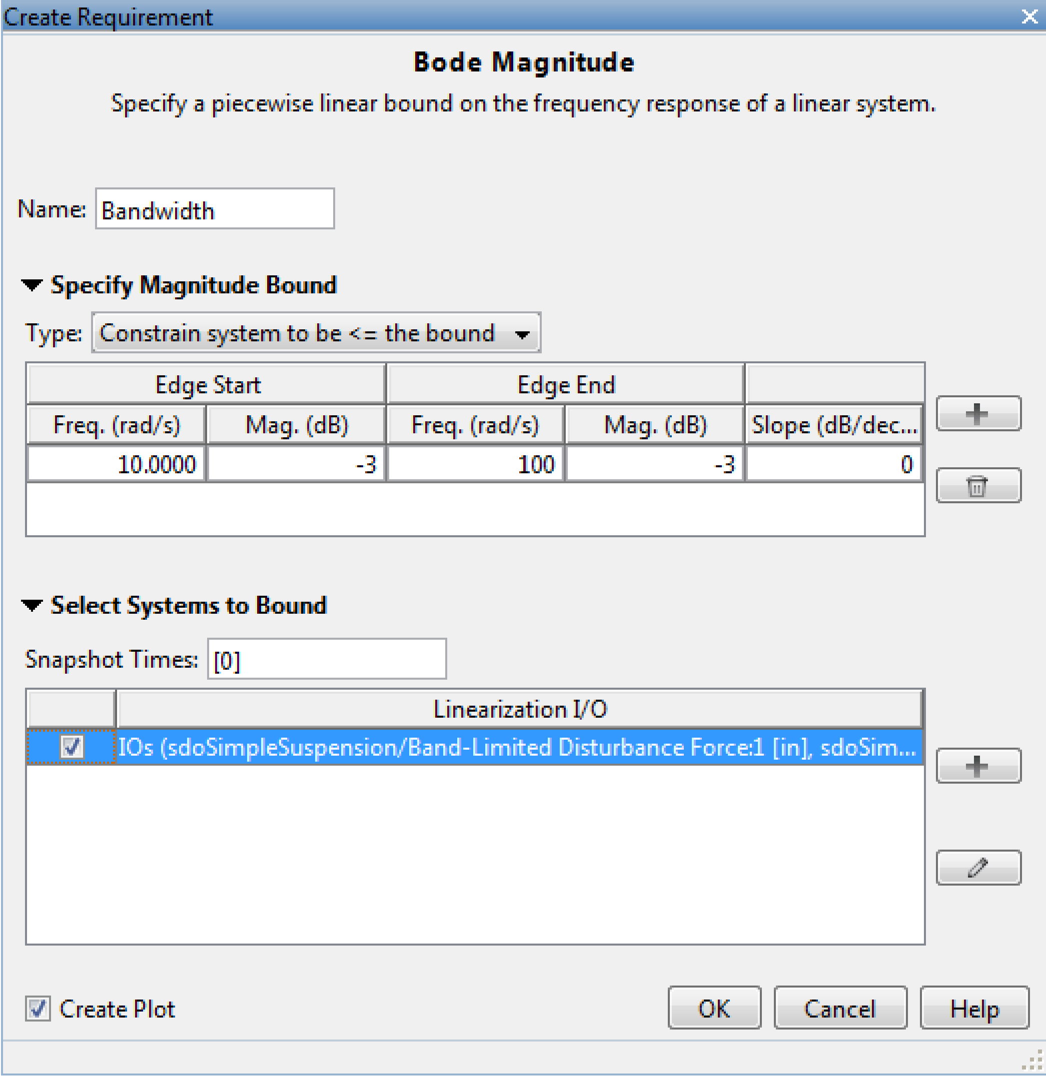
- Click **OK**. A new variable, `IOs`, appears in the **Response Optimizer** browser.

Add Bandwidth and Damping-Ratio Requirements

Tune the spring and damper values to satisfy bandwidth and damping ratio requirements.

To specify the bandwidth requirement:

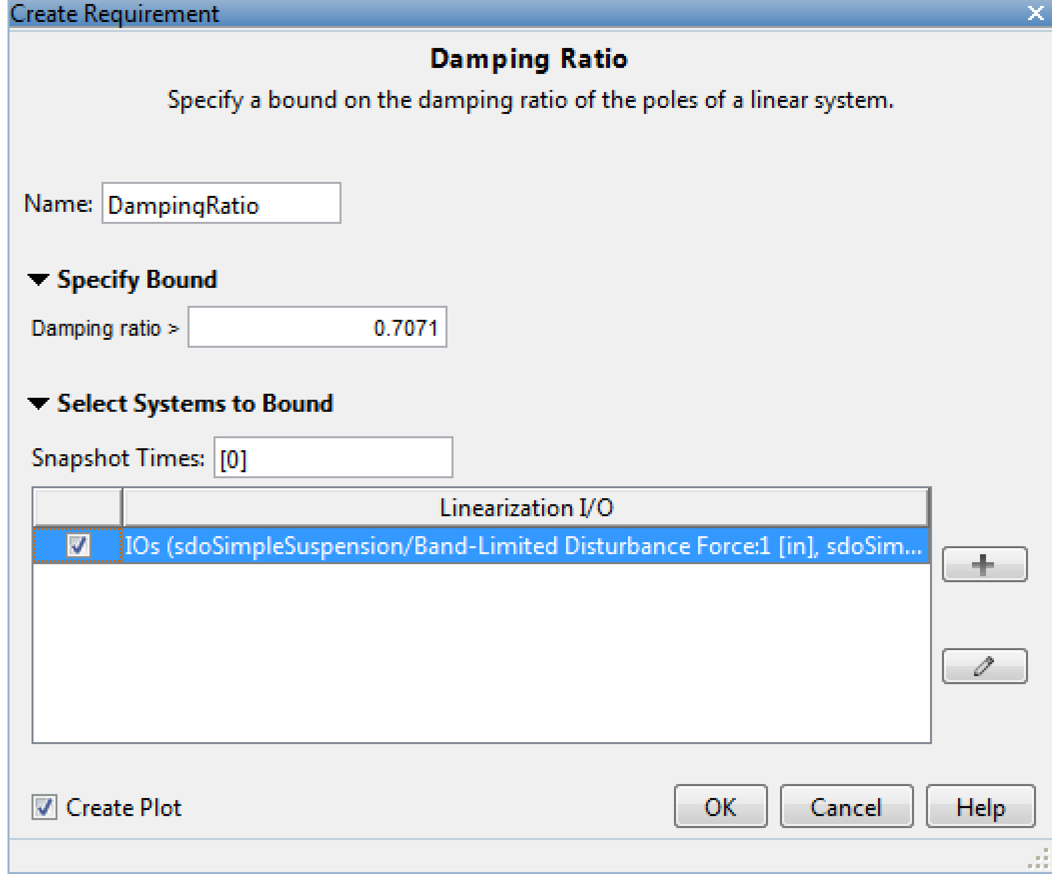
- Open a dialog to specify bounds on the Bode magnitude. In the **New** list, select **Bode Magnitude**.
- Specify the requirement name as `Bandwidth`.
- Specify the edge start frequency and magnitude as 10 rad/s and -3db, respectively.
- Specify the edge end frequency and magnitude as 100 rad/s and -3db, respectively.
- Specify the input/output set to which the requirement applies by clicking **Select Systems to Bound**. Select the `IOs` check box.



- Click **OK**. A new requirement, `Bandwidth`, appears in the **Response Optimizer** browser and a graphical view of the bandwidth requirement is automatically created.

To specify the damping ratio requirement:

- Open a dialog to specify bounds on the damping ratio. In the **New** list, select **Damping Ratio**.
- Specify the damping ratio bound value as 0.7071.
- Specify the input/output set to which the requirement applies by clicking **Select Systems to Bound**. Select the `IOs` check box.



- Click **OK**. A new requirement, `DampingRatio`, appears in the **Response Optimizer** browser and a graphical view of the damping ratio requirement is automatically created.

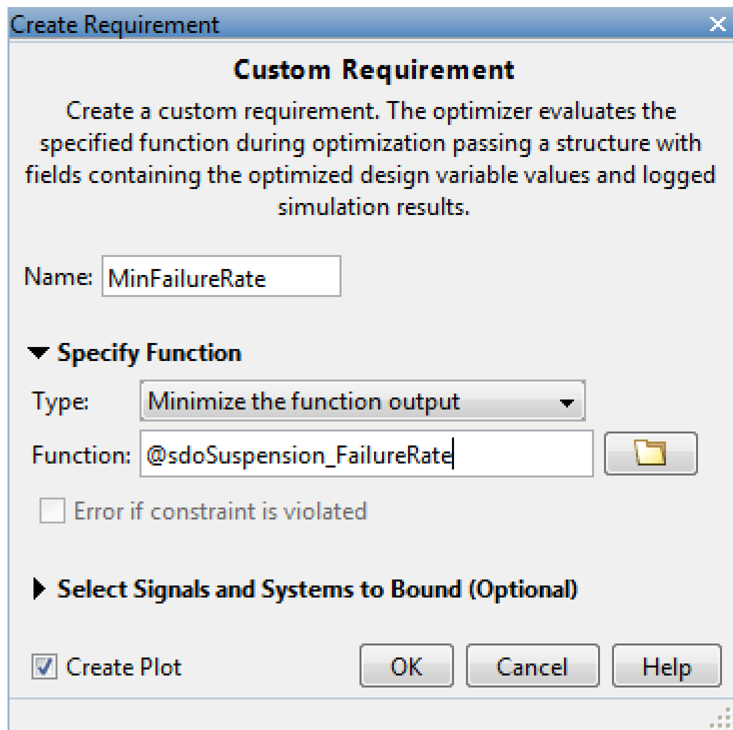
Add a Reliability Requirement

Tune the spring and damper values to minimize the expected failure rate over a lifetime of 100e3 miles. The failure rate is computed using a Weibull distribution on the damping ratio of the system. As the damping ratio increases the failure rate is expected to increase.

Specify the reliability requirement as a custom requirement:

- Open a dialog box to specify the custom requirements. In the **New** list, select **Custom Requirement**.
- Specify the custom requirement name as `MinFailureRate`.

- In the **Specify Function** area, select **Minimize the function output** from the **Type** list.
- Specify the function as @sdoSuspension_FailureRate.



- Click **OK**. A new requirement, `MinFailureRate`, appears in the **Response Optimizer** browser and a graphical view of the custom requirement is automatically created.

The @sdoSuspension_FailureRate function returns expected failure rate for a lifetime of 100e3 miles.

```
type sdoSuspension_FailureRate
```

```
function pFailure = sdoSuspension_FailureRate(data)
%SDOSUSPENDION_FAILURERATE
%
% The sdoSuspension_FailureRate function is used to define a custom
% requirement that can be used in the graphical SDTOOL environment.
%
% The |data| input argument is a structure with fields containing the
% design variable values chosen by the optimizer.
%
% The |pFailure| return argument is the failure rate to be minimized by the
% SDOTOOL optimization solver. The failure rate is given by a Weibull
% distribution that is a function of the mass, spring and damper values.
% The design minimizes the failure rate for a 100e3 mile lifetime.
%

% Copyright 2012 The MathWorks, Inc.

%Get the spring and damper design values
allVarNames = {data.DesignVars.Name};
idx         = strcmp(allVarNames,'k');
```

```
k           = data.DesignVars(idx).Value;
idx         = strcmp(allVarNames,'b');
b           = data.DesignVars(idx).Value;

%Get the nominal mass from the model workspace
wksp = get_param('sdoSimpleSuspension','ModelWorkspace');
m    = evalin(wksp,'m0');

%The expected failure rate is defined by the Weibull cumulative
%distribution function, 1-exp(-(x/l)^k), where k=3, l is a function of the
%mass, spring and damper values, and x the lifetime.
d       = b/2/sqrt(m*k);
pFailure = 1-exp(-(100e3*d/250e3)^3);
end
```

Optimize the Design

Before running the optimization be sure to have completed the earlier steps. Alternatively, you can load the `sdoSimpleSuspension_sdosession` from the model workspace into the **Response Optimizer**.

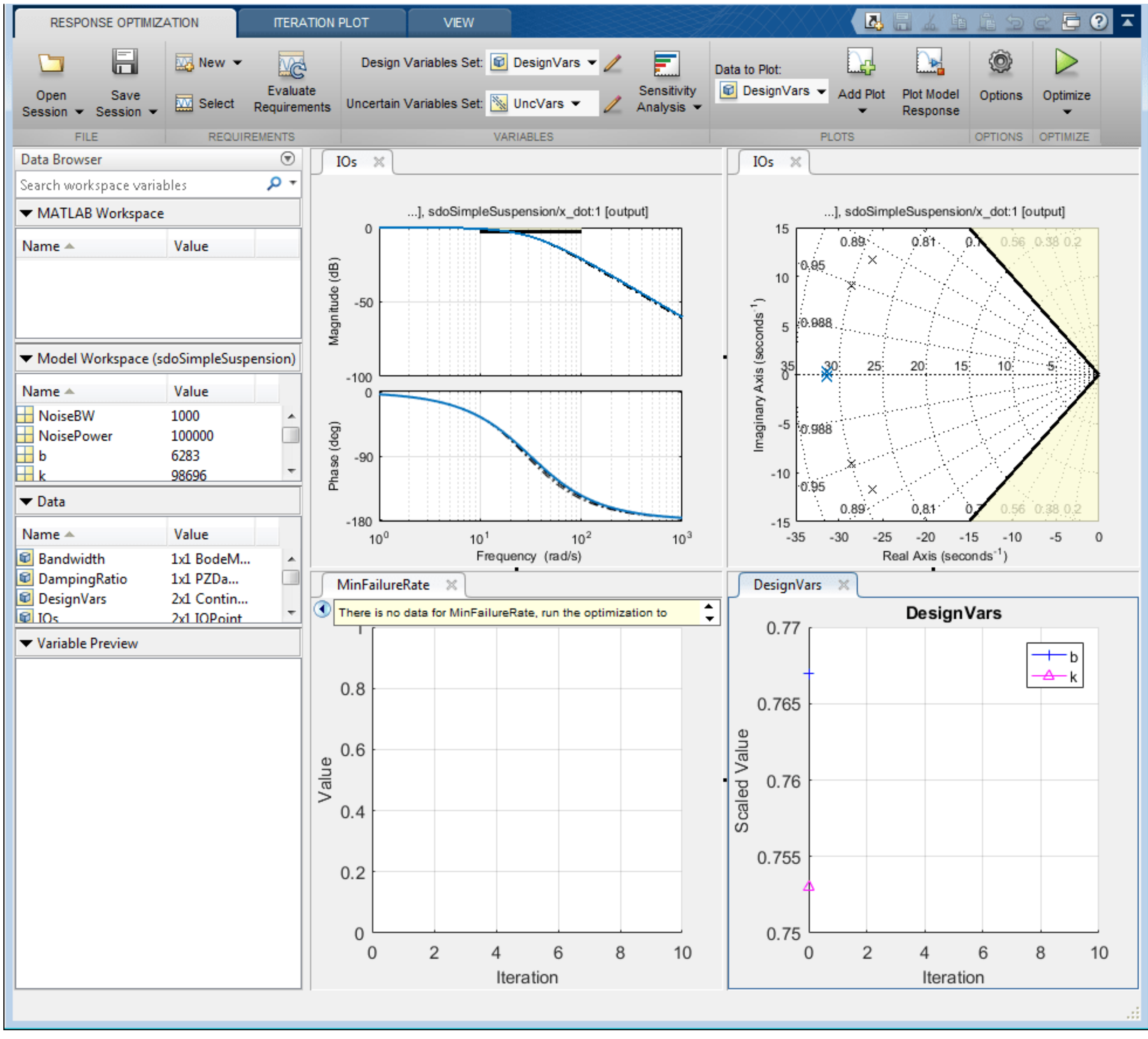
To save the initial design variable values and later compare them with the optimized values configure the optimization:

- Click **Options**.
- Select the `Save optimized variable values as new design variable set` option.

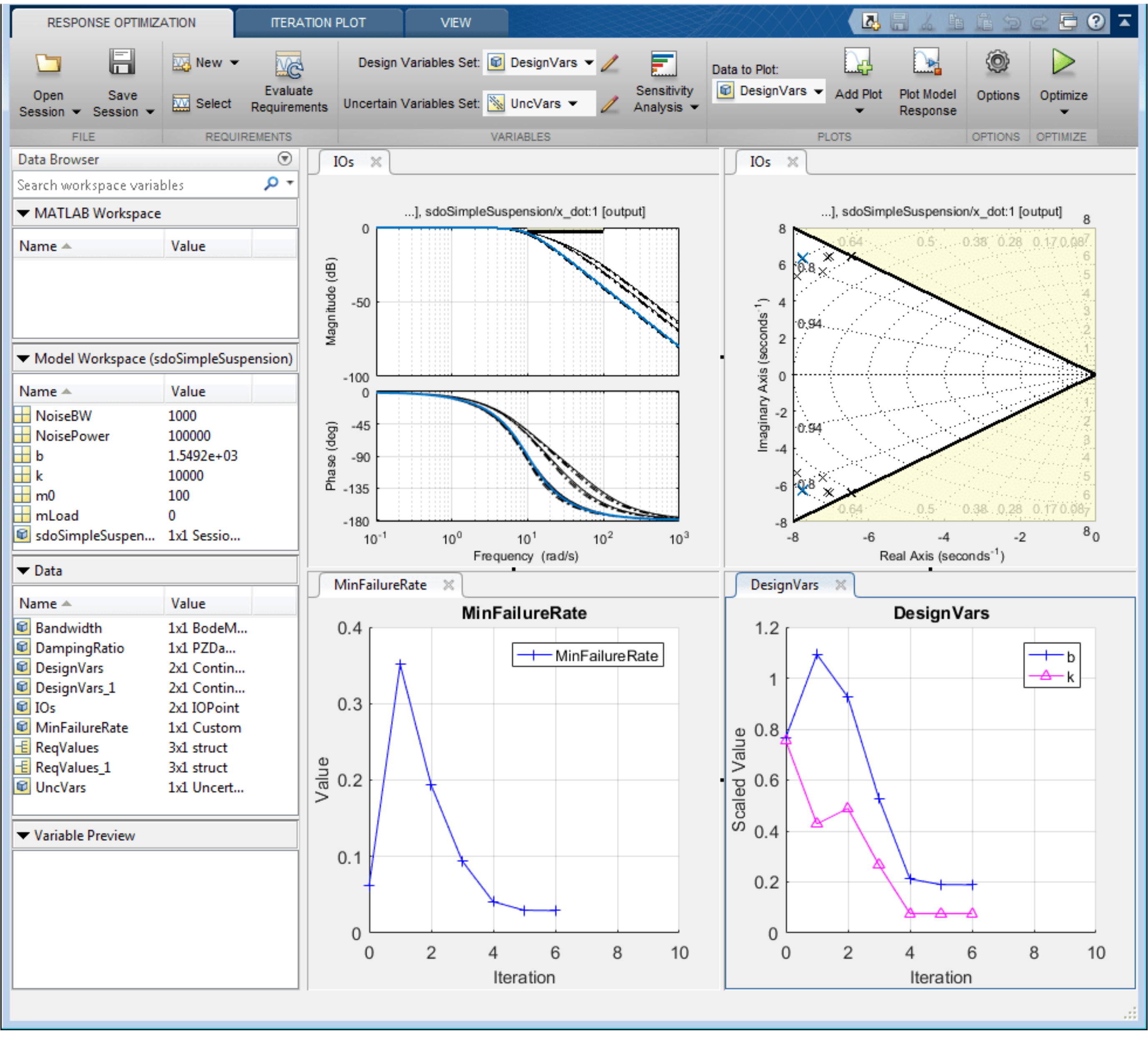
To study how the design variable values change during optimization:

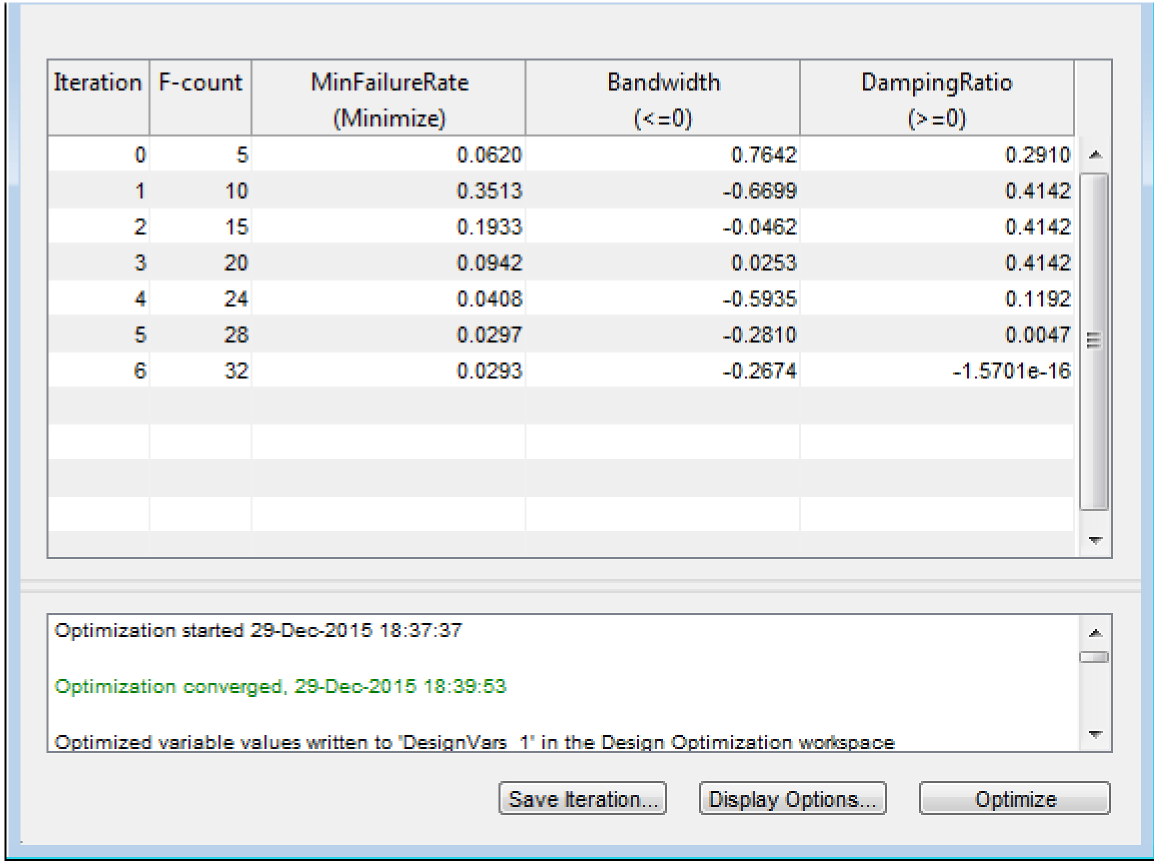
- In the **Data to Plot** list, select **DesignVars**.
- In the **Add Plot** list, and select **Iteration Plot**.
- View the design variables in an appropriately scaled manner. Right-click on the `DesignVars` plot and select **Show scaled values**.

To evaluate the requirements at the initial design point, click **Evaluate Requirements**. The requirement plots are updated and a `ReqValues` variable is added to the **Response Optimizer** browser.



To optimize the design, click **Optimize**. The plots are updated during optimization. At the end of optimization, the optimal design values are written to the `DesignVars1` variable. The requirement values for the optimized design are written to the `ReqValues1` variable.



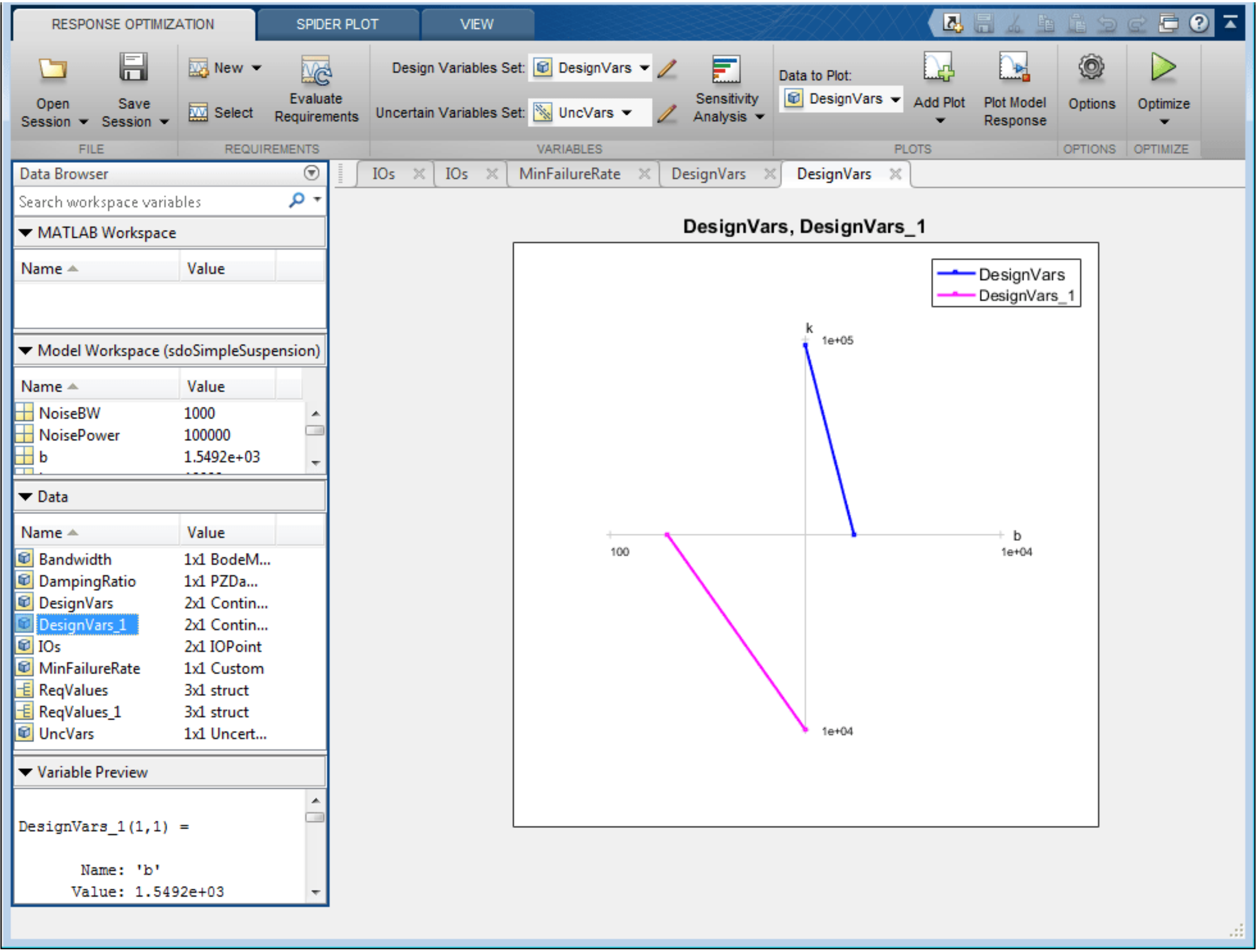


Iteration	F-count	MinFailureRate (Minimize)	Bandwidth (<=0)	DampingRatio (>=0)
0	5	0.0620	0.7642	0.2910
1	10	0.3513	-0.6699	0.4142
2	15	0.1933	-0.0462	0.4142
3	20	0.0942	0.0253	0.4142
4	24	0.0408	-0.5935	0.1192
5	28	0.0297	-0.2810	0.0047
6	32	0.0293	-0.2674	-1.5701e-16

Analyze the Design

To compare design variables before and after optimization:

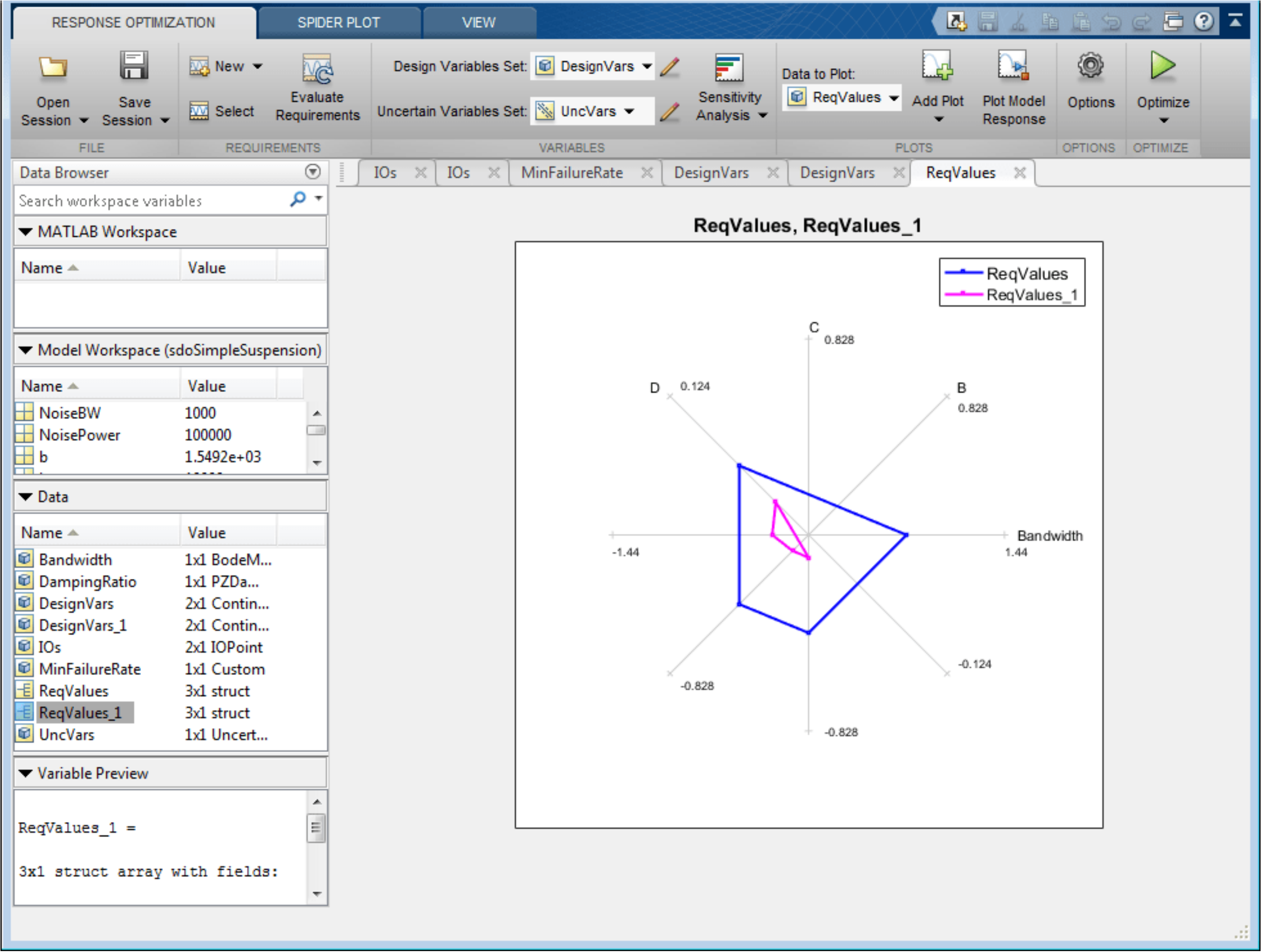
- In the **Data to Plot** list, select **DesignVars**.
- In the **Add Plot** list, select **Spider Plot**.
- To add the optimized design variables to the same plot, select `DesignVars1` in the **Response Optimizer** browser and drag it onto the Spider plot. Alternatively, in the **Data to Plot** list, select `DesignVars1`. Then, in the **Add Plot** list, select **Spider plot 1** from the **Add to Existing Plot** section.



The plot shows that the optimizer reduced both the `k` and `b` values for the optimal design.

To compare requirements before and after optimization:

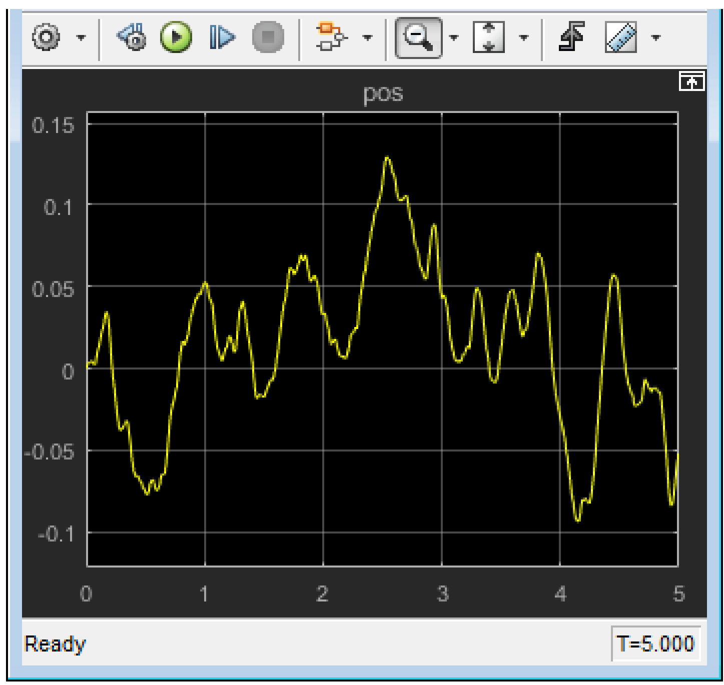
- In the **Data to Plot** list, select **ReqValues**.
- In the **Add Plot** list, select **Spider Plot**.
- To add the optimized requirement values to the same plot, select `ReqValues1` in the **Response Optimizer** browser and drag it onto the Spider plot. Alternatively, in the **Data to Plot** list, select `ReqValues1`. Then, in the **Add Plot** list, select **Spider plot 2** from the **Add to Existing Plot** section.



The plot shows that the optimal design has a lower failure rate (the MinFailureRate axis) and better satisfies the bandwidth requirement. The value plotted on the bandwidth axis is the difference between the bandwidth bound and the bandwidth value. The optimization satisfies the bound by keeping this value negative; a more negative value indicates better satisfaction of the bound.

The improved reliability and bandwidth are achieved by pushing the damping ratio closer to the damping ratio bound. The plot has two axes for the damping ratio requirement, one for each system pole, and the plotted values are the difference between the damping ratio bound and the damping ratio value. The optimization satisfies the bound by keeping this value negative.

Finally the simulated mass position is smoother than the initial position response (indication of a lower bandwidth as required) at the expense of larger position deflection.



Related Examples

To learn how to optimize the suspension design using the `sdo.optimize` command, see “Design Optimization to Meet Frequency-Domain Requirements (Code)” on page 3-224.

```
% Close the model
bdclose('sdoSimpleSuspension')
```

Specify Custom Signal Objective with Uncertain Variable (GUI)

This example shows how to specify a custom objective function for a model signal. You calculate the objective function value using a variable that models parameter uncertainty.

Competitive Population Dynamics Model

The Simulink® model `sdoPopulation` models a simple two-organism ecology using the competitive Lotka-Volterra equations:

$$\frac{dP_1}{dt} = R_1 P_1 (1 - \frac{P_1(t-\tau_1) + \alpha P_2(t-\tau_2)}{K})$$

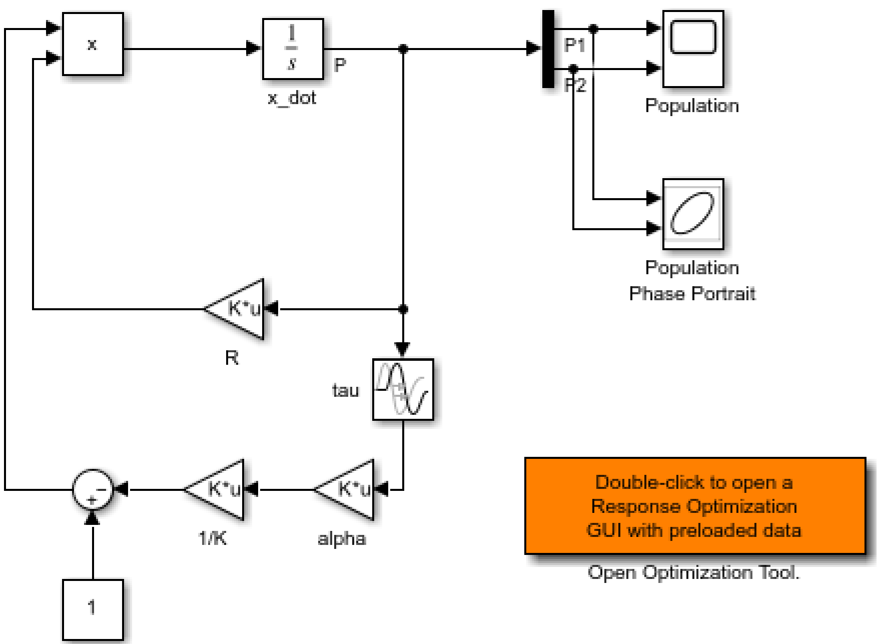
$$\frac{dP_2}{dt} = R_2 P_2 (1 - \frac{P_2(t-\tau_2) + \alpha P_1(t-\tau_1)}{K})$$

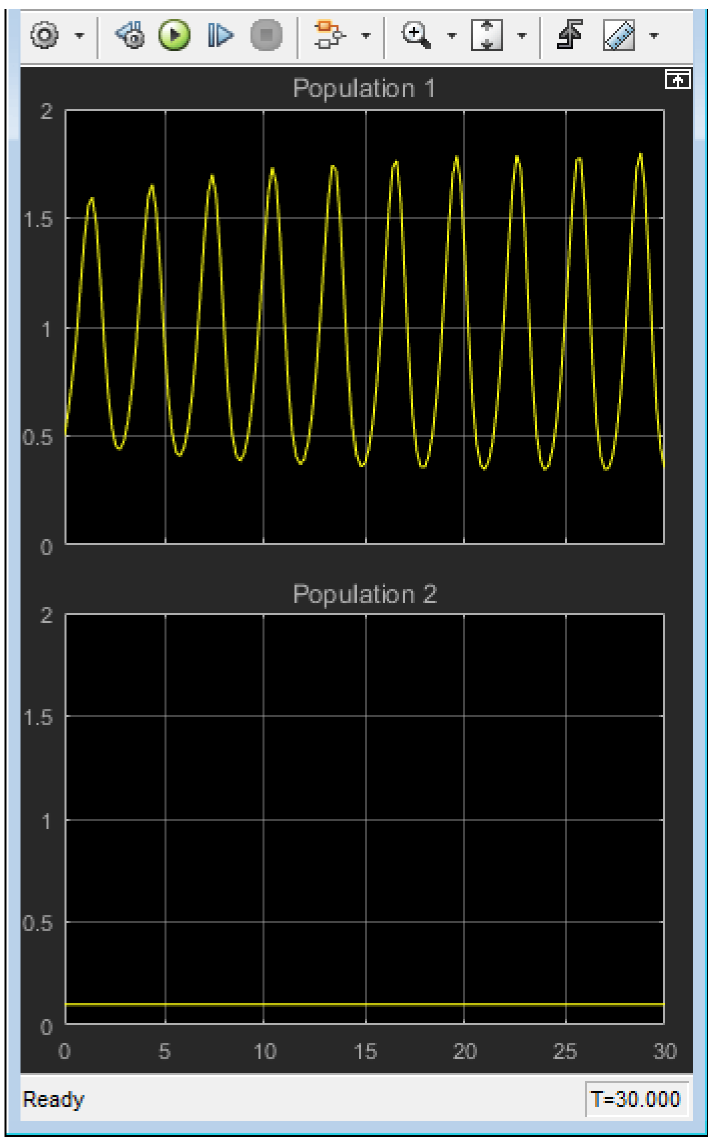
- P_n is the population size of the n-th organism.
- R_n is the inherent per capita growth rate of each organism.
- τ_n is the competitive delay for each organism.
- K is the carrying capacity of the organism environment.
- α is the proximity of the two populations and how strongly they affect each other.

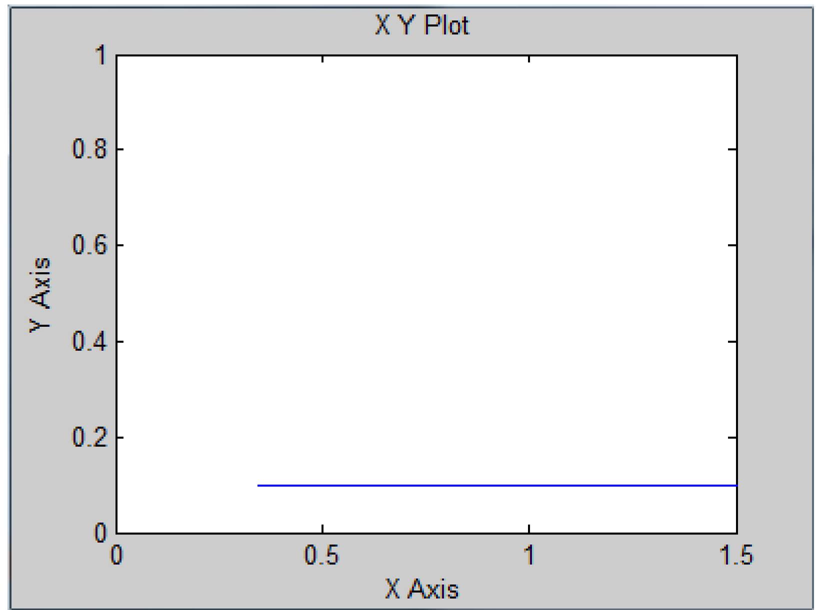
The model uses normalized units.

Open the model.

```
open_system('sdoPopulation')
```


x
1/s
P
x_dot
P1
P2
Population
Population
Phase Portrait
K*u
R
tau
K*u
K*u
1/K
alpha
1
Double-click to open a
Response Optimization
GUI with preloaded data
Open Optimization Tool.
Copyright 2012-2013 The MathWorks, Inc.


Population 1
2
1.5
1
0.5
0
Population 2
2
1.5
1
0.5
0
0
5
10
15
20
25
30
Ready
T=30.000



The two-dimensional signal, P, models the population sizes for P1 (first element) and P2 (second element). The model is initially configured with one organism, P1, dominating the ecology. The Population scope shows the P1 population oscillating between high and low values, while P2 is constant at 0.1. The Population Phase Portrait block shows the population sizes of the two organisms in relation to each other.

Population Stabilization Design Problem

Tune the R_2, τ_2, and α values to meet the following design requirements.

- Minimize the population range, that is, the maximum difference between P1 and P2.
- Stabilize P1 and P2, that is, ensure that neither organism population dies off or grows extremely large.

You must tune the parameters for different values of the carrying capacity, K. This ensures robustness to environment carrying-capacity uncertainty.

Open Response Optimizer

Double-click the Open Optimization Tool block in the model to open a pre-configured **Response Optimizer** session. The session specifies the following variables:

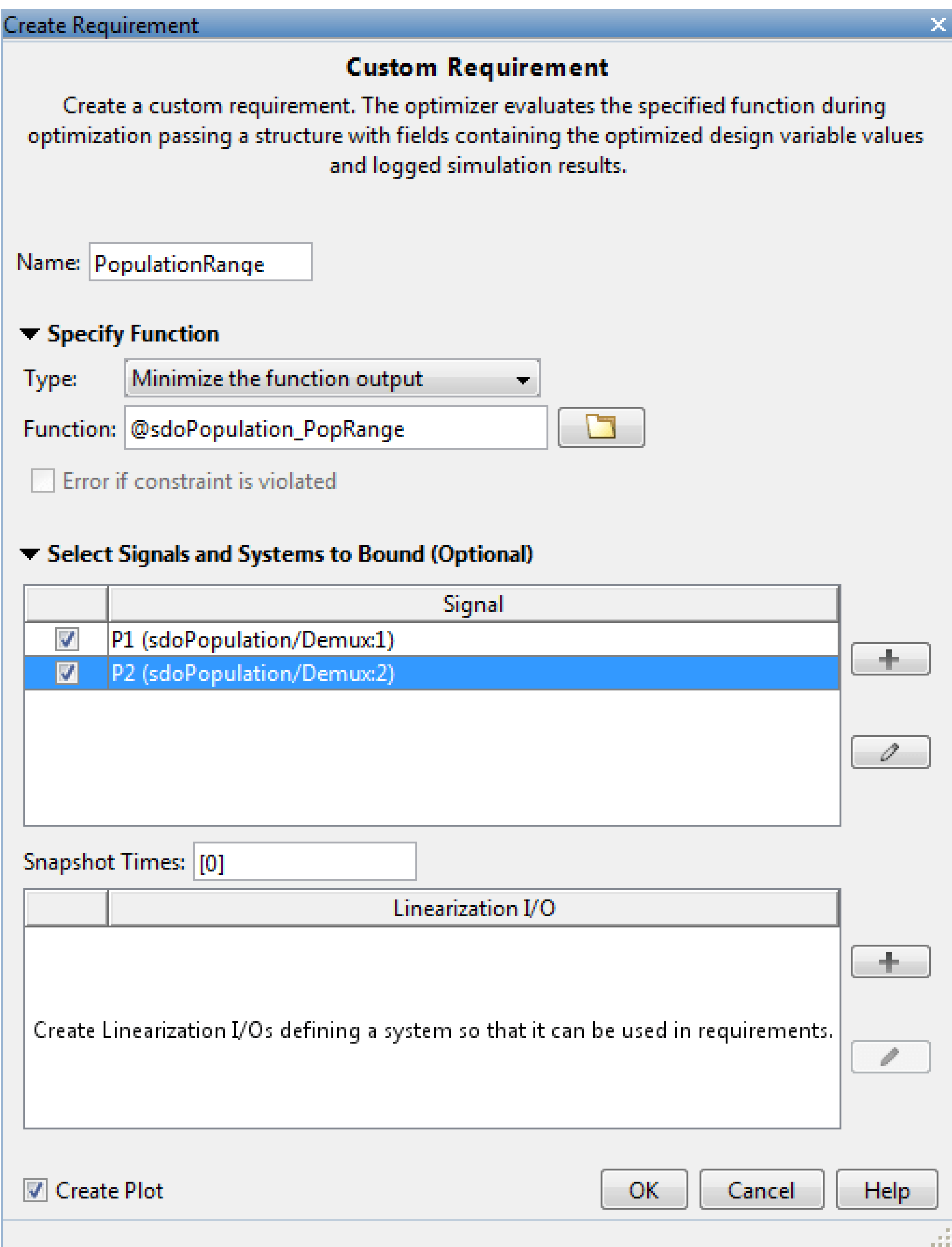
- `DesignVars` - Design variables set for the R_2, τ_2, and α model parameters.
- `K_unc` - Uncertain parameter modeling the carrying capacity of the organism environment (K). `K_unc` specifies the nominal value and two sample values.
- `P1` and `P2` - Logged signals representing the populations of the two organisms.

Specify Custom Signal Objective Function

Specify a custom requirement to minimize the maximum difference between the two population sizes. Apply this requirement to the P1 and P2 model signals.

1 Open the Create Requirement dialog box. In the **New** list, select **Custom Requirement**.
2 Specify the following in the Create Requirement dialog box:

- **Name** - Enter `PopulationRange`.
- **Type** - Select **Minimize the function output** from the list.
- **Function** - Enter `@sdoPopulation_PopRange`. For more information about this function, see **Custom Signal Objective Function Details**.
- **Select Signals and Systems to Bound (Optional)** - Select the `P1` and `P2` check boxes.



3. Click **OK**.

A new variable, PopulationRange, appears in the **Response Optimizer** browser.

Custom Signal Objective Function Details

PopulationRange uses the sdoPopulation_PopRange function. This function computes the maximum difference between the populations, across different environment carrying capacity values. By minimizing this value, you can achieve both design goals. The function is called by the optimizer at each iteration step.

To view the function, type edit sdoPopulation_PopRange. The following discusses details of this function.

Input/Output

The function accepts data, a structure with the following fields:

- DesignVars - Current iteration values of R_2, τ_2, and α.
- Nominal - Logged signal data, obtained by simulating the model using parameter values specified by data.DesignVars and nominal values for all other parameters. The Nominal field is itself a structure with fields for each logged signal. The field names are the logged signal names. The custom requirement uses the logged signals, P1 and P2. Therefore, data.Nominal.P1 and data.Nominal.P2 are timeseries objects corresponding to P1 and P2.
- Uncertain - Logged signal data, obtained by simulating the model using the sample values of the uncertain variable K_unc. The Uncertain field is a vector of N structures, where N is the number of sample values specified for K_unc. Each element of this vector is similar to data.Nominal and contains simulation results obtained from a corresponding sample value specified for K_unc.

The function returns the maximum difference between the population sizes across different carrying capacities. The following code snippet in the function performs this action:

```
val = max(maxP(1)-minP(2),maxP(2)-minP(1));
```

Data Time Range

When computing the design goals, discard the initial population growth data to eliminate biases from the initial-condition. The following code snippet in the function performs this action:

```
%Get the population data
tMin = 5; %Ignore signal values prior to this time
iTime = data.Nominal.P1.Time > tMin;
sigData = [data.Nominal.P1.Data(iTime), data.Nominal.P2.Data(iTime)];
```

iTime represents the time interval of interest, and the columns of sigData contain P1 and P2 data for this interval.

Optimization for Different Values of Carrying Capacity

The function includes the effects of varying the carrying capacity by iterating through the elements of data.Uncertain. The following code snippet in the function performs this action:

```
...
for ct=1:numel(data.Uncertain)
```

```
    iTime = data.Uncertain(ct).P1.Time > tMin;
    sigData = [data.Uncertain(ct).P1.Data(iTime), data.Uncertain(ct).P2.Data(iTime)];

    maxP = max([maxP; max(sigData)]);  %Update maximum if new signals are bigger
    minP = min([minP; min(sigData)]);  %Update minimum if new signals are smaller
end
...
```

The maximum and minimal populations are obtained across all the simulations contained in `data.Uncertain`.

Optimize Design

Click **Optimize**.

The optimization converges after a number of iterations.

Iteration	F-count	PopulationRange (min)
0	8	1.5024
1	13	1.3350
2	20	0.5918
3	29	0.4814
4	36	0.4443
5	43	0.4361
6	51	0.4322
7	58	0.4316
8	65	0.4294
9	77	0.4294
10	88	0.4294

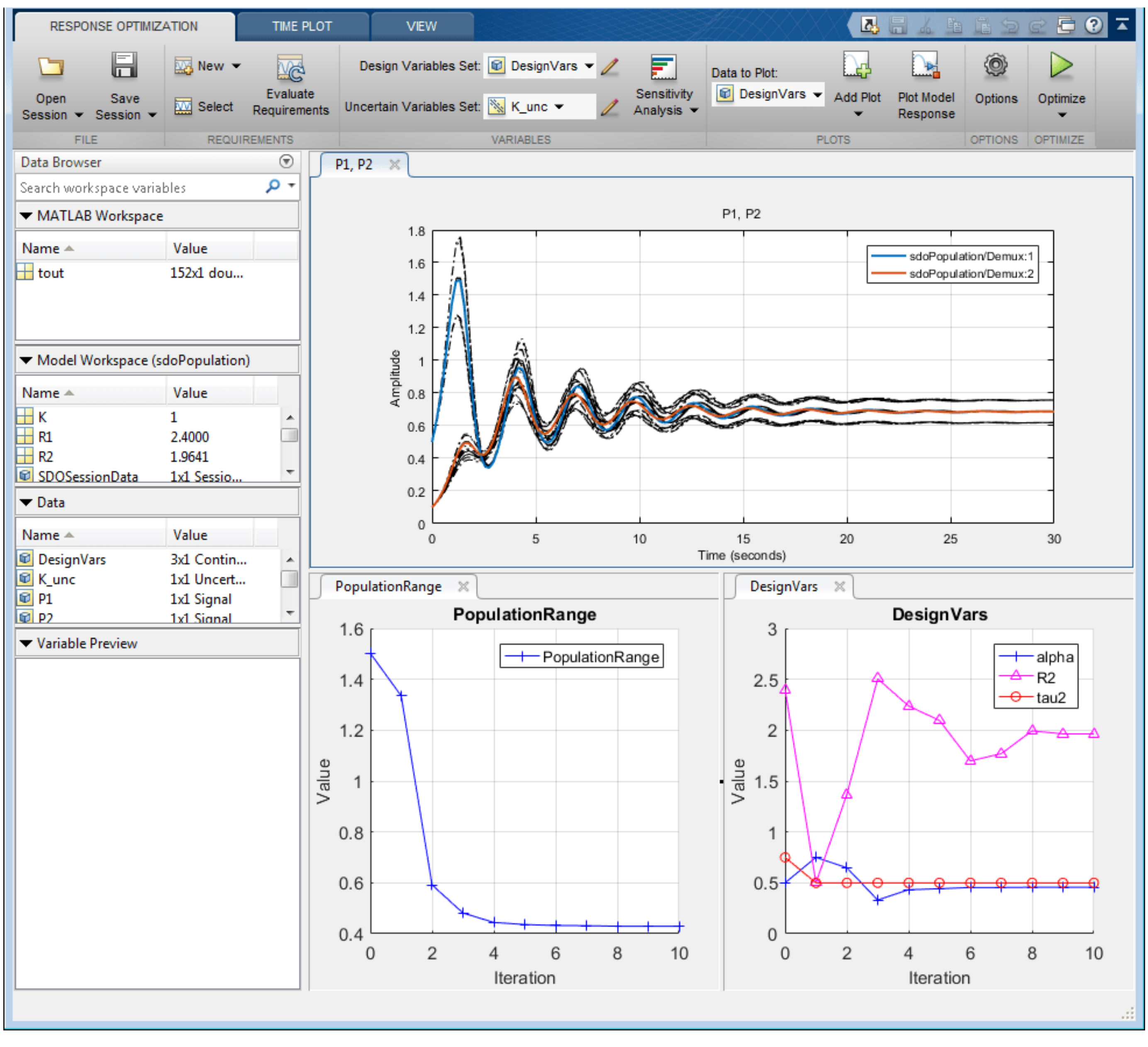
Optimization started 09-Oct-2012 12:01:35

Optimization converged, 09-Oct-2012 12:03:32

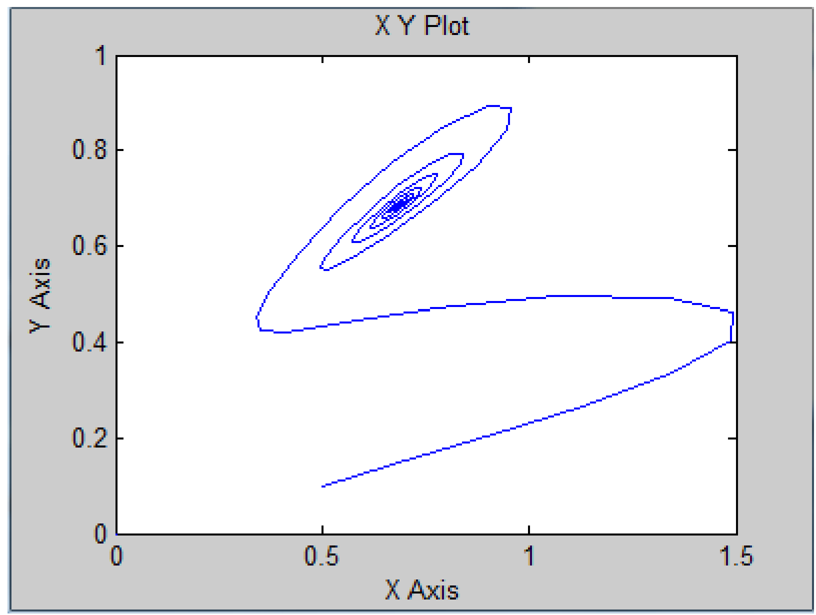
Optimized variable values written to 'DesignVars' in the Design Optimization workspace

Save Iteration... Display Options... Optimize

The `P1,P2` plot shows the population dynamics, with the first organism population in blue and the second organism population in red. The dotted lines indicate the population dynamics for different environment capacity values. The `PopulationRange` plot shows that the maximum difference between the two organism populations reduces over time.



The `Population Phase Portrait` block shows the populations initially varying, but they eventually converge to stable population sizes.




```
% Close the model.
bdclose('sdoPopulation')
```

Design Optimization with Uncertain Variables (Code)

This example shows how to optimize a design when there are uncertain variables. You optimize the dimensions of a Continuously Stirred Tank Reactor (CSTR) to minimize product concentration variation and production cost in case of varying, or uncertain, feed stock.

Continuously Stirred Tank Reactor (CSTR) Model

Continuously Stirred Tank Reactors (CSTRs) are common in the process industry. The Simulink® model, `sdoCSTR`, models a jacketed diabatic (i.e., non-adiabatic) tank reactor described in [1]. The CSTR is assumed to be perfectly mixed, with a single first-order exothermic and irreversible reaction, $A \rightarrow B$. A, the reactant, is converted to B, the product.

In this example, you use the following two-state CSTR model, which uses basic accounting and energy conservation principles:

$$\frac{dC_A}{dt} = \frac{F}{A*h}(C_{feed} - C_A) - r*C_A$$

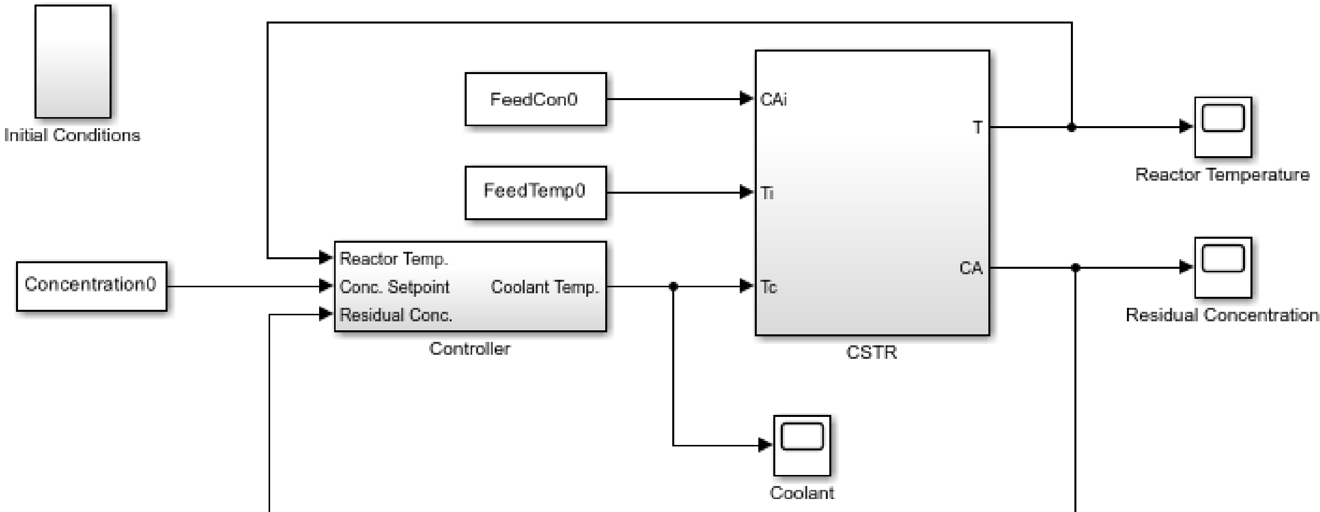
$$\frac{dT}{dt} = \frac{F}{A*h}(T_{feed} - T) - \frac{H}{c_p\rho}r - \frac{U}{c_p*\rho*h}(T - T_{cool})$$

$$r = k_0 * e^{\frac{-E}{R*T}}$$

- C_A, and C_{feed} - Concentrations of A in the CSTR and in the feed [kgmol/m^3]
- T, T_{feed}, and T_{cool} - CSTR, feed, and coolant temperatures [K]
- F and ρ - Volumetric flow rate [m^3/h] and the density of the material in the CSTR [1/m^3]
- h and A - Height [m] and heated cross-sectional area [m^2] of the CSTR.
- k_0 - Pre-exponential non-thermal factor for reaction $A \rightarrow B$ [1/h]
- E and H - Activation energy and heat of reaction for $A \rightarrow B$ [kcal/kgmol]
- R - Boltzmann's gas constant [kcal/(kgmol * K)]
- c_p and U - Heat capacity [kcal/K] and heat transfer coefficients [kcal/(m^2 * K * h)]

Open the Simulink model.

```
open_system('sdoCSTR');
```



The model includes a cascaded PID controller in the `Controller` subsystem. The controller regulates the reactor temperature, T, and reactor residual concentration, C_A.

CSTR Design Problem

Assume that the CSTR is cylindrical, with the coolant applied to the base of the cylinder. Tune the CSTR cross-sectional area, A, and CSTR height, h, to meet the following design goals:

- Minimize the variation in residual concentration, C_A. Variations in the residual concentration negatively affect the quality of the CSTR product. Minimizing the variations also improves CSTR profit.

- Minimize the mean coolant temperature T_{cool}. Heating or cooling the jacket coolant temperature is expensive. Minimizing the mean coolant temperature improves CSTR profit.

The design must allow for variations in the quality of supply feed concentration, C_{feed}, and feed temperature, T_{feed}. The CSTR is fed with feed from different suppliers. The quality of the feed differs from supplier to supplier and also varies within each supply batch.

Specify Design Variables

Select the following model parameters as design variables for optimization:

- Cylinder cross-sectional area A

- Cylinder height h

```
p = sdo.getParameterFromModel('sdoCSTR',{'A','h'});
```

Limit the cross-sectional area to a range of [1 2] m^2.

```
p(1).Minimum = 1;
p(1).Maximum = 2;
```

Limit the height to a range of [1 3] m.

```
p(2).Minimum = 1;
p(2).Maximum = 3;
```

Specify Uncertain Variables

Select the feed concentration and feed temperature as uncertain variables. You evaluate the design using different values of feed temperature and concentration.

```
pUnc = sdo.getParameterFromModel('sdoCSTR',{'FeedCon0','FeedTemp0'});
```

Create a parameter space for the uncertain variables. Use normal distributions for both variables. Specify the mean as the current parameter value. Specify a variance of 5% of the mean for the feed concentration and 1% of the mean for the temperature.

```
uSpace = sdo.ParameterSpace(pUnc);
uSpace = setDistribution(uSpace,'FeedCon0',makedist('normal',pUnc(1).Value,0.05*pUnc(1).Value));
uSpace = setDistribution(uSpace,'FeedTemp0',makedist('normal',pUnc(2).Value,0.01*pUnc(2).Value))
```

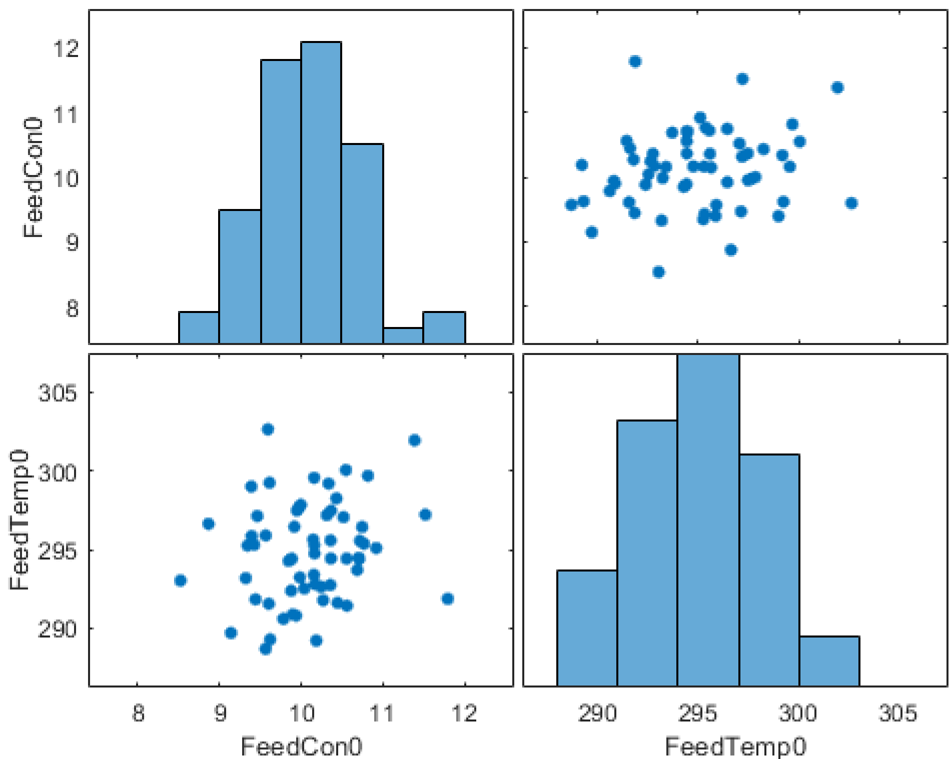
The feed concentration is inversely correlated with the feed temperature. Add this information to the parameter space.

```
%uSpace.RankCorrelation = [1 -0.6; -0.6 1];
```

The rank correlation matrix has a row and column for each parameter with the (i,j) entry specifying the correlation between the i and j parameters.

Sample the parameter space. The scatter plot shows the correlation between concentration and temperature.

```
rng('default'); %For reproducibility
uSmpl = sdo.sample(uSpace,60);
sdo.scatterPlot(uSmpl)
```



Ideally you want to evaluate the design for every combination of points in the design and uncertain spaces, which implies 30*60 = 1800 simulations. Each simulation takes around 0.5 sec. You can use parallel computing to speed up the evaluation. For this example you instead only use the samples that have maximum & minimum concentration and temperature values, reducing the evaluation time to around 1 min.

```
[~,iminC] = min(uSmpl.FeedCon0);
[~,imaxC] = max(uSmpl.FeedCon0);
[~,iminT] = min(uSmpl.FeedTemp0);
[~,imaxT] = max(uSmpl.FeedTemp0);
uSmpl = uSmpl(unique([iminC,imaxC,iminT,imaxT]) ,:);
```

Specify Design Requirements

The design requirements require logging model signals. During optimization, the model is simulated using the current value of the design variables. Logged signals are used to evaluate the design requirements.

Log the following signals:

- CSTR concentration, available at the second output port of the `sdoCSTR/CSTR` block

```
Conc = Simulink.SimulationData.SignalLoggingInfo;
Conc.BlockPath              = 'sdoCSTR/CSTR';
Conc.OutputPortIndex        = 2;
Conc.LoggingInfo.NameMode   = 1;
Conc.LoggingInfo.LoggingName = 'Concentration';
```

- Coolant temperature, available at the first output of the `sdoCSTR/Controller` block

```
Coolant = Simulink.SimulationData.SignalLoggingInfo;
Coolant.BlockPath               = 'sdoCSTR/Controller';
Coolant.OutputPortIndex         = 1;
Coolant.LoggingInfo.NameMode    = 1;
Coolant.LoggingInfo.LoggingName = 'Coolant';
```

Create and configure a simulation test object to log the required signals.

```
simulator = sdo.SimulationTest('sdoCSTR');
simulator.LoggingInfo.Signals = [Conc,Coolant];
```

Create Objective/Constraint Function

Create a function to evaluate the CSTR design. This function is called at each optimization iteration.

Use an anonymous function with one argument that calls the `sdoCSTR_design` function.

```
evalDesign = @(p) sdoCSTR_design(p,simulator,pUnc,uSmpl);
```

The `evalDesign` function:

- Has one input argument that specifies the CSTR dimensions
- Returns the optimization objective value

The `sdoCSTR_design` function uses a `for` loop that iterates through the sample values specified for the feed concentration. Within the loop, the function:

- Simulates the model using the current iterate, feed concentration, and feed temperature values
- Calculates the residual concentration variation and coolant temperature costs

To view the objective function, type `edit sdoCSTR_design`.

Evaluate Initial Design

Call the `evalDesign` function with the initial CSTR dimensions.

```
dInit = evalDesign(p)
```

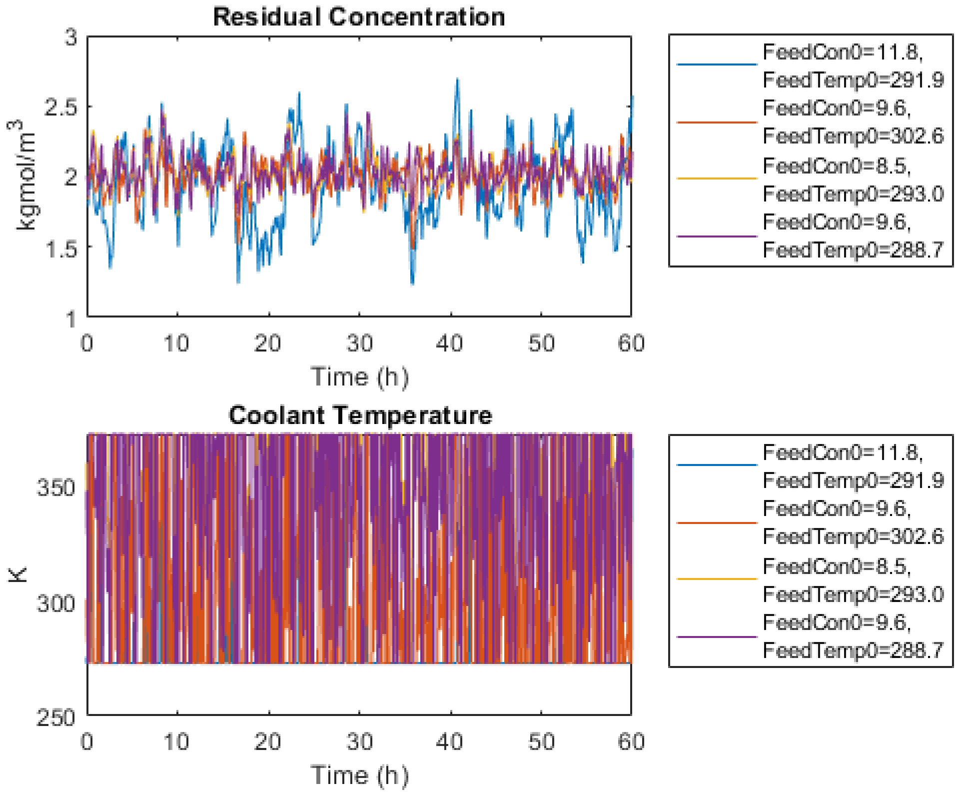
```
dInit = 

  struct with fields:

              F: 11.3356
       costConc: 6.4390
    costCoolant: 4.8965
```

Plot the model response for the initial design. Simulate the model using the sample feed concentration values. The plot shows the variation in the residual concentration and coolant temperature.

```
sdoCSTR_plotModelResponse(p,simulator,pUnc,uSmpl);
```



The `sdoCSTR_plotModelResponse` function plots the model response. To view this function, type `edit sdoCSTR_plotModelResponse`.

Optimize Design

Pass the objective function and initial CSTR dimensions to `sdo.optimize`.

```
pOpt = sdo.optimize(evalDesign,p)
```

```
 Optimization started 01-Sep-2022 14:06:36

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      4      5.17535            0
    1      8      3.81522            0         2.01         7.83
    2     12      2.63963            0         0.57         3.03
    3     16      2.53426            0        0.159        0.292
    4     20      2.50995            0        0.017        0.432
    5     24      2.50266            0        0.125         1.44
    6     28      2.50097            0       0.0966        0.234
    7     32      2.47473            0       0.0135       0.0719
    8     37      2.47473            0     0.000955       0.0694
Local minimum possible. Constraints satisfied.

fmincon stopped because the size of the current step is less than
the value of the step size tolerance and constraints are
satisfied to within the value of the constraint tolerance.
```

```
pOpt(1,1) =

       Name: 'A'
      Value: 2
    Minimum: 1
    Maximum: 2
       Free: 1
      Scale: 0.5000
       Info: [1x1 struct]


pOpt(2,1) =

       Name: 'h'
      Value: 2.2850
    Minimum: 1
    Maximum: 3
       Free: 1
      Scale: 2
       Info: [1x1 struct]


2x1 param.Continuous
```

Evaluate Optimized Design

Call the `evalDesign` function with the optimized CSTR dimensions.

```
dFinal = evalDesign(pOpt)
```

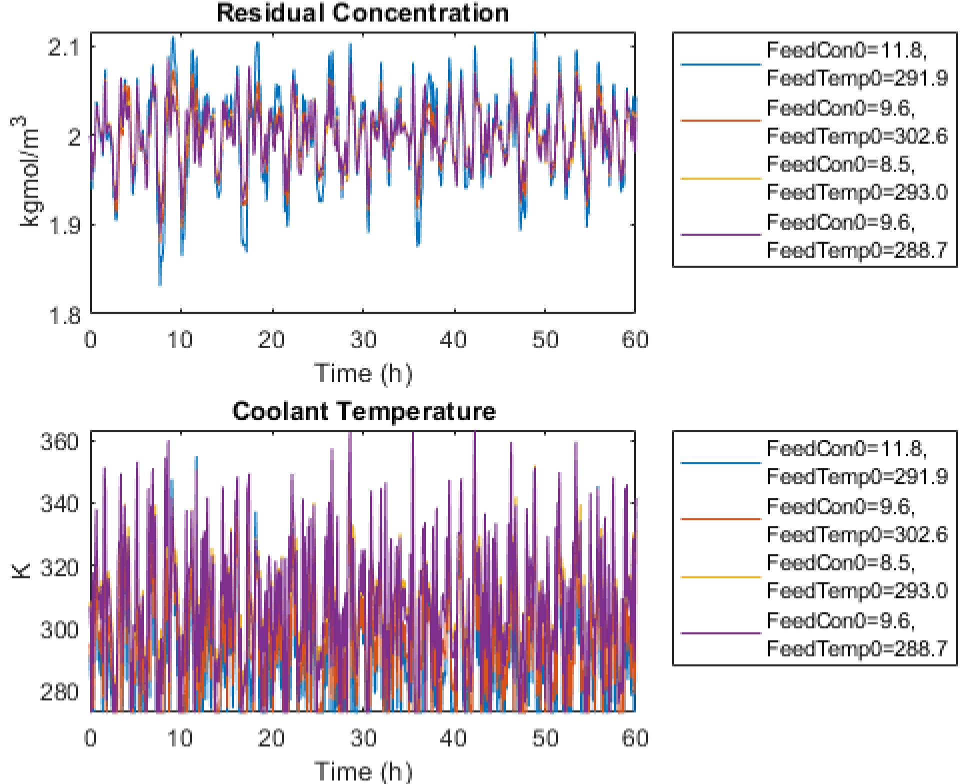
```
dFinal =

  struct with fields:

              F: 2.4747
       costConc: 1.4505
    costCoolant: 1.0242
```

Plot the model response for the optimized design. Simulate the model using the sample feed concentration values. The optimized design reduces the residual concentration variation and average coolant temperature for different feed stocks.

```
sdoCSTR_plotModelResponse(pOpt,simulator,pUnc,uSmpl);
```



Related Examples

To learn how to use sensitivity analysis to explore the CSTR design space and select an initial design for optimization, see “Design Exploration Using Parameter Sampling (Code)” on page 4-157.

References

[1] Bequette, B.W. *Process Dynamics: Modeling, Analysis and Simulation.* 1st ed. Upper Saddle River, NJ: Prentice Hall, 1998.

```
% Close the model
bdclose('sdoCSTR')
```

See Also

`sdo.optimize` | `sdo.getValueFromModel` | `sdo.getParameterFromModel`

Related Examples

- “Discrete-Valued Variables in Response Optimization (Code)” on page 3-88

Generate MATLAB Code for Design Optimization Problems (GUI)

This example shows how to automatically generate a MATLAB® function to solve a Design Optimization problem. You use the **Response Optimizer** to define an optimization problem for a hydraulic cylinder design and generate MATLAB code to solve this optimization problem.

Hydraulic Cylinder Design Problem

The "Design Optimization to Meet a Custom Objective (GUI)" on page 3-110 example shows how to use the **Response Optimizer** to optimize a cylinder design. In this example we load a pre-configured **Response Optimizer** session based on that example.

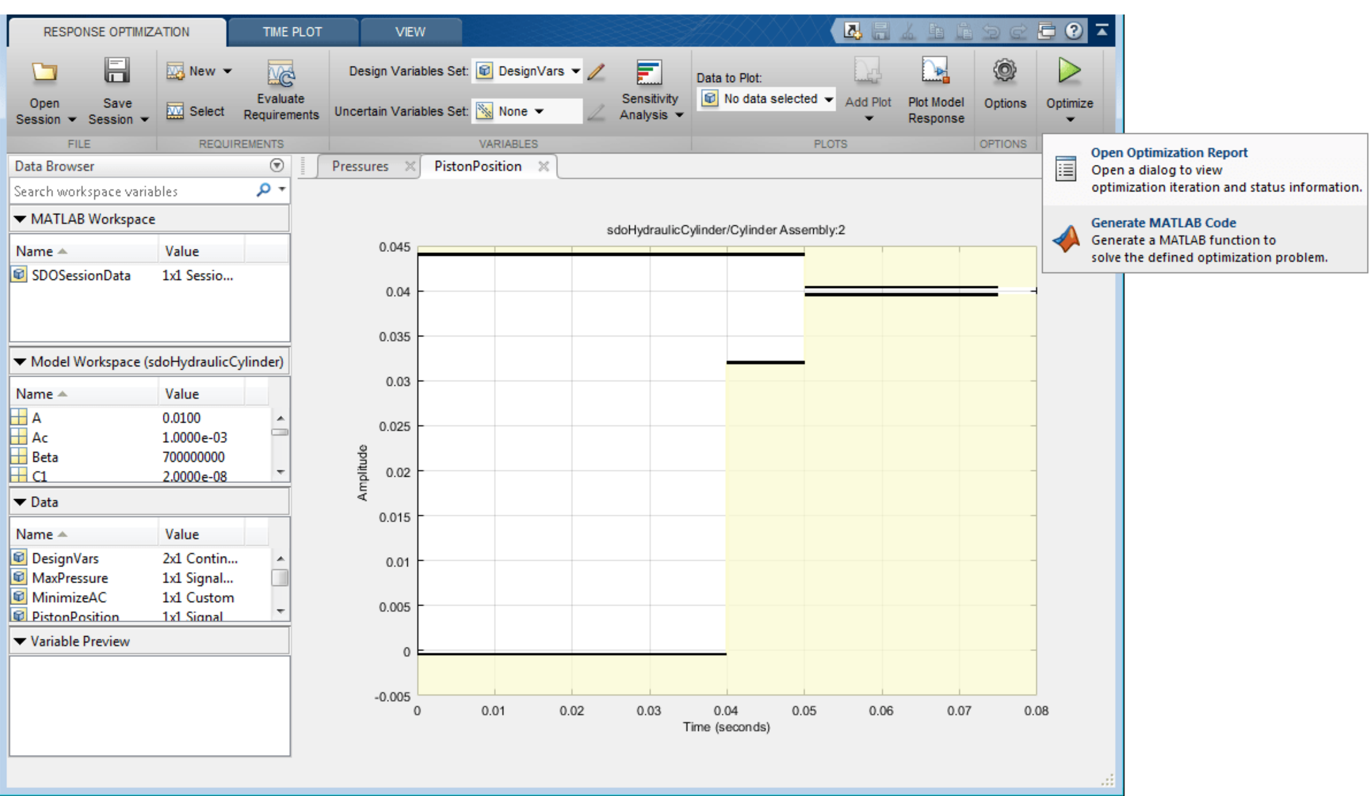
```
load sdoHydraulicCylinder_sdosession
```

Use the following command to open the **Response Optimizer**

```
sdotool(SDOSessionData)
```

Generate MATLAB Code

From the **Optimize** list, select **Generate MATLAB Code**.



The generated code is added to the MATLAB editor as an unsaved MATLAB function.

```
1  function [Optimized_DesignVars, Info] = sdo_sdoHydraulicCylinder(DesignVars)
2  %SDO_SDOHYDRAULICCYLINDER
3  %
4  % Solve a design optimization problem for the sdoHydraulicCylinder model.
5  %
6  % The function returns optimized parameter values, Optimized_DesignVars,
7  % and optimization termination information, Info.
8  %
9  % The, DesignVars, input argument defines the model parameters to optimize,
10 % if omitted the parameters specified in the function body are optimized.
11 %
12 % Modify the function to include or exclude new design requirements or
13 % change the optimization options.
14 %
15 % Auto-generated by SDOTOOL on 15-Mar-2012 13:14:45.
16 %
17
18 %% Open the model.
19 open_system('sdoHydraulicCylinder')
20
21 %% Specify Design Variables
22 %
23 % Specify model parameters as design variables to optimize.
24 if nargin < 1 || isempty(DesignVars)
25     DesignVars = sdo.getParameterFromModel('sdoHydraulicCylinder',{'Ac','K'});
26     DesignVars(1).Minimum = 0.0003;
27     DesignVars(1).Maximum = 0.0013;
28     DesignVars(1).Scale = 0.001;
```

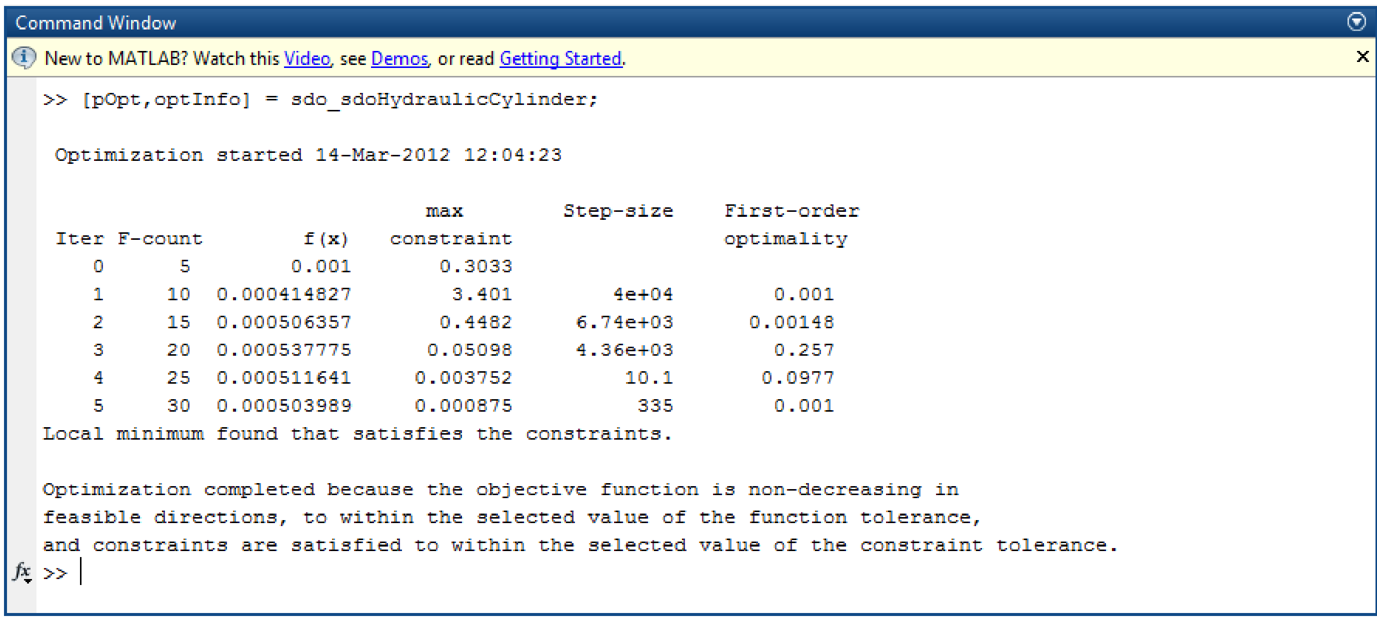
Examine the generated code. Significant code portions are:

- **`Specify Design Variables`** - Definition of the model parameters being optimized.
- **`Specify Design Requirements`** - Definition of the design requirements.
- **`Create Optimization Objective Function`** - Creation of an anonymous function that calls the subfunction `sdoHydraulicCylinder_optFcn`, which evaluates the cylinder design. `sdo.optimize` calls the anonymous function at each iteration.
- **`Evaluate custom parameter requirement functions`** - Evaluates the custom requirement, `MinimizeAC`, that uses the `sdoHydraulicCylinder_customObjective` function.
- **`Optimize the Design`** - Optimization using the `sdo.optimize` command.

Select **Save** from the MATLAB editor to save the generated function.

Run Generated Code

Run the generated function.



The first output argument, `pOpt`, contains the optimized parameter values and the second output argument, `optInfo`, contains optimization information.

Modify the Generated Code

You can:

- Modify the generated `sdo_sdoHydraulicCylinder` function to include or exclude new design requirements or change the optimization options.
- Call the generated `sdo_sdoHydraulicCylinder` function with a different set of parameters to optimize.

For details on how to write an objective/constraint function to use with the `sdo.optimize` command, type `help sdoExampleCostFunction` at the MATLAB command prompt.

Close the model.

Skip Model Simulation Based on Parameter Constraint Violation (GUI)

This example shows how to optimize a design and specify parameter-only constraints that prevent the model from being evaluated in an invalid solution space.

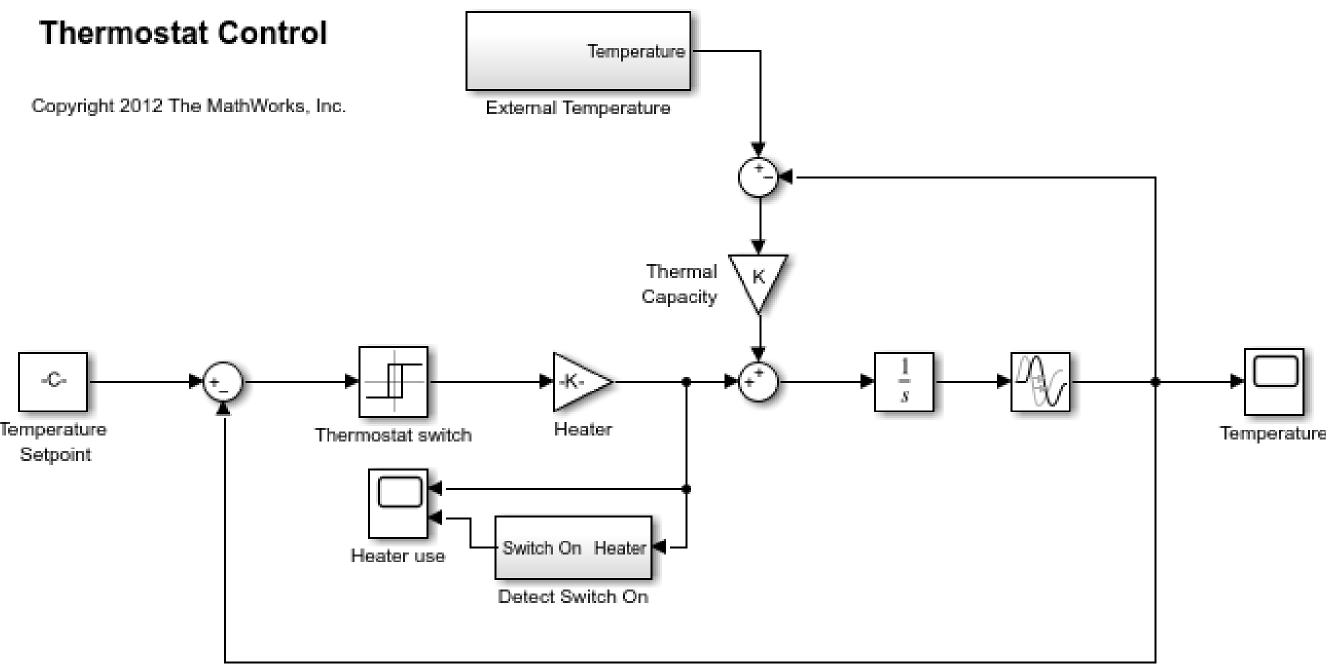
During optimization, the solver may try a design variable set that results in a model simulation error, which can be computationally expensive. If you can define a parameter-only constraint that identifies such a design variable set, then the solver can use the constraint to skip such sets. In other words, you can configure the optimization to be more efficient by disallowing design variable sets that lead to simulation errors.

In this example, you optimize thermostat settings to minimize temperature set-point deviations while satisfying some constraints. One of the constraints applies to the model parameters that define the thermostat switch on/switch off points. If the switch-off point is greater than the switch-on point, evaluating the model leads to a simulation error.

Thermostat Model

Open the model.

```
open_system('sdoThermostat');
```



The model describes a simple heater & thermostat that regulate the temperature of a room. The room is subject to external temperature fluctuations. The room temperature is computed using a first-order heat-flow equation:

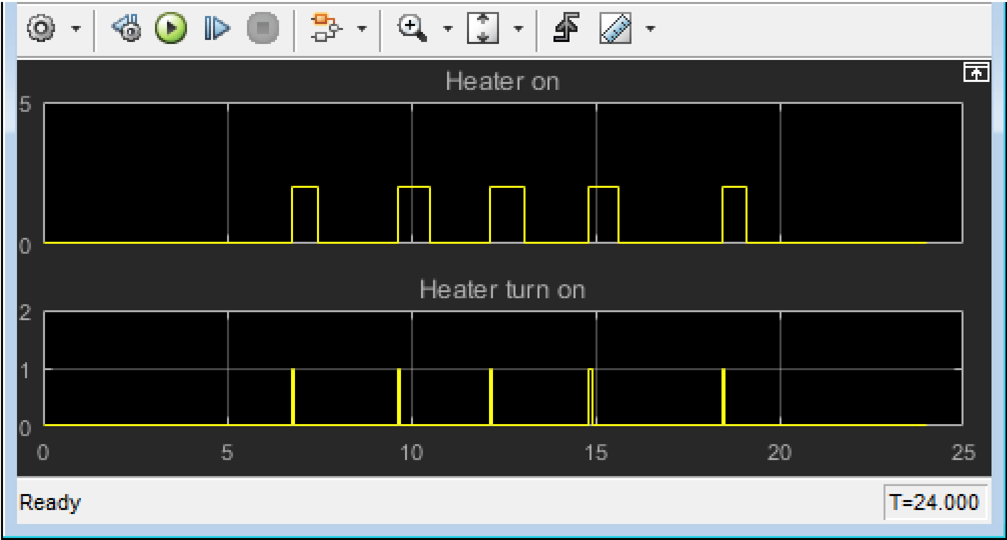
$$\frac{dT}{dt} = K(T_e - T) + Q$$

Where:

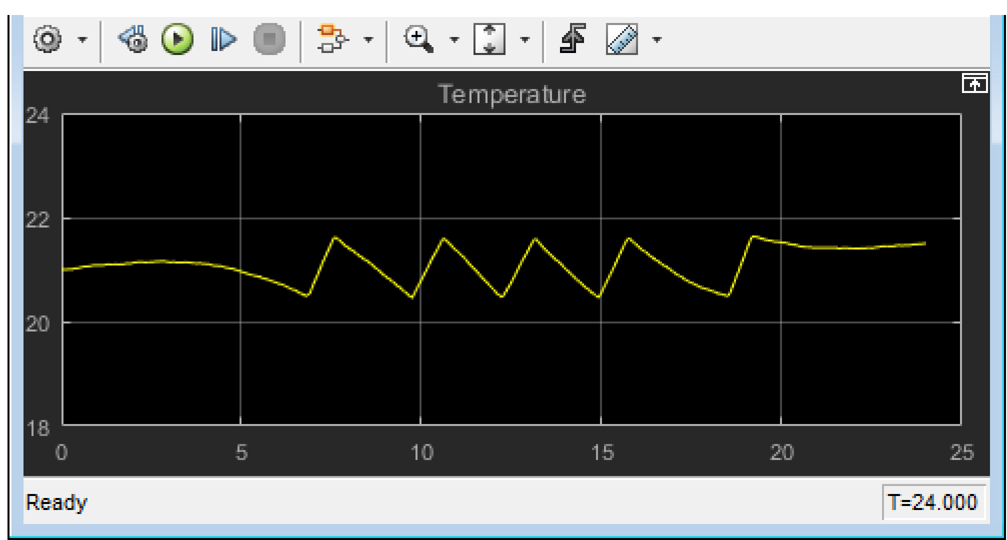
- T is the room temperature (C).
- T_e the external temperature (C).
- Q the heat supplied by the heater (W).
- K the room thermal capacity (J/C).

The heater is controlled by a thermostat that turns on when the difference between the room temperature and temperature set-point exceeds a threshold. The heater turns off when the error drops below a threshold.

The heater operation is displayed in the `Heater use` scope. The upper axis is the delivered heat and the lower axis shows the times when the heater is switched on.



The room temperature is displayed in the `Temperature` scope.



Thermostat Design Problem

You tune the thermostat turn-on and turn-off temperature thresholds, and also the heater power. The `Thermostat switch` block specifies the turn-on and turn-off thresholds using the variables `H_on` and `H_off`. The `Heater` block specifies the heater power using the variable `Hgain`.

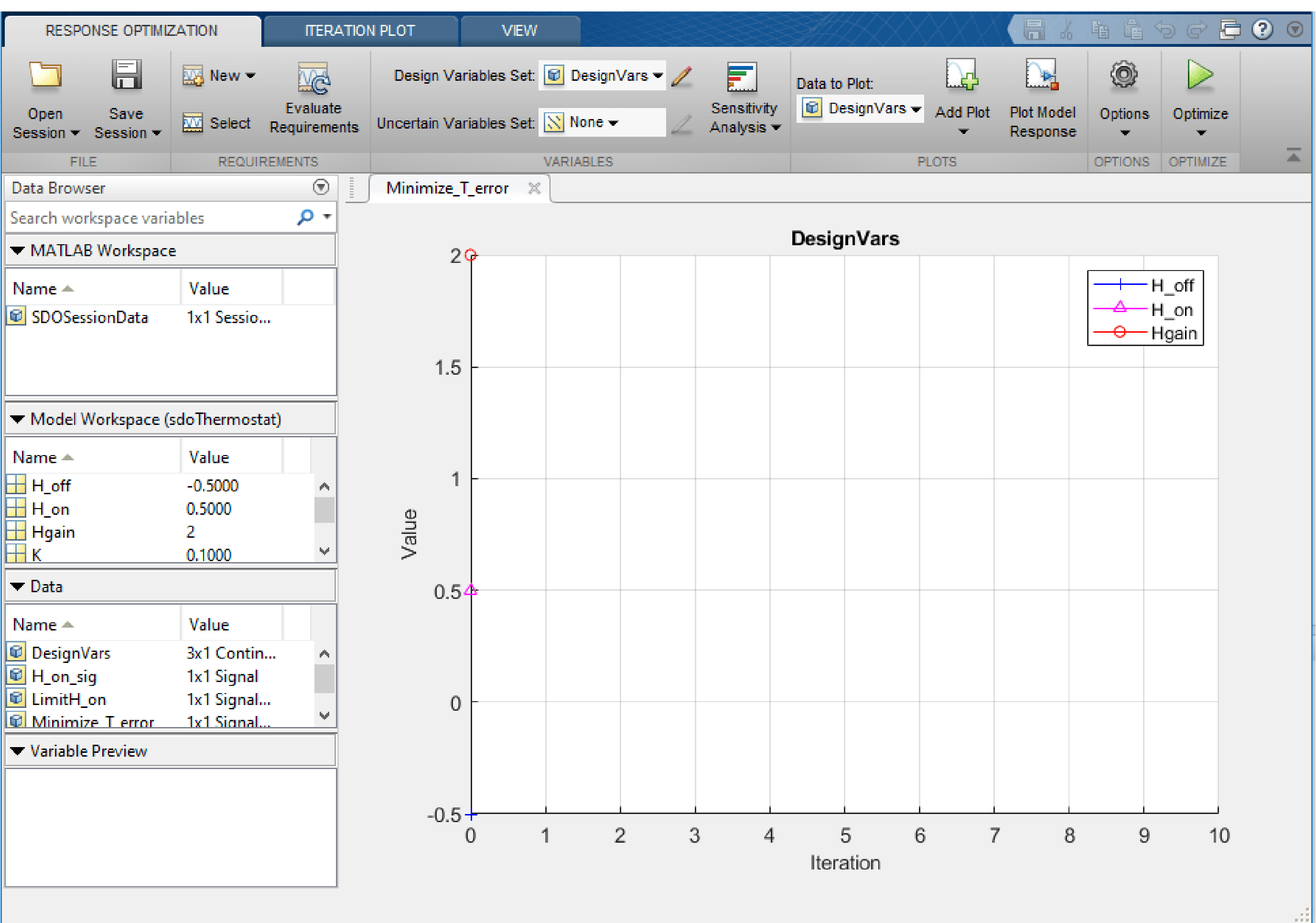
The design requirements are:

- Minimize the difference between the room temperature and temperature set-point over a 24 hour period.
- The heater must not turn on more than 12 times during the 24 hour period.
- The thermostat turn-on temperature must be greater than the thermostat turn-off temperature. If this constraint is violated, the model is invalid and cannot be simulated or evaluated.

Open the Response Optimizer

Open a pre-configured **Response Optimizer** session using the following commands.

```
load sdoThermostat_sdosession
sdotool(SDOSessionData)
```



The pre-configured session specifies the following variables:

- `DesignVars` - Design variables set for the `H_on`, `H_off`, and `Hgain` model parameters.
- `Minimize_T_error` - Requirement to minimize the temperature deviation from the set-point.
- `LimitH_on` - Requirement to limit the number of times the thermostat is turned on.
- `H_on_sig` and `T_error` - Logged signals. `H_on_sig` represents when the heater is on. `T_error` is the difference between the room temperature and the set-point.

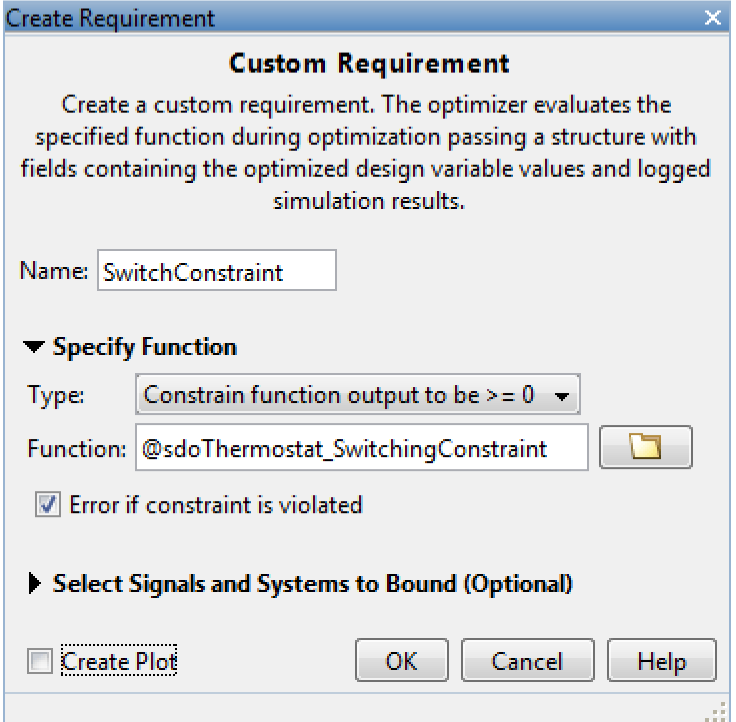
Specify Parameter Constraint

The `H_on > H_off` requirement is not yet defined. Use a custom requirement to specify this constraint and configure the requirement to error if it is not satisfied.

In the **New** drop-down list, select **Custom Requirement**. The Create Requirement dialog opens.

In this dialog, specify the following:

- **Name** - `SwitchConstraint`.
- **Type** - Select `Constrain the function output to be >= 0` from the **Type** list.
- **Function** - `@sdoThermostat_SwitchingConstraint`.
- **Error if constraint is violated** - Select this check box.



The software calls the `sdoThermostat_SwitchingConstraint` function at each optimization iteration with a structure containing all the design variables. The output of the `sdoThermostat_SwitchingConstraint` function is the difference between the `H_on` and `H_off` values. This difference must be positive for the requirement to be satisfied.

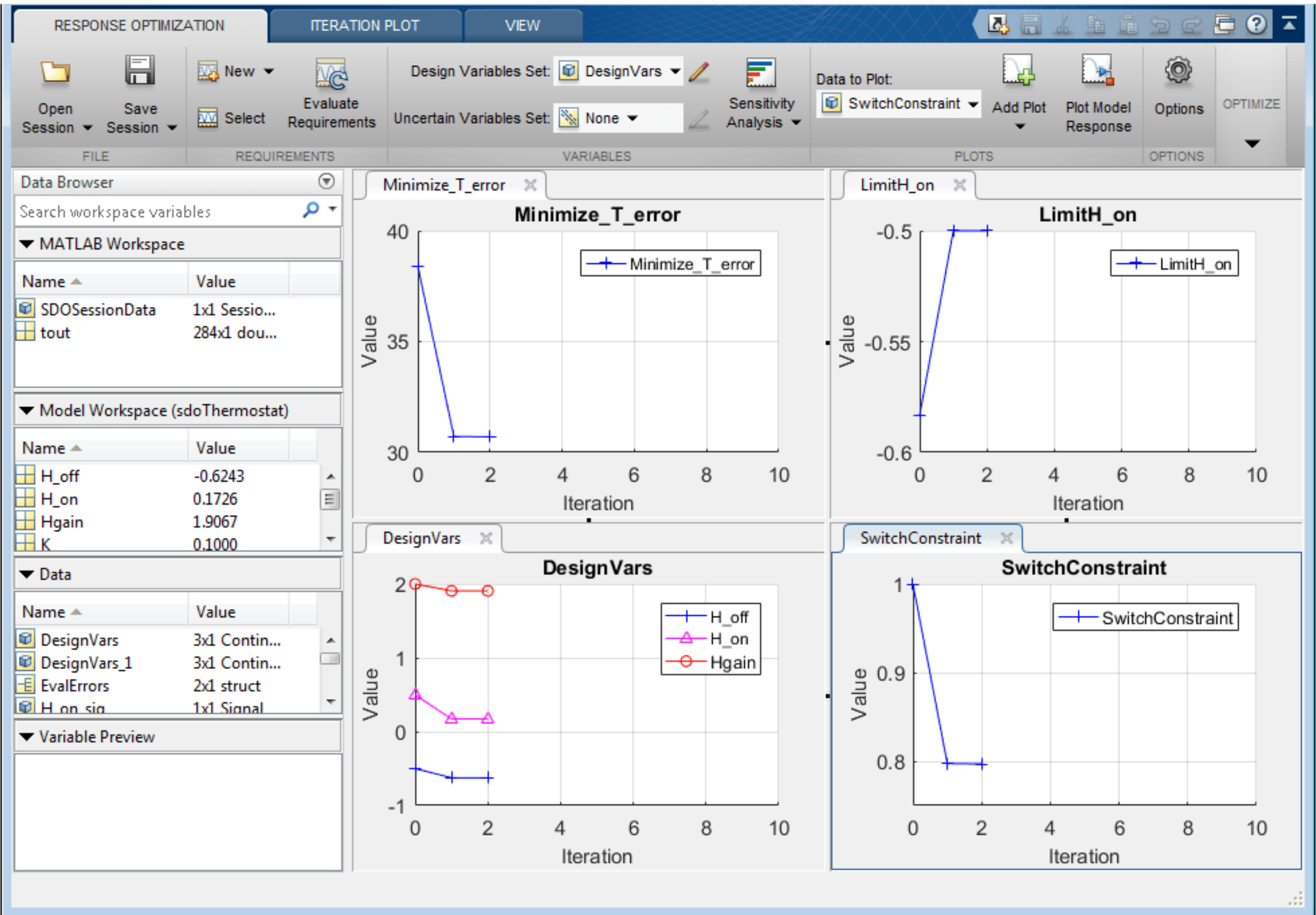
The software evaluates custom requirements that test parameter-only constraints, such as `SwitchConstraint`, before simulating the model and evaluating the remaining requirements.

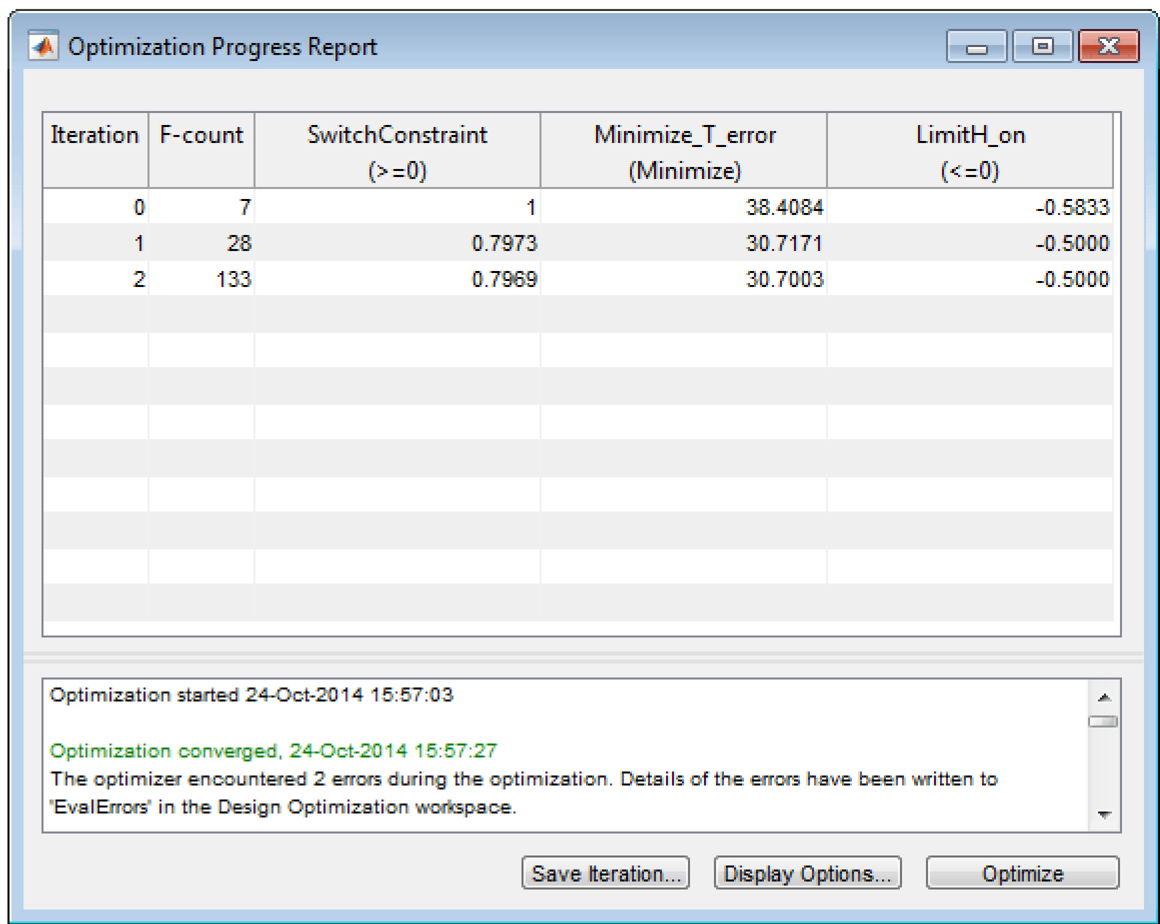
- If the constraint is violated while the **Error if constraint is violated** check box is *selected*, the software does not simulate the model to evaluate the remaining requirements. Instead, the solver assigns the cost function a `NaN` value for this iteration, evaluates the terminating conditions, and continues.
- If the constraint is violated while the **Error if constraint is violated** check box is *cleared*, the solver will attempt to simulate the model to evaluate the remaining requirements. Simulating the model may lead to a hard error; for example, simulating the thermostat model when `SwitchConstraint` is violated will lead to an error. In this case, the solver assigns the cost function a `NaN` value for this iteration, evaluates the terminating conditions, and continues.

To examine the constraint function, type `edit sdoThermostat_SwitchingConstraint`. The requirement that `H_on` > `H_off` is implemented as `H_on` - `H_off` > 0

Optimize the Design

Click **Optimize**.



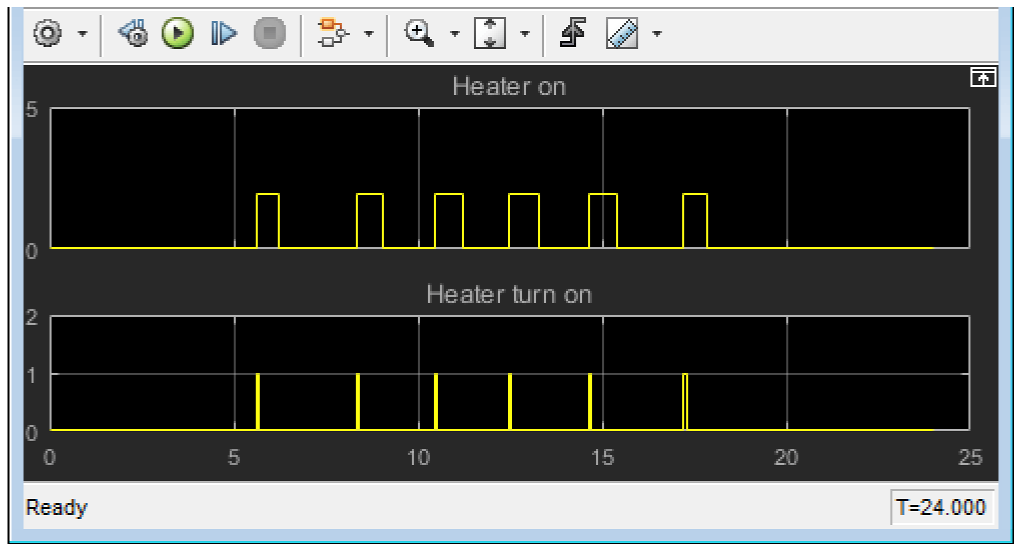


The Optimization Progress window appears and updates at each iteration. The optimization successfully minimizes the temperature error while satisfying the switching constraints.

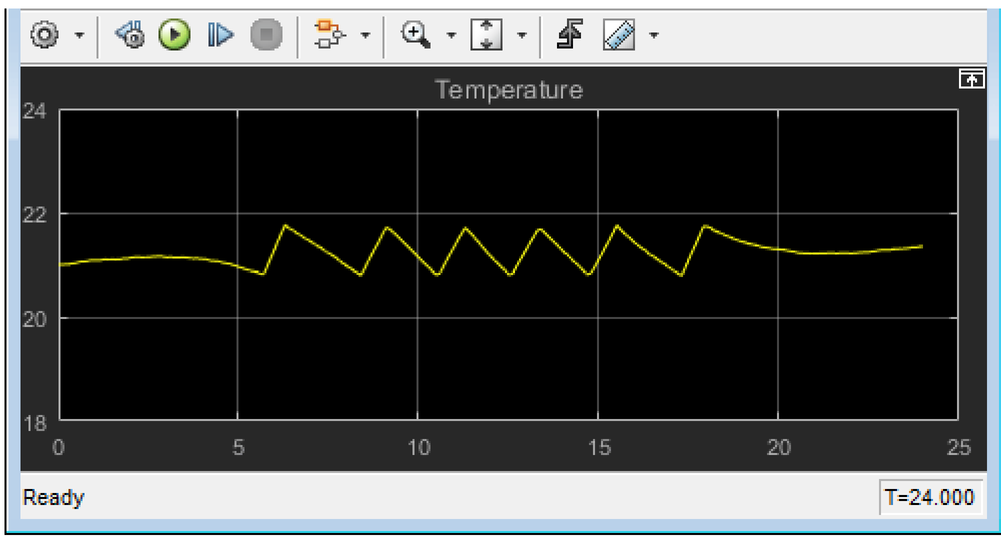
During this optimization, the `H_on` and `H_off` values never approach the `H_on` > `H_off` constraint boundary. So, there is never a danger of violating the constraint. However, changing the optimization algorithm may produce different behavior. For example, changing the optimization algorithm from the one used here, 'Interior-Point', to 'Active-Set' results in `H_on` and `H_off` values that are at the constraint boundary. This violation triggers the `SwitchConstraint` requirement and prevents model simulation for the relevant iterations.

View Optimized Model Response

Simulate the model with the optimized thermostat settings. The optimized heater operation is displayed in the `Heater use` scope where the upper axis is the delivered heat and the lower axis the heater switch on times.



The optimized room temperature is displayed in the `Temperature` scope.



Close the model.

```
bdclose('sdoThermostat')
```

Optimizing Parameters for Robustness

What Is Robustness?

A design is robust when its response does not violate design requirements under model parameter variations. Your model may contain parameters whose values are not precisely known. Such parameters vary over a given range of values and are defined as uncertain parameters. You may know the nominal value and the range of values in which these uncertain parameters vary.

You can use Simulink Design Optimization software to incorporate the parameter uncertainty to test the robustness of your design. When you optimize parameters for robustness, the optimization solver uses the responses computed using all the uncertain parameter values to adjust the design variable values.

You can specify the same parameter both as a design *and* uncertain variable. However, you cannot use a parameter both as a design and uncertain variable in the same optimization run. Also, you cannot add uncertainty to controller or plant parameters during optimization-based control design in the **Control System Designer**.

The uncertain variables can be scalar, vector, matrix or an expression.

You can test and optimize parameters for model robustness in the following ways:

- **Before Optimization**. Specify the parameter uncertainty *before* you optimize the parameters to meet the design requirements. In this case, the optimization method optimizes the signals based on both nominal parameter values as well as the uncertain values. This mode requires more computational time.
- **After Optimization**. Specify the parameter uncertainty *after* you have optimized the model parameters to meet design requirements. You can then test the effect of the uncertain parameters by plotting the model's response. If the response violates the design requirements, you can optimize the parameters again by including the parameter uncertainty during the optimization.

Related Examples

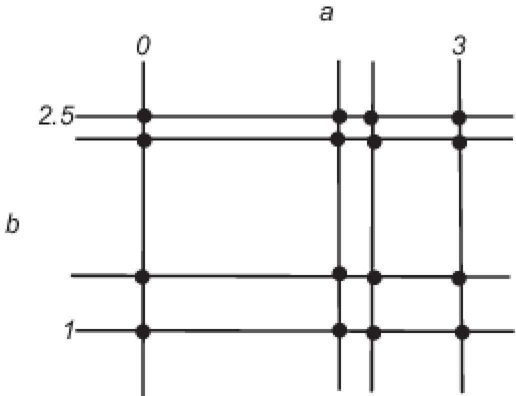
“Optimize Parameters for Robustness (GUI)” on page 3-179

More About

“Sampling Methods for Uncertain Parameters” on page 3-177

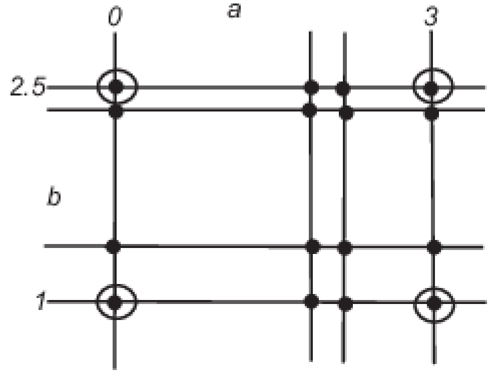
Sampling Methods for Uncertain Parameters

Sample values for uncertain parameters are a vector of numerical values. You can specify the vector yourself or generate a vector of random numbers using the software. The sample values you specify can be uniformly distributed or random. For example, four sample values for two uncertain parameters *a* and *b* in the range `[0 3]` and `[1 2.5]` may look like the following figure.



There are two methods to determine the number of sample values to use during optimization:

- Only the combination of minimum and maximum values (circled)

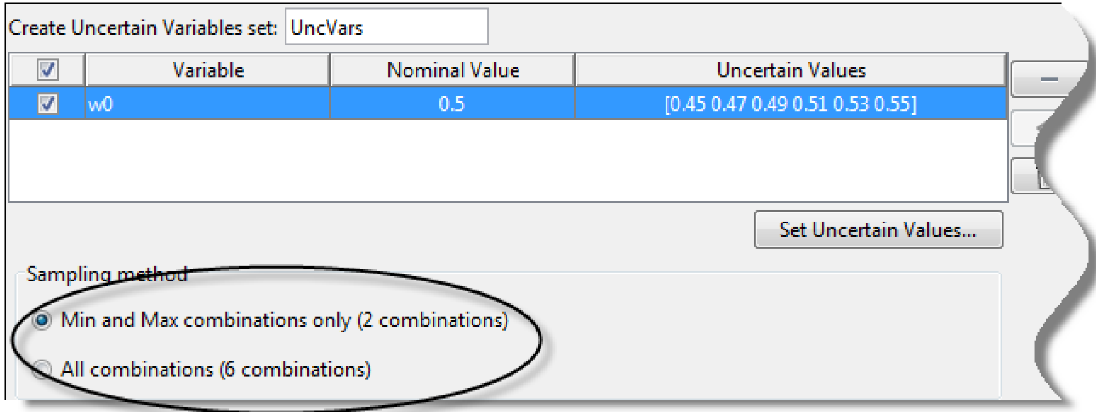


- Combination of the entire set of values (all solid dots in the previous figure)

Tip Using only the minimum and maximum values during optimization increases the computation speed when compared to using the entire set of values.

For the previous example, there are 4 combinations using the minimum and maximum values and 16 combinations if you use all sample values.

In the **Response Optimizer**, you specify the sampling method using the options as shown in the following figure.



Related Examples

"Optimize Parameters for Robustness (GUI)" on page 3-179

More About

- "What Is Robustness?" on page 3-177

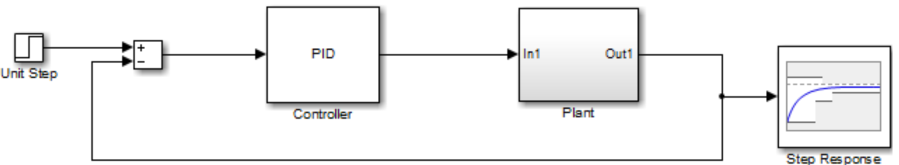
Optimize Parameters for Robustness (GUI)

This example shows how to optimize parameters for model robustness.

1. Load a saved **Response Optimizer** session.

```
load sldo_model1_desreq_optim_sdosession;
sdotool(SDOSessionData);
```

   The `sdotool` command opens the Simulink model `sldo_model1_desreq_optim.slx` and a saved **Response Optimizer** session.

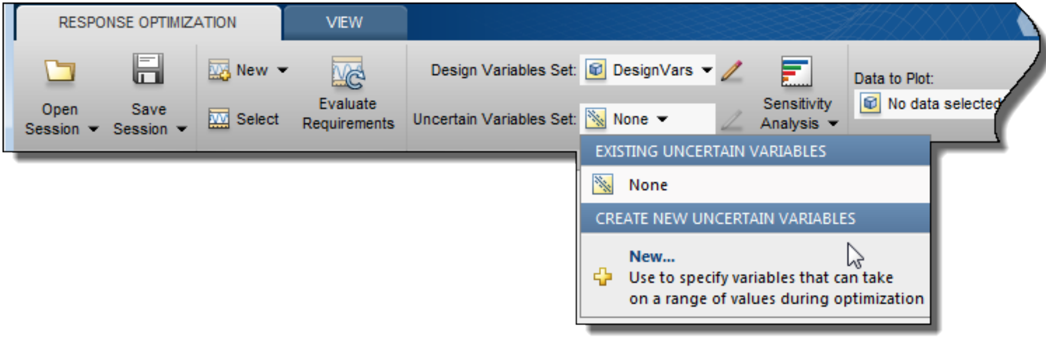


   The parameters of this model, `Kp`, `Ki` and `Kd`, have already been optimized to meet the following step response requirements:

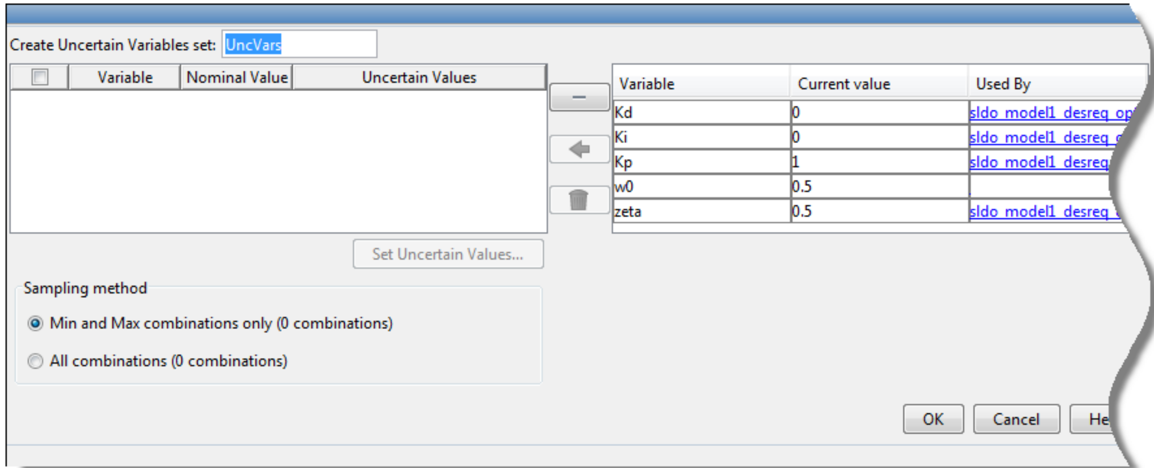
   - Maximum overshoot of 5%
   - Maximum rise time of 10 seconds
   - Maximum settling time of 30 seconds

2. Specify parameter uncertainty.

   a. In the **Uncertain Variables Set** drop-down list, select **New**.

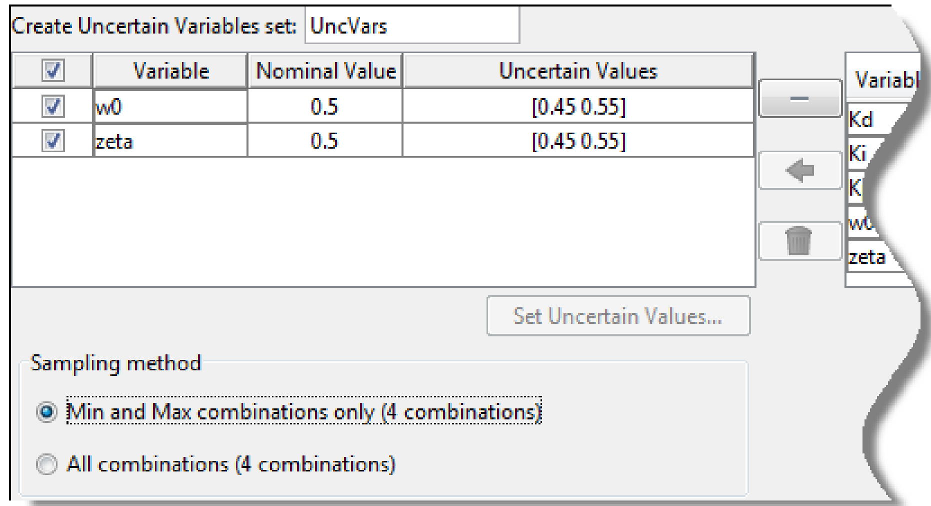


A window opens where you specify uncertain variables.



b Click `w0` and `zeta` to select them.

c Click to add the selected parameters to an uncertain variables set.



The software displays the following parameter settings:

- **Variable** — Parameter name
- **Nominal Value** — Nominal value of the parameters as specified in the Simulink model
- **Uncertain Values** — Values that the uncertain parameter can take. By default, the maximum and minimum values vary by 10% of the nominal value.

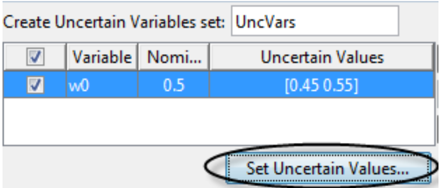
  The total number of sample values to use during optimization is a combination of the maximum and minimum values of the uncertain parameters.

The check-box indicates that the parameter is included in the uncertain variable set. The default uncertain variable set name is `UncVars`.

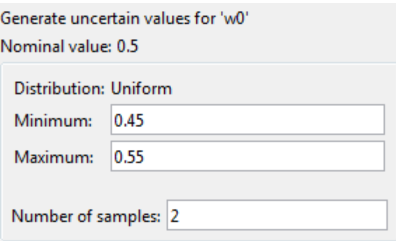
Click **OK**. A new variable `UncVars` appears in **Data** area of the **Response Optimizer**.

Specify Random Values

Instead of specifying sample values, you can auto-generate random values in a specific range. Select a parameter and click **Set Uncertain Values**.

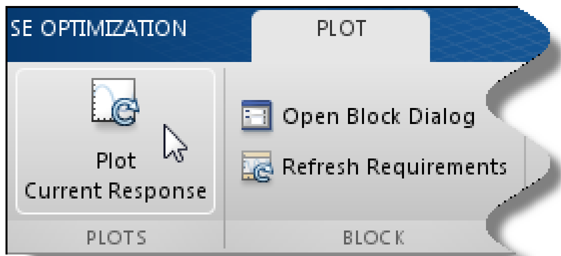


A window opens where you specify the range and the number of samples.

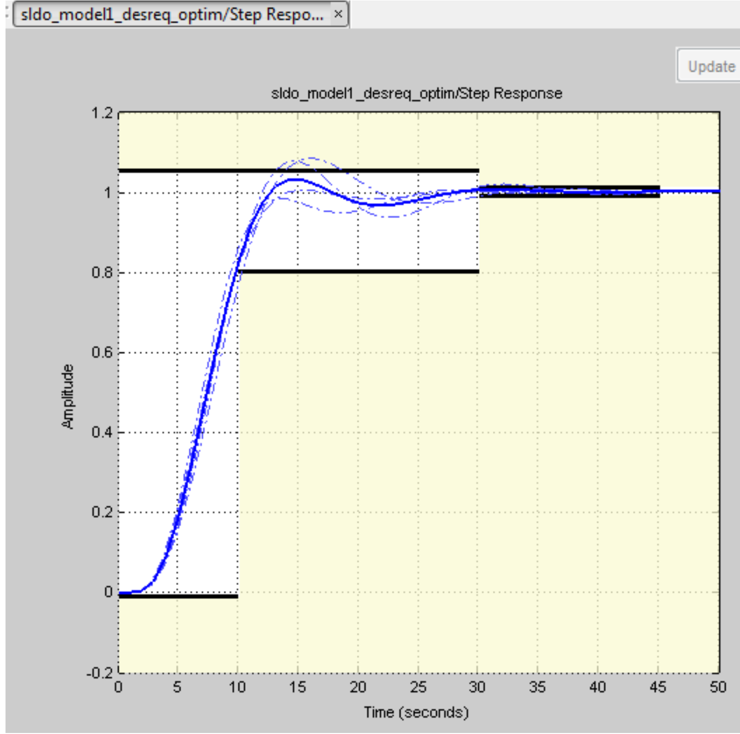


3 Test the model robustness to the uncertain parameters.

   a Click **Plot Model Response**.



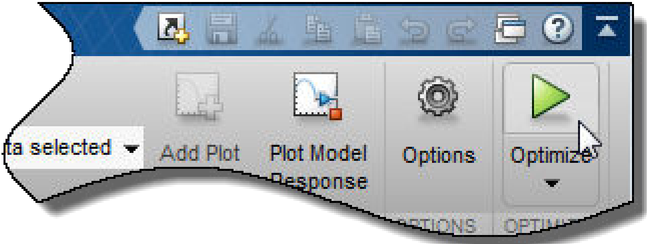
The step response plot, displaying the requirements, updates.



- The solid curve corresponds to the model response computed using the optimized parameters and nominal values of the uncertain parameter.
- The four dashed curves correspond to the model response with the minimum and maximum values of the uncertain parameters.

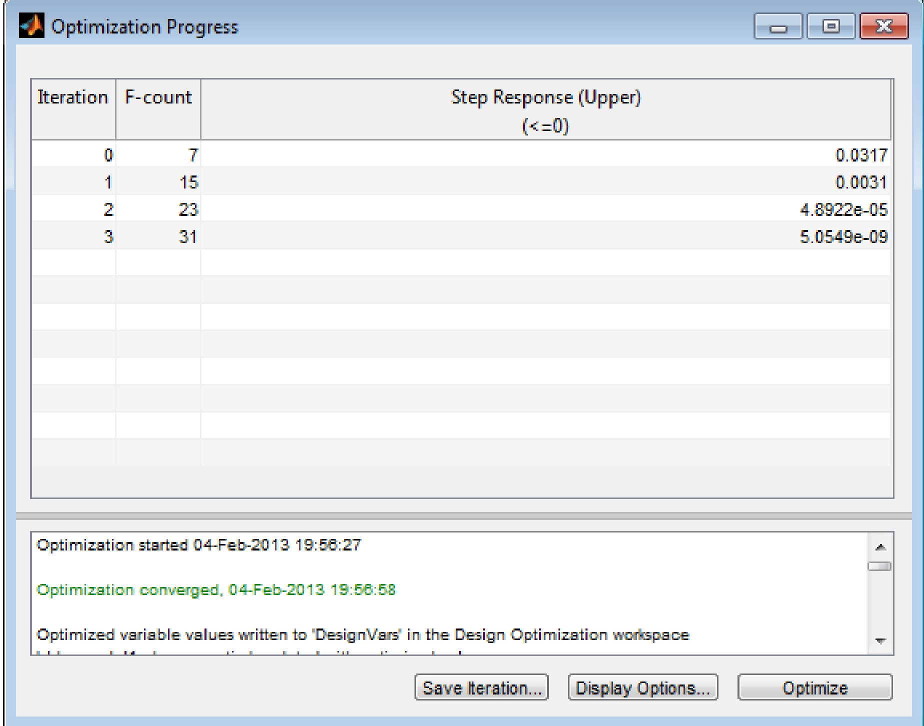
  The dashed plot lines show that the response during the period of 10 to 20 seconds violates the design requirements.

4 Optimize the parameters for model robustness. Click **Optimize**.



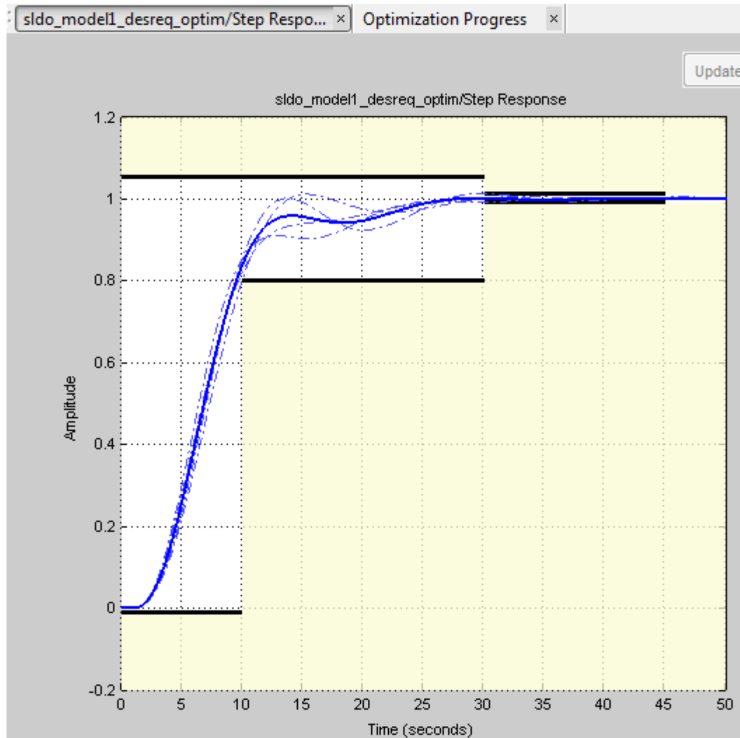
The Optimization Progress window opens which displays the optimization iterations.

After the optimization completes, the message `Optimization converged` indicates that the final model response computed by varying the uncertain parameters meets the specified design requirements.



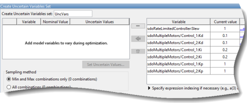
5 Examine the responses.

Tip To view only the final responses of the model, right-click the white area in the plot and uncheck **Responses** > **Show Iteration Responses**.



The final responses appear as the thick solid and dashed curves. The nominal and uncertain responses with parameter variations now meet the design requirements.

If your model contains referenced models, you can create an uncertain variable set using variables in the referenced models, using the **Create Uncertain Variables Set** dialog. For example, the first variable in the dialog box, `Slew`, is listed as `sdoRateLimitedController:Slew`. `sdoRateLimitedController` is the name of the referenced model with the variable `Slew`. The `Slew` variable has the same value for all instances of the `sdoRateLimitedController` model. In contrast, the variable `Kd` can have a different value for each instance of the referenced model containing it. For example, the second variable in the dialog box is listed as `sdoMultipleMotors/Control_1:Kd`. The upper-level model `sdoMultipleMotors` has block `Control_1`, which is a referenced model that has variable `Kd`. The value of this variable can be different than `Kd` in block `Control_2`, which is the third variable in the dialog box. To enable instance-specific values, `Kd` is specified as a model argument in the referenced model workspace.



More About

- “What Is Robustness?” on page 3-177
- “Sampling Methods for Uncertain Parameters” on page 3-177

See Also

Related Examples

- “Design Optimization with Uncertain Variables (Code)” on page 3-159

Use Accelerator Mode During Simulations

About Accelerating Optimization

Simulink Design Optimization software supports Normal and Accelerator simulation modes. You can accelerate the design optimization computations by changing the simulation mode of your Simulink model to Accelerator. For information about these modes, see “How Acceleration Modes Work”.

The default simulation mode is Normal. In this mode, Simulink uses interpreted code, rather than compiled C code during simulations.

In the Accelerator mode, Simulink Design Optimization software runs simulations during optimization with compiled C code. Using compiled C code speeds up the simulations and reduces the time to optimize the model response signals.

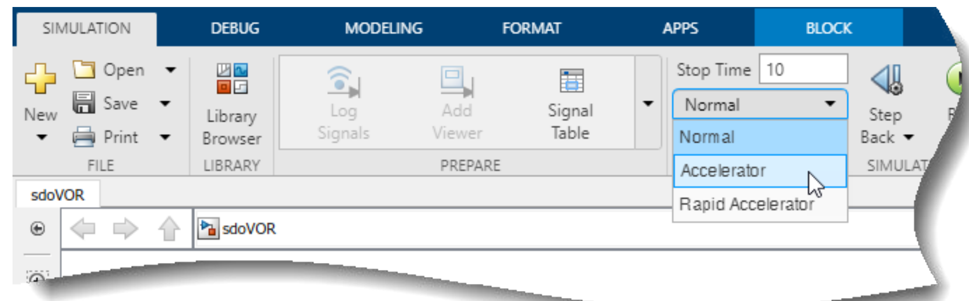
Limitations

If the model structure changes during optimization, the model is compiled to regenerate the C code for each iteration. In this case, using the Accelerator mode increases the computation time. To learn more about code regeneration, see “Code Regeneration in Accelerated Models”.

Setting Accelerator Mode

To set the simulation mode to Accelerator, open the Simulink model window and perform one of the following actions:

- Under **Simulation**, choose Accelerator from the drop-down list as shown in the next figure.



Tip To obtain the maximum performance from the Accelerator mode, close all Scope blocks in your model.

See Also

More About

- “Ways to Speed Up Design Optimization Tasks”

Speed Up Response Optimization Using Parallel Computing

When to Use Parallel Computing for Response Optimization

You can use Simulink Design Optimization software with Parallel Computing Toolbox software to speed up the response optimization of a Simulink model. Using parallel computing may reduce model optimization time in the following cases:

- The model contains a large number of tuned parameters, and the `Gradient descent` method is selected for optimization.
- The `Pattern search` method is selected for optimization.
- The model contains a large number of uncertain parameters and uncertain parameter values.
- The model is complex and takes a long time to simulate.

When you use parallel computing, the software distributes independent simulations to run them in parallel on multiple MATLAB sessions, also known as *workers*. Distributing the simulations significantly reduces the optimization time because the time required to simulate the model dominates the total optimization time.

For information on how the software distributes the simulations and the expected speedup, see "How Parallel Computing Speeds Up Optimization" on page 3-187.

For information on configuring your system and using parallel computing, see "Use Parallel Computing for Response Optimization" on page 3-190.

How Parallel Computing Speeds Up Optimization

You can enable parallel computing with the `Gradient descent` and `Pattern search` optimization methods. When you enable parallel computing, the software distributes independent simulations during optimization on multiple MATLAB sessions. The following sections describe which simulations are distributed and the potential speedup using parallel computing.

Parallel Computing with the Gradient Descent Method

When you select `Gradient descent` as the optimization method, the model is simulated during the following computations:

- Constraint and objective value computation — One simulation per iteration
- Constraint and objective gradient computations — Two simulations for every tuned parameter per iteration
- Line search computations — Multiple simulations per iteration

The total time, $Ttotal$, taken per iteration to perform these simulations is given by the following equation:

$$Ttotal = T + (Np \times 2 \times T) + (Nls \times T) = T \times (1 + (2 \times Np) + Nls)$$

where T is the time taken to simulate the model and is assumed to be equal for all simulations, Np is the number of tuned parameters, and Nls is the number of line searches. Nls is difficult to estimate and you generally assume it to be equal to one, two, or three.

When you use parallel computing, the software distributes the simulations required for constraint and objective gradient computations. The simulation time taken per iteration when the gradient computations are performed in parallel, *TtotalP*, is approximately given by the following equation:

$$TtotalP = T + \left(ceil\left(\frac{Np}{Nw}\right) \times 2 \times T\right) + (Nls \times T) = T \times \left(1 + 2 \times ceil\left(\frac{Np}{Nw}\right) + Nls\right)$$

where *Nw* is the number of MATLAB workers.

Note The equation does not include the time overheads associated with configuring the system for parallel computing and loading Simulink software on the remote MATLAB workers.

The expected speedup for the total optimization time is given by the following equation:

$$\frac{TtotalP}{Ttotal} = \frac{1 + 2 \times ceil\left(\frac{Np}{Nw}\right) + Nls}{1 + (2 \times Np) + Nls}$$

For example, for a model with N_p=3, N_w=4, and N_{ls}=3, the expected speedup equals $\frac{1 + 2 \times ceil\left(\frac{3}{4}\right) + 3}{1 + (2 \times 3) + 3} = 0.6$.

For an example of the performance improvement achieved with the `Gradient descent` method, see “Improving Optimization Performance Using Parallel Computing” on page 3-208.

Parallel Computing with the Pattern Search Method

The `Pattern search` optimization method uses search and poll sets to create and compute a set of candidate solutions at each optimization iteration.

The total time, *Ttotal*, taken per iteration to perform these simulations, is given by the following equation:

$$Ttotal = (T \times Np \times Nss) + (T \times Np \times Nps) = T \times Np \times (Nss + Nps)$$

where *T* is the time taken to simulate the model and is assumed to be equal for all simulations, *Np* is the number of tuned parameters, *Nss* is a factor for the search set size, and *Nps* is a factor for the poll set size. *Nss* and *Nps* are typically proportional to *Np*.

When you use parallel computing, Simulink Design Optimization software distributes the simulations required for the search and poll set computations, which are evaluated in separate `parfor` loops. The simulation time taken per iteration when the search and poll sets are computed in parallel, *TtotalP*, is given by the following equation:

$$\begin{aligned} TtotalP &= \left(T \times ceil\left(Np \times \frac{Nss}{Nw}\right)\right) + \left(T \times ceil\left(Np \times \frac{Nps}{Nw}\right)\right) \\ &= T \times \left(ceil\left(Np \times \frac{Nss}{Nw}\right) + ceil\left(Np \times \frac{Nps}{Nw}\right)\right) \end{aligned}$$

where *Nw* is the number of MATLAB workers.

Note The equation does not include the time overheads associated with configuring the system for parallel computing and loading Simulink software on the remote MATLAB workers.

The expected speed up for the total optimization time is given by the following equation:

$$\frac{TtotalP}{Ttotal} = \frac{ceil(Np \times \frac{Nss}{Nw}) + ceil(Np \times \frac{Nps}{Nw})}{Np \times (Nss + Nps)}$$

For example, for a model with N_p=3, N_w=4, N_{ss}=15, and N_{ps}=2, the expected speedup equals $\frac{ceil(3 \times \frac{15}{4}) + ceil(3 \times \frac{2}{4})}{3 \times (15 + 2)} = 0.27$.

Note Using the `Pattern search` method with parallel computing may not speed up the optimization time. To learn more, see “Why do I not see the optimization speedup I expected using parallel computing?” on page 3-201

For an example of the performance improvement achieved with the `Pattern search` method, see “Improving Optimization Performance Using Parallel Computing” on page 3-208.

See Also

Related Examples

- “Use Parallel Computing for Response Optimization” on page 3-190

Use Parallel Computing for Response Optimization

Configure Your System for Parallel Computing

You can speed up model optimization using parallel computing on multicore processors or multiprocessor networks. Use parallel computing with the **Response Optimizer** and `sdo.optimize` to optimize using the `fmincon`, `lsqnonlin`, and `patternsearch` methods. Parallel computing is not supported for the `fminsearch` (**Simplex search**) method.

When you optimize model parameters using parallel computing, the software uses the available parallel pool. If none is available, and you select **Automatically create a parallel pool** in your Parallel Computing Toolbox preferences, the software starts a parallel pool using the settings in those preferences. To open a parallel pool that uses a specific cluster profile, use:

```
parpool(MyProfile);
```

`MyProfile` is the name of a cluster profile.

For information regarding creating a cluster profile, see "Add and Modify Cluster Profiles" (Parallel Computing Toolbox).

Model Dependencies

Model dependencies are any referenced models, data such as model variables, S-functions, and additional files necessary to run the model. Before starting the optimization, verify that the model dependencies are complete. Otherwise, you may get unexpected results.

Making Model Dependencies Accessible to Remote Workers

When you use parallel computing, the Simulink Design Optimization software helps you identify model dependencies. To do so, the software uses the Dependency Analyzer. The dependency analysis may not find all the files required by your model. To learn more, see "Dependency Analyzer Scope and Limitations". If your model has dependencies that are undetected or inaccessible by the parallel pool workers, then add them to the list of model dependencies.

The dependencies are made accessible to the parallel pool workers by specifying one of the following:

- File dependencies: the model dependency files are copied to the parallel pool workers.
- Path dependencies: the paths to the model dependencies are added to the paths of the parallel pool workers. If you are working in a multi-platform scenario, ensure that the paths are compatible across platforms.

Using file dependencies is recommended, however, in some cases it can be better to choose path dependencies. For example, if parallel computing is set up on a local multi-core computer, using path dependencies is preferred as using file dependencies creates multiple copies of the dependent files on the local computer.

For more information, see:

- "Optimize Design Using Parallel Computing (GUI)" on page 3-191 (Not supported in Simulink Online.)
- "Optimize Design Using Parallel Computing (Code)" on page 3-193

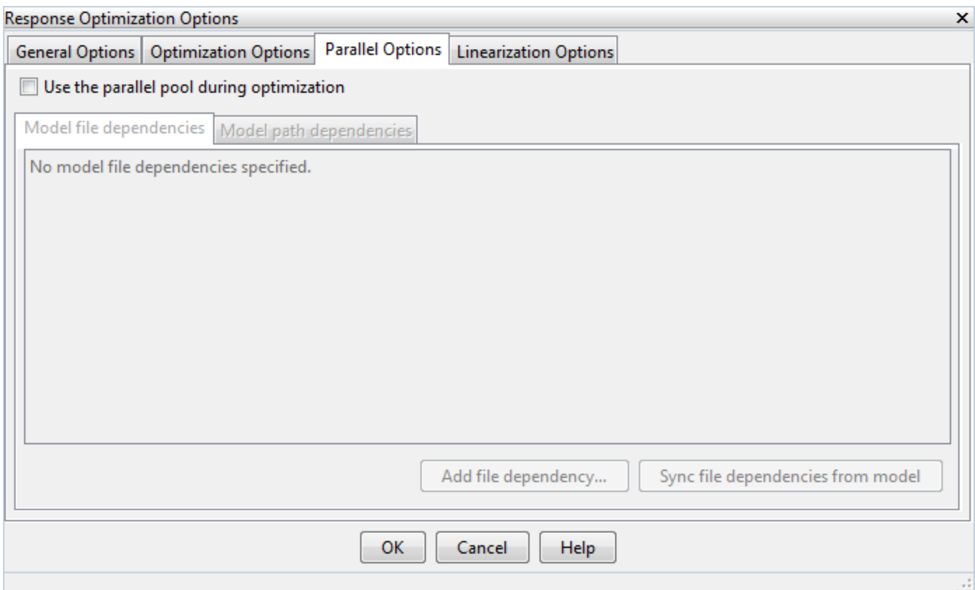
Optimize Design Using Parallel Computing (GUI)

To optimize a model response using parallel computing in the **Response Optimizer**:

1. Ensure that the software can access parallel pool workers that use the appropriate cluster profile.

   For more information, see “Configure Your System for Parallel Computing” on page 3-190.
2. Open the **Response Optimizer** for the Simulink model.
3. Configure the design variables, design requirements, and, optionally, optimization settings.

   For more information, see “Specify Design Variables” on page 3-56, “Specify Time-Domain Design Requirements in the App” on page 3-16, “Specify Frequency-Domain Design Requirements in the App” on page 3-43, and “Specify Optimization Options” on page 3-62.
4. On the **Response Optimization** tab, click **Options** to open the **Response Optimization Options** dialog box.
5. Select the **Parallel Options** tab.

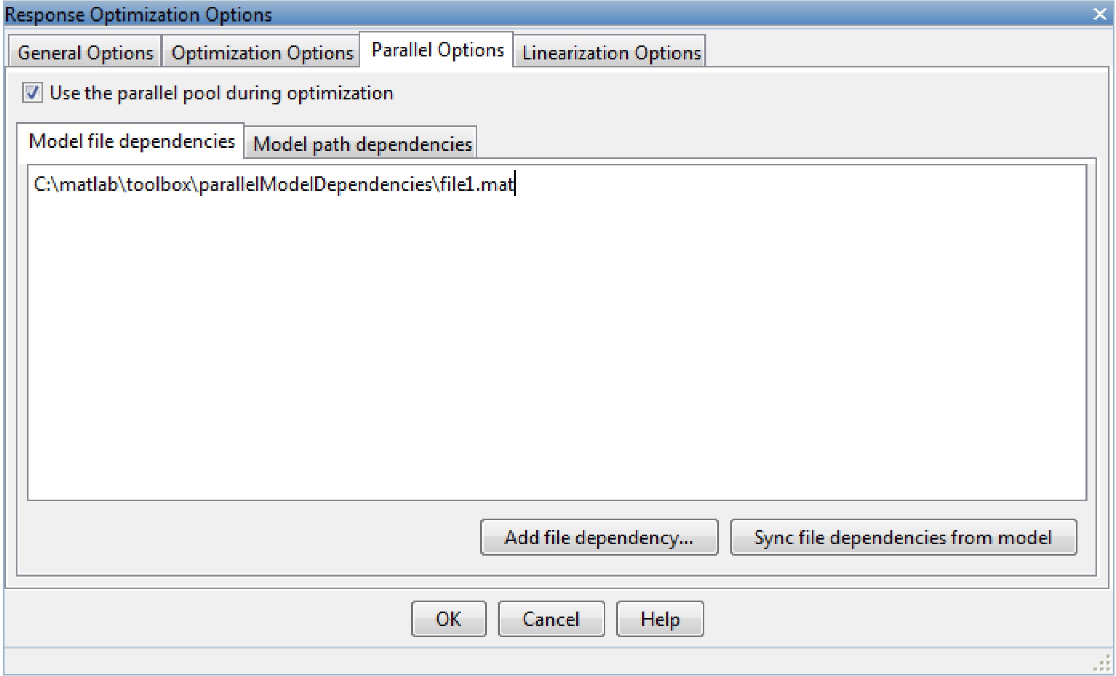


6. Select the **Use the parallel pool during optimization** check box.

   This option checks for dependencies in your Simulink model. The file dependencies are displayed in the **Model file dependencies** list box, and corresponding path to the files in **Model path dependencies**. The files listed in **Model file dependencies** are copied to the remote workers.

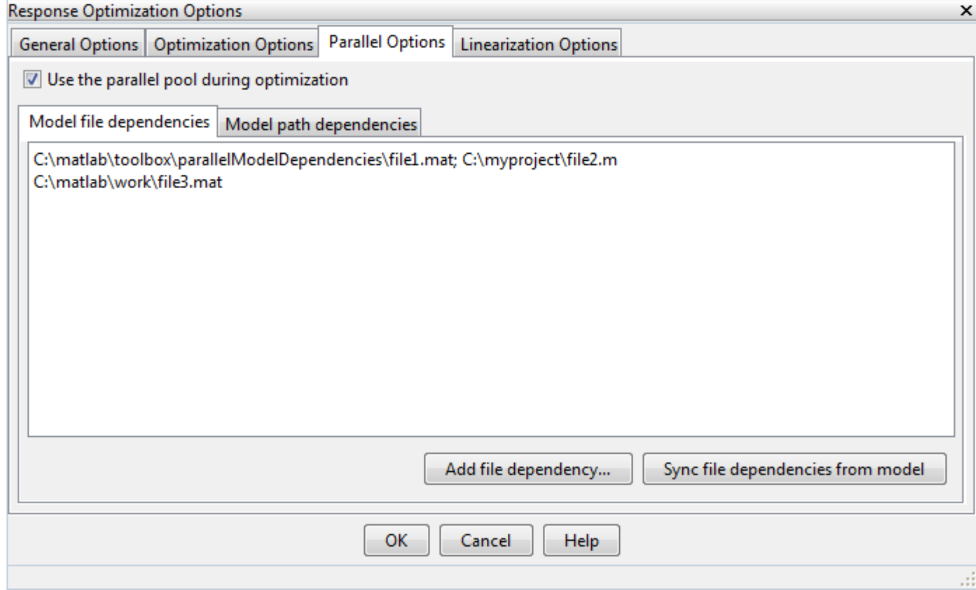
   Note The automatic dependencies check may not detect all the dependencies in your model.

   For more information, see “Model Dependencies” on page 3-190. In this case, add the undetected dependencies manually.



7 Add any file dependencies that the automatic check does not detect.

Specify the files in the **Model file dependencies** list box separated by semicolons or on separate lines.



Alternatively, click **Add file dependency** to open a dialog box, and select the file to add.

Note If you do not want to copy the files to the remote workers, delete all entries in the **Model file dependencies** list box. Populate the **Model path dependencies** list box by clicking the **Sync path dependencies from model**, and add any undetected path dependencies. In addition,

in the list box, update the paths on local drives to make them accessible to remote workers. For example, change `C:\` to `\\\\hostname\\C$\\`.

8 If you modify the Simulink model, resync the dependencies to ensure that any new dependencies are detected. Click **Sync file dependencies from model** in the **Parallel Options** tab to rerun the automatic dependency check for your model.

   This action updates the **Model file dependencies** list box with any new file dependency found in the model.

9 Click **OK**.

10 In the **Response Optimizer**, click **Optimize** to optimize the model response using parallel computing.

For information on troubleshooting problems related to optimization using parallel computing, see “Troubleshooting” on page 3-194.

Optimize Design Using Parallel Computing (Code)

To optimize a model response using parallel computing at the command line:

1. Ensure that the software can access parallel pool workers that use the appropriate cluster profile.

   For more information, see “Configure Your System for Parallel Computing” on page 3-190.

2. Open the model.
3. Specify design requirements and design variables. For example see, “Design Optimization to Meet Step Response Requirements (Code)”.
4. Enable parallel computing using an optimization option set, `opt`.

```
opt = sdo.OptimizeOptions;
opt.UseParallel = true;
```

5. Find the model dependencies.

```
[dirs,files] = sdo.getModelDependencies(modelname)
```

Note `sdo.getModelDependencies` may not detect all the dependencies in your model. For more information, see “Model Dependencies” on page 3-190. In this case, add the undetected dependencies manually.

6. Modify `files` to include any file dependencies that `sdo.getModelDependencies` does not detect.

```
files = vertcat(files,'C:\matlab\work\filename.m')
```

Note If you do not want to copy the files to the remote workers, use the path dependencies. Add any undetected path dependencies to `dirs` and update the paths on local drives to make them accessible to remote workers. See `sdo.getModelDependencies` for more details.

7. Add the file dependencies for optimization.

```
opt.ParallelFileDependencies = files;
```

8. Run the optimization.

```
[pOpt,opt_info] = sdo.optimize(opt_fcn,param,opt);
```

For information on troubleshooting problems related to optimization using parallel computing, see “Troubleshooting” on page 3-194.

Troubleshooting

Why Are the Optimization Results With and Without Using Parallel Computing Different?

- Different numerical precision on the client and worker machines can produce marginally different simulation results. Thus, the optimization method can take a different solution path and produce a different result.
- When you use parallel computing with the `Pattern search` method, the search is more comprehensive and can result in a different solution.

  To learn more, see “Parallel Computing with the Pattern Search Method” on page 3-188.

Why Don’t I See the Optimization Speed up I Expected Using Parallel Computing?

- When you optimize a model that does not have a large number of parameters or does not take long to simulate, you might not see a speedup in the optimization time. In such cases, the overhead associated with creating and distributing the parallel tasks outweighs the benefits of running the optimization in parallel.
- Using the `Pattern search` method with parallel computing might not speed up the optimization time. Without parallel computing, the method stops the search at each iteration when it finds a solution better than the current solution. The candidate solution search is more comprehensive when you use parallel computing. Although the number of iterations might be larger, the optimization without using parallel computing might be faster.

  To learn more about the expected speedup, see “Parallel Computing with the Pattern Search Method” on page 3-188.

Why Doesn’t the Optimization Using Parallel Computing Make Any Progress?

To troubleshoot the problem:

1. Run the optimization for a few iterations without parallel computing to see if the optimization progresses.
2. Check whether the remote workers have access to all model dependencies. Model dependencies include data variables and files required by the model to run.

   To learn more, see “Model Dependencies” on page 3-190.

Why Doesn’t the Optimization Using Parallel Computing Stop When I Click the Stop Optimization Button?

When you use parallel computing with the `Pattern search` method, the software must wait until the current optimization iteration completes before it notifies the workers to stop. The optimization does not terminate immediately when you click **Stop**, and, instead, appears to continue running.

See Also

`sdo.optimize` | `sdo.OptimizeOptions` | `sdo.getModelDependencies` | `parpool`

Related Examples

- “Optimizing Time-Domain Response of Simulink Models Using Parallel Computing” on page 3-217

More About

- “Speed Up Response Optimization Using Parallel Computing” on page 3-187
- “Ways to Speed Up Design Optimization Tasks”

Use Fast Restart Mode During Response Optimization

This topic shows how to speed up response optimization using Simulink fast restart. You can use the fast restart feature to speed up response optimization of tunable parameters of a model.

Fast restart enables you to perform iterative simulations without compiling a model or terminating the simulation each time. Using fast restart, you compile a model only once. You can then tune parameters and simulate the model again without spending time on compiling. Fast restart associates multiple simulation phases with a single compile phase to make iterative simulations more efficient. You see a speedup of design optimization tasks using fast restart in models that have a long compilation phase. See “How Fast Restart Improves Iterative Simulations”.

When you enable fast restart, you can only change tunable properties of the model during simulation. For more information about the limitations, see “Limitations”.

You can optimize using fast restart in the **Response Optimizer** (Not supported in Simulink Online) or at the command line on page 3-196.

Response Optimizer App Workflow for Fast Restart

To optimize a model response using fast restart in the **Response Optimizer**:

1. Open the Simulink model.
2. Enable fast restart in the model.

   Click **Fast Restart** in the model window.
3. Open the **Response Optimizer** for the model.
4. Configure the design variables, design requirements, and, optionally, optimization settings.

   For more information, see “Specify Design Variables” on page 3-56, “Specify Time-Domain Design Requirements in the App” on page 3-16, “Specify Frequency-Domain Design Requirements in the App” on page 3-43, and “Specify Optimization Options” on page 3-62.
5. Click **Optimize** to optimize the model response in fast restart mode.
6. Disable fast restart.

   In the model window, click **Fast Restart** .

Command-Line Workflow for Fast Restart

To optimize a model response using fast restart at the command line:

1. Open the Simulink model.
2. Create a model simulation scenario. You must create a simulation scenario with logging information before configuring the model for fast restart. You cannot modify logging information once the model has been compiled for fast restart.

   ```
   Simulator = sdo.SimulationTest('model');
   ```

   Specify model signals to log during model simulation.

For response optimization problems that include frequency-domain requirements, the model is linearized using Simulink Control Design. Use the `SystemLoggingInfo` property of the `sdo.SimulationTest` object, `Simulator`, to specify linear systems to log when simulating the model. For an example, see “Design Optimization to Meet Frequency-Domain Requirements (Code)” on page 3-224.

Note In fast restart mode, you cannot use the `linearize` command from Simulink Control Design to specify and compute linear systems. Using `linearize` generates an error.

---

3. Specify design requirements, `Requirements`, and design variables, `param`. For and example, see “Design Optimization to Meet Step Response Requirements (Code)”.
4. Configure the model and simulation scenario for fast restart.

   ```
   Simulator = fastRestart(Simulator,'on');
   ```
5. Create an optimization cost function, `myCostfcn`, and pass `Simulator` to the cost function as an input. For more information, see “Write a Cost Function” on page 2-49. In the cost function, the simulator configured for fast restart is used to update the model parameters, simulate the model, and log signals.

   Use an anonymous function with one argument that calls `myCostfcn`.

   ```
   optimfcn = @(param) myCostfcn(param,Simulator,Requirements);
   ```

   Here, `myCostfcn` is a cost function that takes design variables, `param`, simulation scenario, `Simulator`, and design requirements, `Requirements`, as inputs.
6. Run the optimization.

   ```
   [param_opt,opt_info] = sdo.optimize(optimfcn,param);
   ```
7. Restore the simulator fast restart settings.

   ```
   Simulator = fastRestart(Simulator,'off');
   ```

Troubleshooting

Why Don’t I See the Optimization Speedup I Expected Using Fast Restart?

You see a speedup of design optimization tasks using fast restart in models that have a long compilation phase. If the compilation phase of your model is not long, you do not see a significant change in optimization speed.

See Also

`sdo.SimulationTest` | `sdo.optimize` | `fastRestart`

More About

- “Ways to Speed Up Design Optimization Tasks”

Optimization Does Not Make Progress

Should I worry about the scale of my responses and how constraints and design requirements are discretized?

No, Simulink Design Optimization software automatically normalizes constraints, design requirement and response data.

Why don't the responses and parameter values change at all?

The optimization problem you formulated might be nonsmooth. This means that small parameter changes have no effect on the amount by which response signals satisfy or violate the constraints and only large changes will make a difference. Try switching to a search-based method such as simplex search or pattern search. Alternatively, look for initial guesses outside of the dead zone where parameter changes have no effect. If you are optimizing the response of a Simulink model, you could also try removing nonlinear blocks such as Quantizer or Dead Zone.

Why does the optimization stall?

When optimizing a Simulink model, certain parameter combinations can make the simulation stall for models with strong nonlinearities or frequent mode switching. In these cases, the ODE solvers take smaller and smaller step sizes. Stalling can also occur when the model's ODEs become too stiff for some parameter combinations. A symptom of this behavior is when the Simulink model status is `Running` and clicking the **Stop** button fails to interrupt the optimization. When this happens, you can try one of the following solutions:

- Switch to a different ODE solver, especially one of the stiff solvers.
- Specify a minimum step size.
- Disable zero crossing detection if chattering is occurring.
- Tighten the lower and upper bounds on parameters that cause simulation difficulties. In particular, eliminate regions of the parameter space where some model assumptions are invalid and the model behavior can become erratic.

Optimization Convergence

What to do if the optimization does not get close to an acceptable solution?

- If you are using pattern search, check that you have specified appropriate maximum and minimum values for all your tuned parameters or compensator elements. The pattern search method looks inside these bounds for a solution. When they are set to their default values of `Inf` and `-Inf`, the method searches within ±100% of the initial values of the parameters. In some cases this region is not large enough and changing the maximum and minimum values can expand the search region.
- Your optimization problem might have local minima. Consider running one of the search-based methods first to get closer to an acceptable solution.
- Reduce the number of tuned parameters and compensator elements by removing from the design variables or from the **Compensators** pane those parameters that you know only mildly influence the optimized responses. After you identify reasonable values for the key parameters, add the fixed parameters back to the tunable list and restart the optimization using these reasonable values as initial guesses.
- The software may have encountered errors during the optimization. Review the errors to determine if you can make changes to improve the optimization results. Changes may require modifications to the model, requirements, or optimization settings.

  - In the **Response Optimizer**, the software creates a structure named `EvalErrors` in the **Data** area when the optimization completes with errors. Export this structure to the MATLAB workspace and examine its contents at the command line. `EvalErrors` has two fields, `Errors` and `DesignVars`, containing the errors encountered during optimization and the corresponding design variable values. To reproduce a specific error, use `sdo.setValueInModel` to run the model using the design variables that correspond to the error.
  - At the command line, the second output of `sdo.optimize`, `opt_info`, is a structure that provides information regarding the optimization. `opt_info.exitflag` identifies the reason the optimization terminated. For more information regarding exit flags, see “Exit Flags and Exit Messages”.

Why does the optimization terminate before exceeding the maximum number of iterations, with a solution that does not satisfy all the constraints or design requirements?

- It might not be possible to achieve your specifications. Try relaxing the constraints or design requirements that the response signals violate the most. After you find an acceptable solution to the relaxed problem, tighten some constraints again and restart the optimization.
- The optimization might have converged to a local minimum that is not a feasible solution. Restart the optimization from a different initial guess and/or use one of the search-based methods to identify another local minimum that satisfies the constraints.

What to do if the optimization takes a long time to converge even though it is close to a solution?

- In the **Response Optimizer**, click **Stop** to interrupt the optimization when you think the current optimized response signals are acceptable.

  When you use **Optimization Based Tuning**, click **Stop Optimization** in the **Optimization** tab of the **Response Optimization** dialog in the **Control System Designer**, when you think the current optimized response signals are acceptable.
- If you use the gradient descent method, try restarting the optimization. Restarting resets the Hessian estimate and might speed up convergence.
- Increase the convergence tolerances in the Optimization Options dialog to force earlier termination.
- Relax some of the constraints or design requirements to increase the size of the feasibility region.

What to do if the response becomes unstable and does not recover?

While the optimization formulation has explicit safeguards against unstable or divergent response signals, the optimization can sometimes venture into an unstable region where simulation results become erratic and gradient methods fail to find a way back to the stable region. In these cases, you can try one of the following solutions:

- Add or tighten the lower and upper bounds on compensator element and parameter values. Instability often occurs when you allow some parameter values to become too large.
- Use a search-based method to find parameter values that stabilize the response signals and then start the gradient-based method using these initial values.
- When optimizing responses in **Control System Designer**, you can try adding additional design requirements that achieve the same or similar goal. For example, in addition to a settling time design requirement on a step response plot, you could add a settling time design requirement on a root-locus plot that restricts the location of the real parts of the poles. By adding overlapping design requirements in this way, you can force the optimization to meet the requirements.

Optimization Speed and Parallel Computing

How can I speed up the optimization?

- The optimization time is dominated by the time it takes to simulate the model. When optimizing a Simulink model, you can enable the Accelerator mode by choosing `Accelerator` from the dropdown list under **Simulation** in the Simulink Editor, to dramatically reduce the optimization time.

  Note The Rapid Accelerator mode in Simulink software is not supported for speeding up the optimization. For more information, see "Use Accelerator Mode During Simulations" on page 3-186.

- The choice of ODE solver can also significantly affect the overall optimization time. Use a stiff solver when the simulation takes many small steps, and use a fixed-step solver when such solvers yield accurate enough simulations for your model. (These solvers must be accurate in the entire parameter search space.)
- Reduce the number of tuned compensator elements or parameters and constrain their range to narrow the search space.
- When specifying parameter uncertainty (not available when optimizing responses in **Control System Designer**), keep the number of sample values small since the number of simulations grows exponentially with the number of samples. For example, a grid of 3 parameters with 10 sample values for each parameter requires 10^3=1000 simulations per iteration.

Why are the optimization results with and without using parallel computing different?

- Different numerical precision on the client and worker machines can produce marginally different simulation results. Thus, the optimization method can take a different solution path and produce a different result.
- When you use parallel computing with the `Pattern search` method, the search is more comprehensive and can result in a different solution.

  To learn more, see "Parallel Computing with the Pattern Search Method" on page 3-188.

Why do I not see the optimization speedup I expected using parallel computing?

- When you optimize a model that does not have a large number of parameters or does not take long to simulate, you might not see a speedup in the optimization time. In such cases, the overhead associated with creating and distributing the parallel tasks outweighs the benefits of running the optimization in parallel.
- Using the `Pattern search` method with parallel computing might not speed up the optimization time. Without parallel computing, the method stops the search at each iteration when it finds a solution better than the current solution. The candidate solution search is more comprehensive when you use parallel computing. Although the number of iterations might be larger, the optimization without using parallel computing might be faster.

To learn more about the expected speedup, see “Parallel Computing with the Pattern Search Method” on page 3-188.

Why does the optimization using parallel computing not make any progress?

To troubleshoot the problem:

1. Run the optimization for a few iterations without parallel computing to see if the optimization progresses.
2. Check whether the remote workers have access to all model dependencies. Model dependencies include data variables and files required by the model to run.

   To learn more, see “Model Dependencies” on page 3-190.

Why does the optimization using parallel computing not stop when I click the Stop optimization button?

When you use parallel computing with the `Pattern search` method, the software must wait until the current optimization iteration completes before it notifies the workers to stop. The optimization does not terminate immediately when you click **Stop**, and, instead, appears to continue running.

Undesirable Parameter Values

What to do if the optimization drives the tuned compensator elements and parameters to undesirable values?

- When a tuned compensator element or parameter is positive, or when its value is physically constrained to a given range, enter the lower and upper bounds (**Minimum** and **Maximum**) in one of the following:
  - Dialog box to select design variables (in **Response Optimizer**)
  - **Compensators** pane (in **Control System Designer**)

  This information helps guide the optimization method towards a reasonable solution.
- Specify initial guesses that are within the range of desirable values.
- In the **Compensators** pane in **Control System Designer**, verify that no integrators/differentiators are selected for optimization. Optimizing the pole/zero location of integrators/differentiators can result in drastic changes in the system gain and lead to undesirable values.

What to do if the optimization violates bounds on parameter values?

The `Gradient descent` optimization method `fmincon` violates the parameter bounds when it cannot simultaneously satisfy the signal constraints and the bounds. When this happens, try one of the following:

- Specify a different value for the parameter bound and restart the optimization. A guideline is to adjust the bound by 1% of the typical value.

  For example, for a parameter with a typical value of `1` and lower bound of `0`, change the lower bound to `0.01`.
- Relax the signal constraints and restart the optimization. This approach results in a different solution path for the `Gradient descent` method.
- Restart the optimization immediately after it terminates by clicking **Optimize** in the **Response Optimizer**. This approach uses the previous optimization results as the starting point for the next optimization cycle to refine the results.
- Use the following two-step approach to perform the optimization:
  1. Run an initial optimization to satisfy the signal constraints.

     For example, run the optimization using the `Simplex search` method. This method satisfies the signal constraints but does not support the bounds on parameter values. The results obtained using this method provide the starting point for the optimization performed in the next step. To learn more about this method, see the `fminsearch` function reference page in the Optimization Toolbox documentation.
  2. Reconfigure the optimization by selecting a different optimization method to satisfy both the signal constraints and the parameter bounds.

     For example, change the optimization method to `Gradient descent` and run the optimization again.

Tip If Global Optimization Toolbox software is installed, you can select the `Pattern search` optimization method to optimize the model response.

Reverting to Initial Parameter Values

How do I quit an optimization and revert to my initial parameter values?

- Before running an optimization, do one of the following:

  - In the **Response Optimizer**, click **Options**. Uncheck **Update model at end of optimization** in the **General Options** tab.
  - In the **Response Optimizer**, click **Options**. Select **Save optimized variable values as new design variable set** in the **General Options** tab.
  - Make a copy of the design variable set in the **Data** area.

  If you want to revert to the initial parameter values after the optimization terminates or you stop the optimization by clicking **Stop**, select the design variable that contains the initial values in the **Design Variable Set** drop-down list and click adjacent to **Design variables Set**. Select the design variables in the dialog box and click **Update model variable values** to revert the model parameters to their original values.
- When using the **Control System Designer**, the **Start Optimization** button becomes a **Stop Optimization** button after the optimization has begun. To quit the optimization, click the **Stop Optimization** button. To revert to the initial parameter values, select **Edit > Undo Optimize compensators** from the menu in the **Control System Designer**.

Save and Load Optimization Sessions

Structure of an Optimization Session

The **Response Optimizer** stores and organizes data from a given Simulink model inside a *session*. An optimization session includes the following information:

- Design variables and uncertain variables
- Design requirements
- Optimization results
- Optimization settings
- Plots — Changes to plots layout and plot characteristics, such as axis limits, line colors, are not included.

The default session name is the same as the Simulink model name. The session name displays on the title pane of **Response Optimizer**.

Save a Session

Saving a session lets you reuse your settings and optimization results later. Each **Response Optimizer** session is associated with a Simulink model.

You can save the session as either a MAT-file or workspace variable.

- To save the session as a MAT-file, in the **Response Optimization** tab, in the **Save Session** drop-down list, click **Save to file**. A window opens where you specify the MAT-file name.
- To save the session as a model or MATLAB workspace variable, in the **Save Session** drop-down list, select **Save to model workspace** or **Save to MATLAB workspace**.

Load a Session

To load a previously saved MAT-file or workspace session:

1. Open the **Response Optimizer** for the model.
2. To load a MAT-file, in the **Response Optimization** tab, click the **Open Session** drop-down list, and select **Open from file**. A window opens where you select the MAT-file to load.

   To load a workspace variable, select **Open from model workspace** or **Open from MATLAB workspace** in the **Open Session** drop-down list.

See Also

Related Examples

- "Specify Design Variables" on page 3-56
- "Specify Time-Domain Design Requirements in the App" on page 3-16

- “Specify Frequency-Domain Design Requirements in the App” on page 3-43
- “Specify Optimization Options” on page 3-62

Improving Optimization Performance Using Parallel Computing

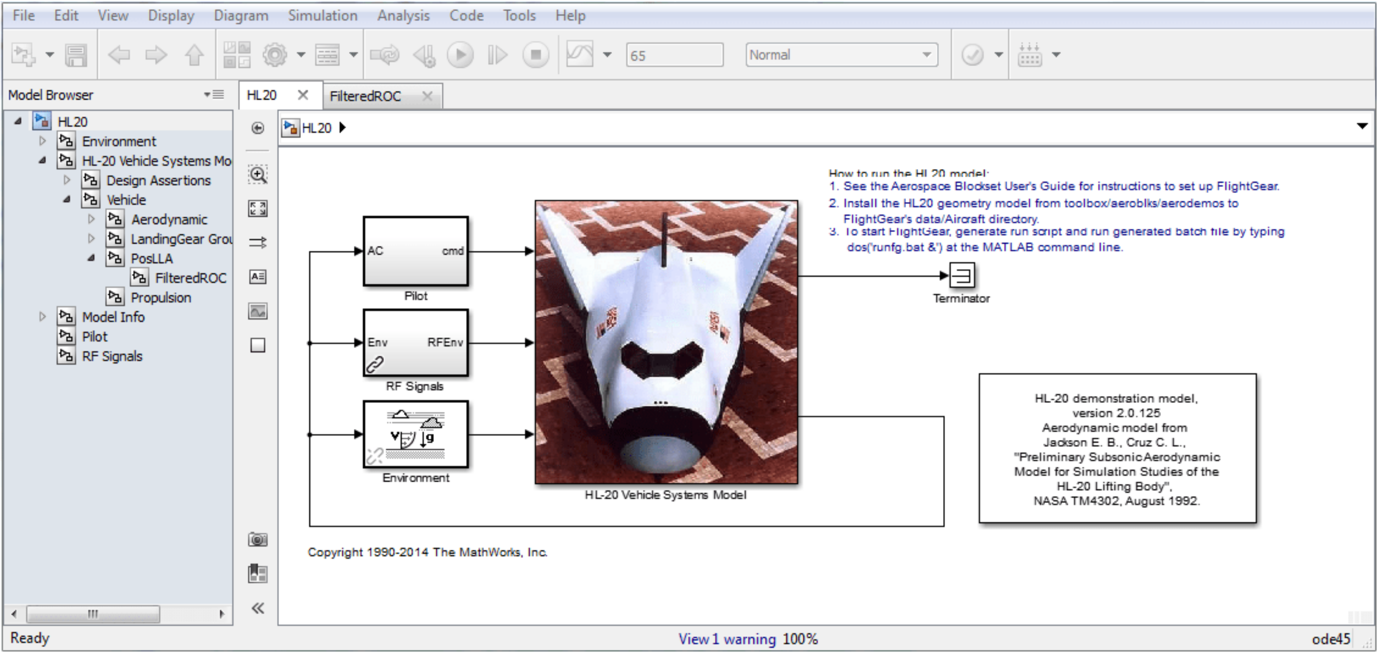
This example shows how to improve optimization performance using the Parallel Computing Toolbox™. The example discusses the speedup seen when using parallel computing to optimize a complex Simulink® model. The example also shows the effect of the number of parameters and the model simulation time when using parallel computing.

Requires Parallel Computing Toolbox™

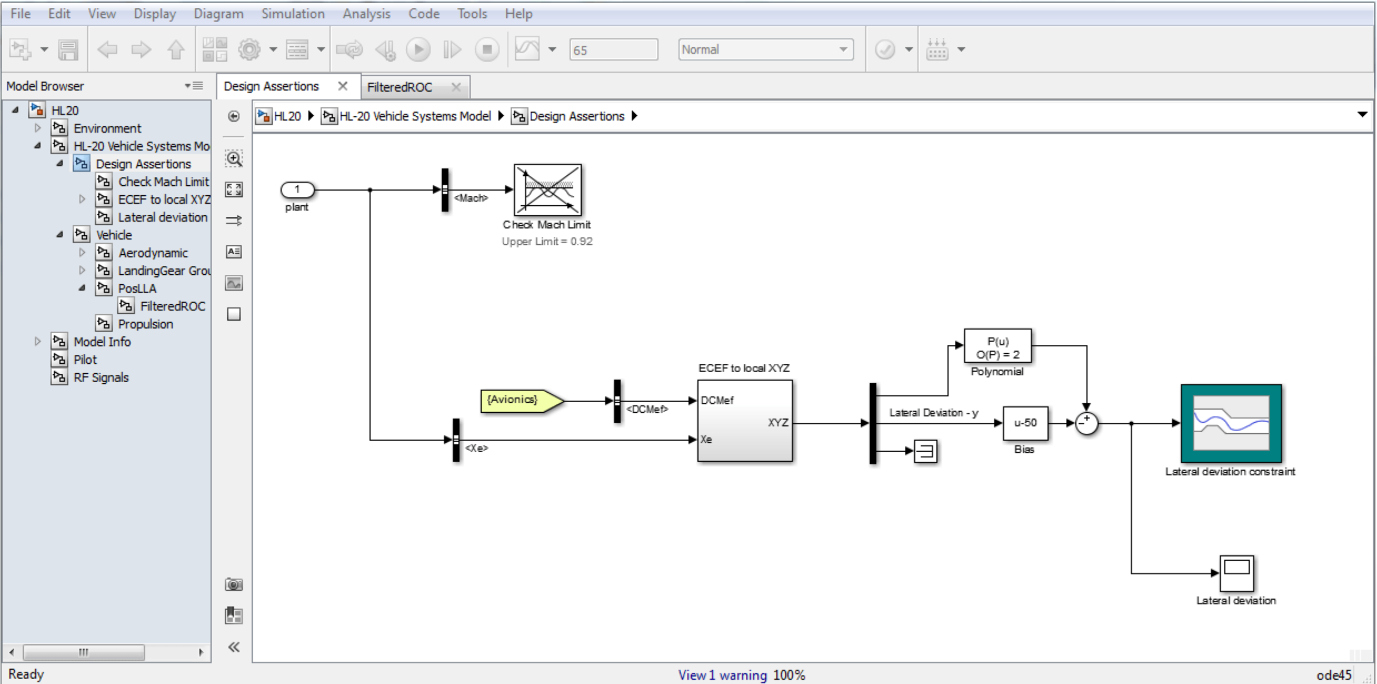
An Example Illustrating Optimization Speedup

The main computational load when using Simulink Design Optimization™ is the simulation of a model. The optimization methods typically require numerous simulations per optimization iteration. As many of the simulations are independent, it is beneficial to use parallel computing to distribute these independent simulations across different processors.

Consider the Simulink model of an HL20 aircraft, which ships with the Aerospace Blockset™. The HL20 model is a complex model and includes mechanical, electrical, avionics, and environmental components. A typical simulation of the HL20 model takes around 60 seconds.



During landing, the aircraft is subjected to two wind gusts from different directions which cause the aircraft to deviate from the nominal trajectory on the runway. Simulink Design Optimization is used to tune the 3 parameters of the controller so that the lateral deviation of the aircraft from a nominal trajectory in the presence of wind gusts is kept within five meters.



The optimization is performed both with and without using parallel computing on dual-core 64bit AMD®, 2.4GHz, 3.4GB Linux® and quad-core 64bit AMD, 2.5GHz, 7.4GB Linux machines. The speed up observed for this problem is shown below.

Total optimization time (s)	Dual-core processor (two workers)			Quad-core processor (four workers)		
	serial	parallel	ratio	serial	parallel	ratio
Gradient descent based optimization speed-up	2140	1360	1.57	2050	960	2.14
Patternsearch based optimization speed-up	3690	2140	1.72	3480	1240	2.81

The HL20 example illustrates the potential speedup when using parallel computing. The next sections discuss the speedup expected for other optimization problems.

When Will an Optimization Benefit from Parallel Computing?

The previous section shows that distributing the simulations during an optimization can reduce the total optimization time. This section quantifies the expected speedup.

In general, the following factors could indicate that parallel computing would result in faster optimization:

- There are a large number of parameters being optimized
- A pattern search method is being used
- A complex Simulink model that takes a long time to simulate
- There are a number of uncertain parameters in the model

Each of these is examined in the following sections.

Number of Parameters and Their Effect on Parallel Computing

The number of simulations performed by an optimization method is closely coupled with the number of parameters.

Gradient Descent Method and Parallel Computing

Consider the simulations required by a gradient-based optimization method at each iteration:

- A simulation for the current solution point
- Simulations to compute the gradient of the objective with respect to the optimized parameters
- Once a gradient is computed, simulations to evaluate the objective along the direction of the gradient (the so called line search evaluations)

Of these simulations, the simulations required to compute gradients are independent and are distributed. Let us look at this more closely:

```
Np  = 1:16;   %Number of parameters (16 = 4 filtered PID controllers)
Nls = 1;      %Number of line search simulations, assume 1 for now
Nss = 1;      %Total number of serial simulations, start with nominal only
```

The gradients are computed using central differences. There are 2 simulations per parameter, and include the line search simulations to give the total number of simulations per iteration:

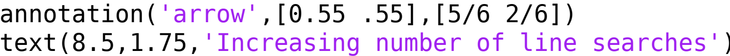
```
Nss = 1+Np*2+Nls;
```

As mentioned above, the computation of gradients with respect to each parameter can be distributed or run in parallel. This reduces the total number of simulations that run in series when using parallel computing as follows:

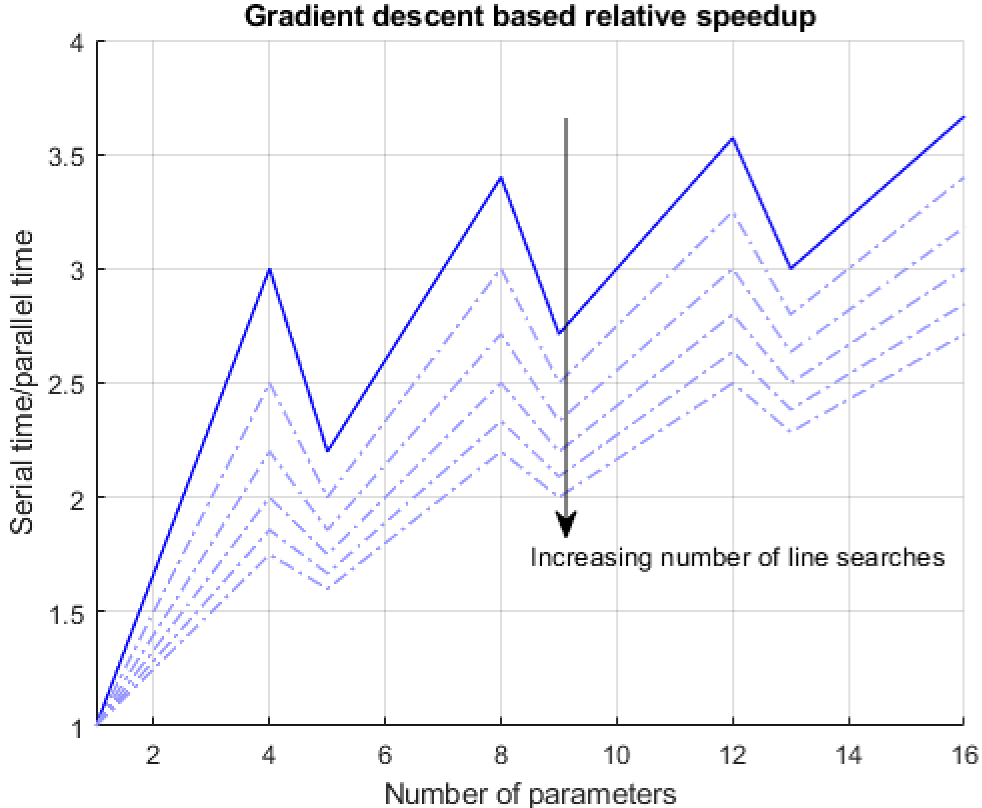
```
Nw  = 4;      %Number of parallel processors
Nps = 1 + ceil(Np/Nw)*2+Nls;
```

The ratio Nss/Nps gives us the speedup which we plot below

```
Nls = 0:5;      %Vary the number of line search simulations
figure;
hAx  = gca;
xlim([min(Np) max(Np)]);
for ct = 1:numel(Nls)
  Rf = (1+Nls(ct)+Np*2)./(1+Nls(ct)+ceil(Np/Nw)*2);
  hLine = line('parent',hAx,'xdata',Np,'ydata',Rf);
  if ct == 1
     hLine.LineStyle = '-';
     hLine.Color = [0 0 1];
     hLine.LineWidth = 1;
  else
     hLine.LineStyle = '-.';
     hLine.Color = [0.6 0.6 1];
     hLine.LineWidth = 1;
  end
end
grid on
title('Gradient descent based relative speedup')
xlabel('Number of parameters')
ylabel('Serial time/parallel time')
```



```
annotation('arrow',[0.55 .55],[5/6 2/6])
text(8.5,1.75,'Increasing number of line searches')
```



The plot shows that the relative speedup gets better as more parameters are added. The upper solid line is the best possible speedup with no line search simulations while the lighter dotted curves increase the number of line search simulations.

The plot also shows local maxima at 4,8,12,16 parameters which corresponds to cases where the parameter gradient calculations can be distributed evenly between the parallel processors. Recall that for the HL20 aircraft problem, which has 3 parameters, the quad core processor speedup observed was 2.14 which matches well with this plot.

Pattern Search Method and Parallel Computing

Pattern search optimization method is inherently suited to a parallel implementation. This is because at each iteration one or two sets of candidate solutions are available. The algorithm evaluates all these candidate solutions and then generates a new candidate solution for the next iteration. Evaluating the candidate solutions can be done in parallel as they are independent. Let us look at this more closely:

Pattern search uses two candidate solution sets, the search set and the poll set. The number of elements in these sets is proportional to the number of optimized parameters

```
Nsearch = 15*Np;      %Default number of elements in the solution set
Npoll   = 2*Np;       %Number of elements in the poll set with a 2N poll method
```

The total number of simulations per iteration is the sum of the number of candidate solutions in the search and poll sets. When distributing the candidate solution sets the simulations are distributed evenly between the parallel processors. The number of simulations that run in series after distribution thus reduces to:

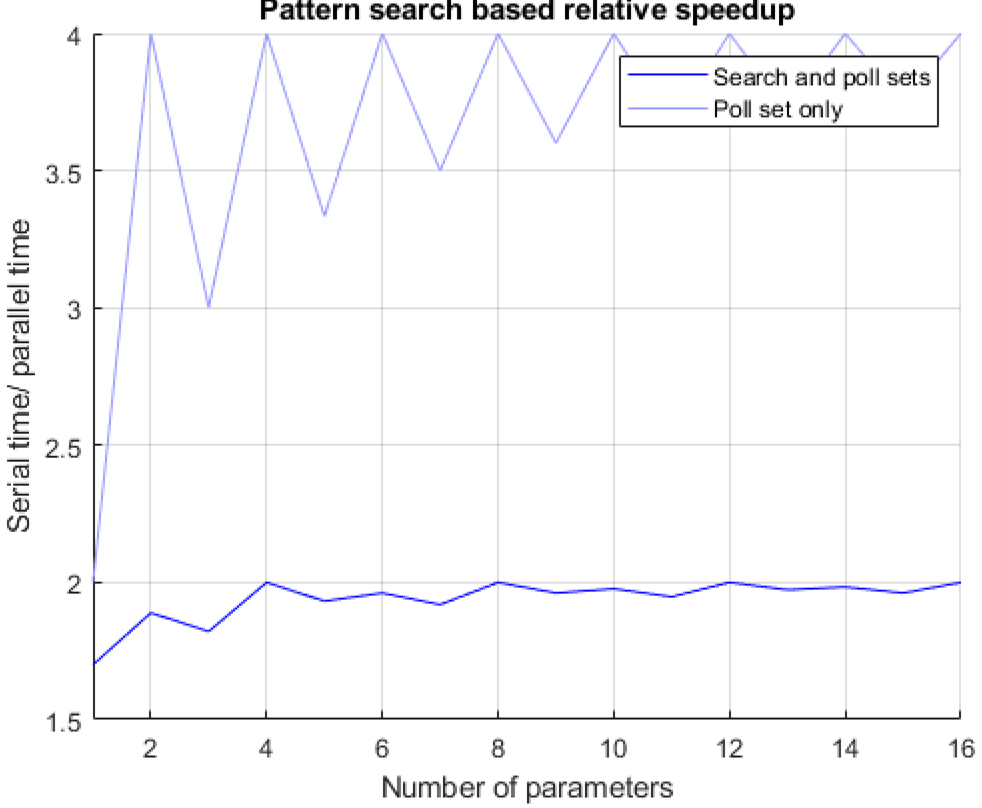
```
Nps = ceil(Nsearch/Nw)+ceil(Npoll/Nw);
```

When evaluating the candidate solutions without using parallel computing, the iteration is terminated as soon as a candidate solution that is better than the current solution is found. Without additional information, the best bet is that about half the candidate solutions will be evaluated. The number of serial simulations is thus:

```
Nss = 0.5*(Nsearch+Npoll);
```

Also note that the search set is only used in the first couple of optimization iterations, after which only the poll set is used. In both cases the ratio Nss/Nps gives us the speedup which we plot below.

```
figure;
hAx  = gca;
xlim([min(Np) max(Np)]);
Rp1 = (Nss)./( Nps );
Rp2 = (Npoll)./( ceil(Npoll/Nw) );
line('parent',hAx,'xdata',Np,'ydata',Rp1,'color',[0 0 1]);
line('parent',hAx,'xdata',Np,'ydata',Rp2,'color',[0.6 0.6 1]);
grid on
title('Pattern search based relative speedup')
xlabel('Number of parameters')
ylabel('Serial time/ parallel time')
legend('Search and poll sets','Poll set only')
```



The dark curve is the speedup when the solution and poll sets are evaluated and the lighter lower curve the speedup when only the poll set is evaluated. The expected speedup over an optimization should lie between the two curves. Notice that even with only one parameter, a pattern search method benefits from distribution. Also recall that for the HL20 aircraft problem, which has 3 parameters, the quad core speedup observed was 2.81 which matches well with this plot.

Overhead of Distributing an Optimization

In the previous sections, the overhead associated with performing the optimization in parallel was ignored. Including this overhead gives an indication of the complexity of a simulation that will benefit from distributed optimization.

The overhead associated with running an optimization in parallel primarily results from two sources:

- opening the parallel pool
- loading the Simulink model and performing an update diagram on the model

There is also some overhead associated with transferring data to and from the remote processors. Simulink Design Optimization relies on shared paths to provide remote processors access to models and the returned data is limited to objective and constraint violation values. Therefore, this overhead is typically much smaller than opening the MATLAB® pool and loading the model. This was true for the HL20 aircraft optimization but may not be true in all cases. However, the analysis shown below can be extended to cover additional overhead.

```
findOverhead = false; % Set true to compute overhead for your system.
if findOverhead
```

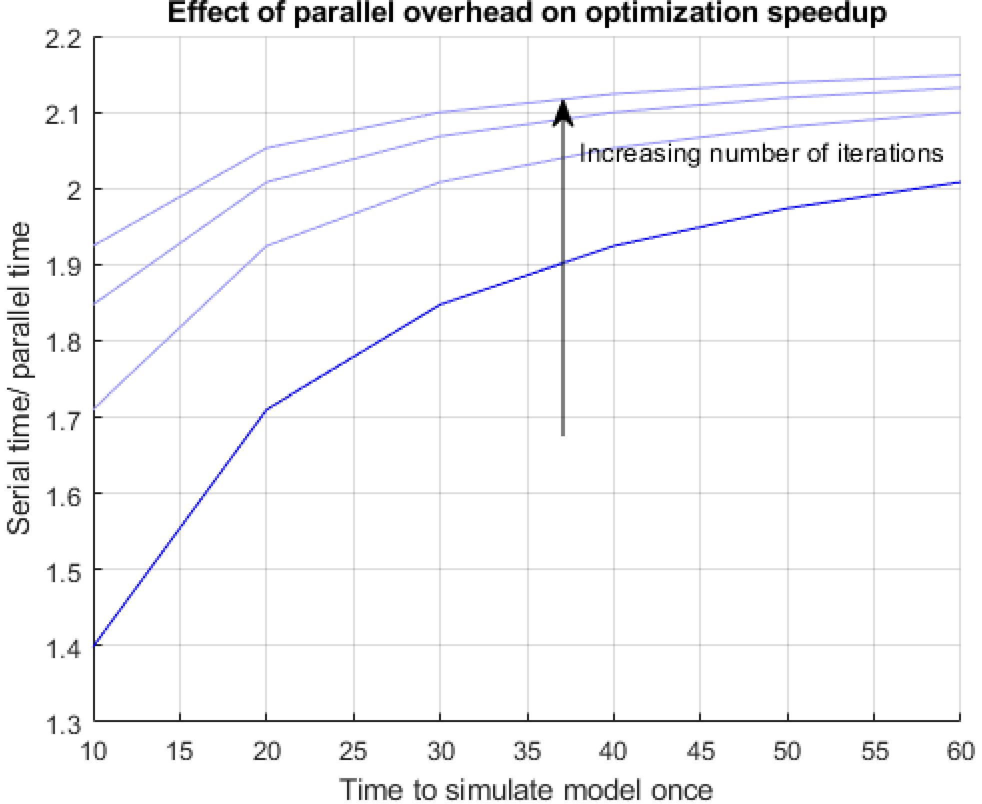
```
  % Compute overhead.
  wState = warning('off','MATLAB:dispatcher:pathWarning');
  t0 = datetime('now');           %Current time
  parpool                         %Open the parallel pool
  load_system('airframe_demo')    %Open a model
  set_param('airframe_demo','SimulationCommand','update')  %Run an update diagram for the model
  Toverhead = datetime('now')-t0; %Time elapsed
  Toverhead = seconds(Toverhead)  %Convert to seconds
  close_system('airframe_demo')
  delete(gcp)                     %Close the parallel pool
  warning(wState);
else
  % Use overhead observed from experiments.
  Toverhead = 28.6418;
end
```

Let us consider a gradient-based algorithm with the following number of serial simulations per iteration:

```
Nw  = 4;                      %Four parallel processors
Np  = 4;                      %Four parameters optimized
Nls = 2;                      %Assume 2 line search simulations
Nss = 1+Np*2+Nls;             %Serial simulations without parallel computing
Nps = 1+ceil(Np/Nw)*2+Nls;    %Serial simulations with parallel computing
```

The speedup is now computed as the ratio of the total parallel time including overhead to the total serial time. For worst case analysis, assume the optimization terminates after one iteration which gives:

```
Niter = 1;
Ts    = 10:10:60;                %Time to simulate model once
Tst   = Niter*Nss*Ts;            %Total serial optimization time
Tpt   = Niter*Nps*Ts+Toverhead;  %Total parallel optimization time
figure;
hAx  = gca;
xlim([min(Ts) max(Ts)]);
Rp = (Tst)./( Tpt );
line('parent',hAx,'xdata',Ts,'ydata',Rp,'color',[0 0 1]);
Niter = 2^1:4;
for ct = 1:numel(Niter)
   Rp = ( Niter(ct)*Nss*Ts )./(Niter(ct)*Nps*Ts+Toverhead);
   line('parent',hAx,'xdata',Ts,'ydata',Rp,'color',[0.6 0.6 1]);
end
grid on
title('Effect of parallel overhead on optimization speedup')
xlabel('Time to simulate model once')
ylabel('Serial time/ parallel time')
annotation('arrow',[0.55 0.55],[0.45 0.85]);
text(38,2.05,'Increasing number of iterations')
```



The dark lower curve shows the speedup assuming one iteration while the lighter upper curves indicate speedup with up to 16 iterations.

A similar analysis could be performed for pattern search based optimization. Experience has shown that optimization of complex simulations that take more than 40 seconds to run typically benefit from parallel optimization.

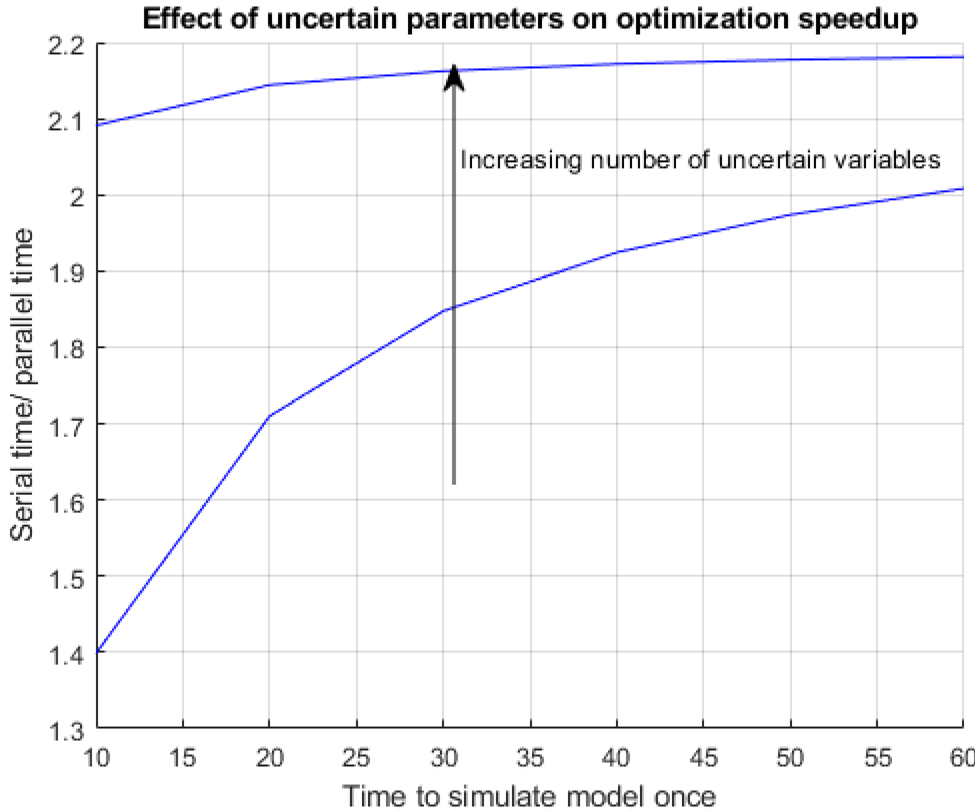
Uncertain Parameters and Their Effect on Parallel Optimization

When using Simulink Design Optimization, you can vary some parameters (say a spring stiffness) and optimize parameters in the face of these variations. The uncertain parameters define additional simulations that need to be evaluated at each iteration. However, conceptually you can think of these additional simulations as extending the simulation without uncertain parameters. This implies that wherever one simulation was carried out, now multiple simulations are carried out. As a result, uncertain parameters do not affect the overhead free optimization speedup and the calculations in earlier sections are valid.

In the case where we considered overhead, uncertain parameters have the effect of increasing the simulation time and reduce the effect of the overhead associated with creating a parallel optimization. To see this consider the following

```
Nu = [0 10];                       %Number of uncertain scenarios
Nss = (1+Nu)*(1+Np*2+Nls);         %Serial simulations without parallel computing
Nps = (1+Nu)*(1+ceil(Np/Nw)*2+Nls); %Serial simulations with parallel computing
figure;
hAx  = gca;
```

```
xlim([min(Ts) max(Ts)]);
for ct = 1:numel(Nu)
   Rp = (Ts*Nss(ct))./(Ts*Nps(ct)+Toverhead);
   line('parent',hAx,'xdata',Ts,'ydata',Rp,'color',[0 0 1]);
end
grid on
title('Effect of uncertain parameters on optimization speedup')
xlabel('Time to simulate model once')
ylabel('Serial time/ parallel time')
annotation('arrow',[0.45 0.45],[0.4 0.9])
text(31,2.05,'Increasing number of uncertain variables')
```



The bottom curve is the case with no uncertain parameters while the top curve is the case with an uncertain parameter that can take on 10 distinct values.

Optimizing Time-Domain Response of Simulink Models Using Parallel Computing

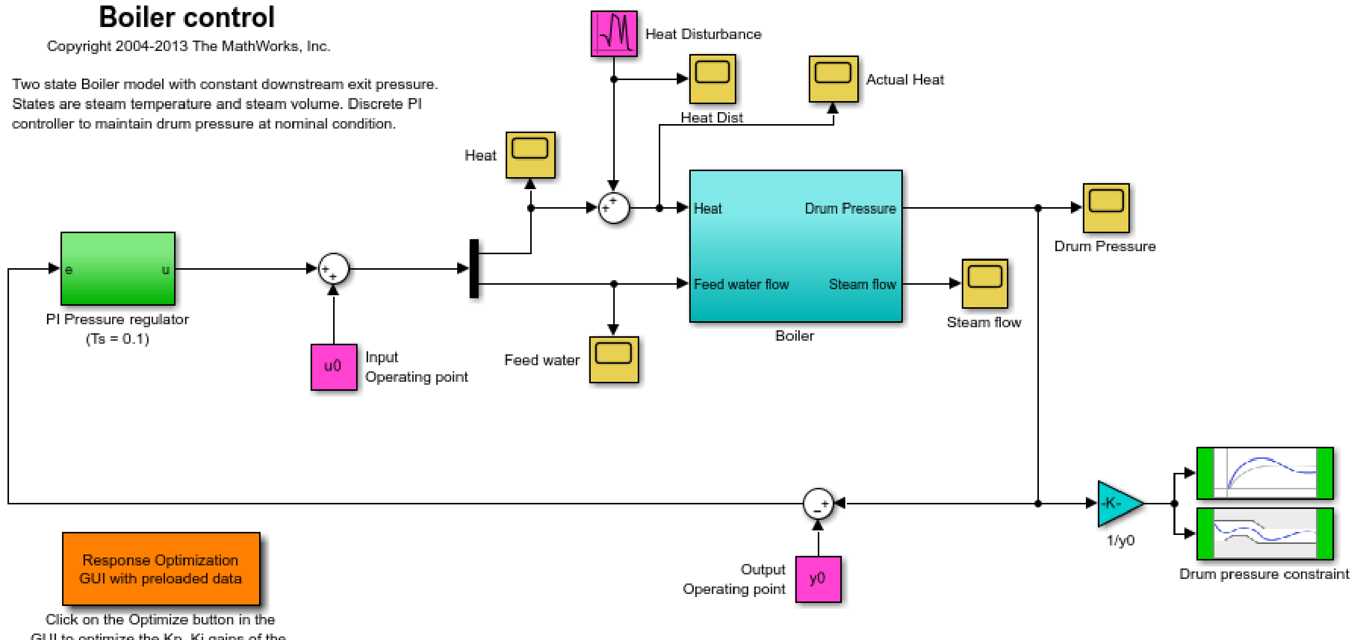
This example shows how to use parallel computing to optimize the time-domain response of a Simulink® model. You use Simulink® Design Optimization™ and Parallel Computing Toolbox™ to tune the gains of a discrete PI controller of a boiler to meet the design requirements. The example also shows how the software automatically handles model file dependencies.

This example requires Parallel Computing Toolbox™.

Opening the Model

The Simulink model consists of a boiler model and a discrete PI controller. When using parallel computing, Simulink Design Optimization performs a model dependency check, which recognizes the boiler model library as an installed library.

```
open_system('boilerpressure_demo')
```



Design Requirements

The boiler pressure is regulated by a discrete PI controller. The design requirement for the controller is to limit the pressure variation of the boiler within +-%5 of the nominal pressure.

The initial controller has fairly good regulation characteristics but in the presence of additional heat disturbances, modeled by the Heat Disturbance block, we want to tune the controller performance to provide tighter pressure regulation.

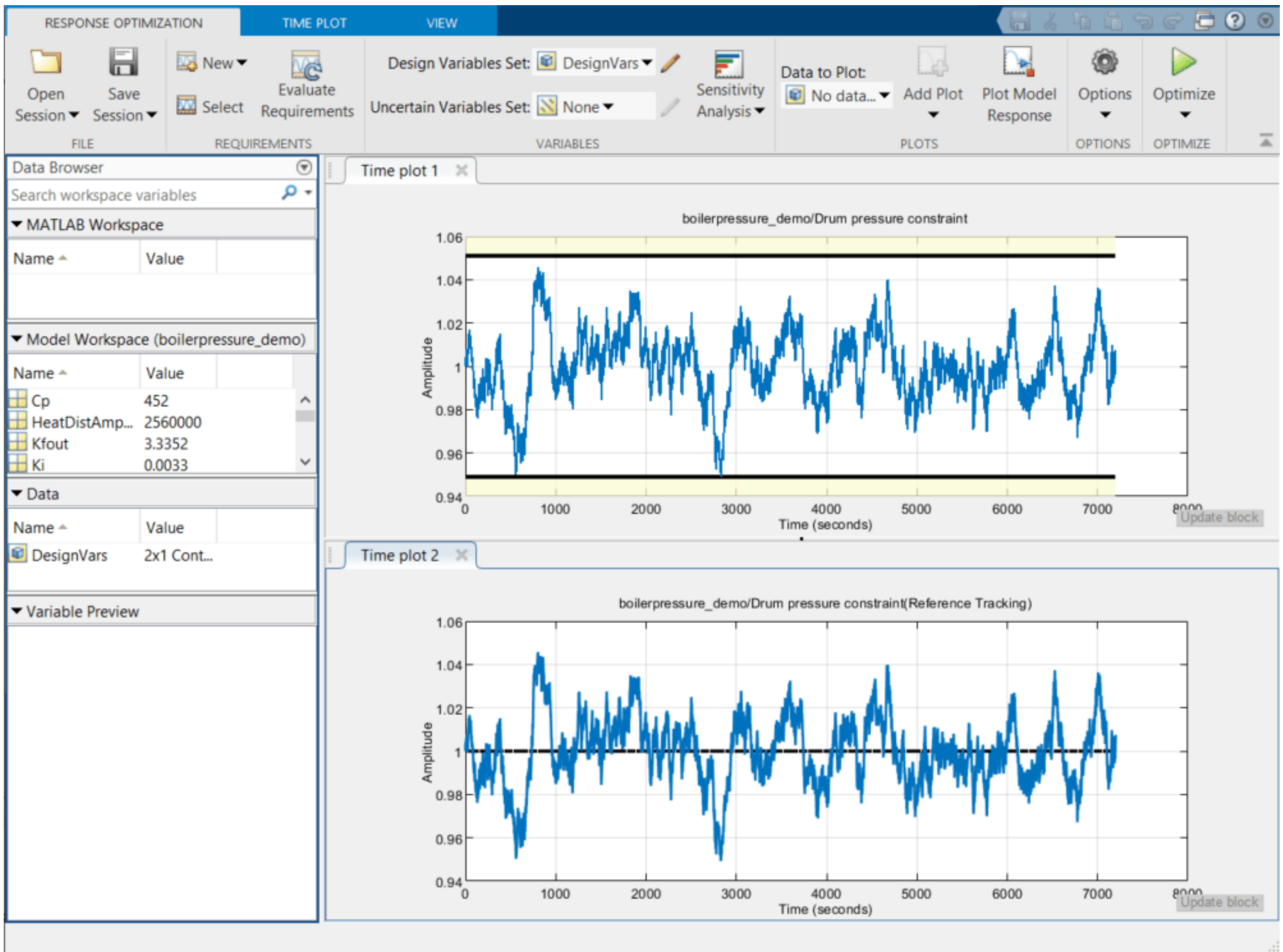
Double-click the 'Response Optimization GUI with preloaded data' block in the Simulink model to open a pre-configured **Response Optimizer** session. The **Response Optimizer** is configured with:

1. Upper and lower bounds representing a +-5% allowable range on the drum pressure

2. A reference tracking objective to minimize the deviation of the drum pressure from nominal

3. The PI controller gains, Kp and Ki, are selected for tuning

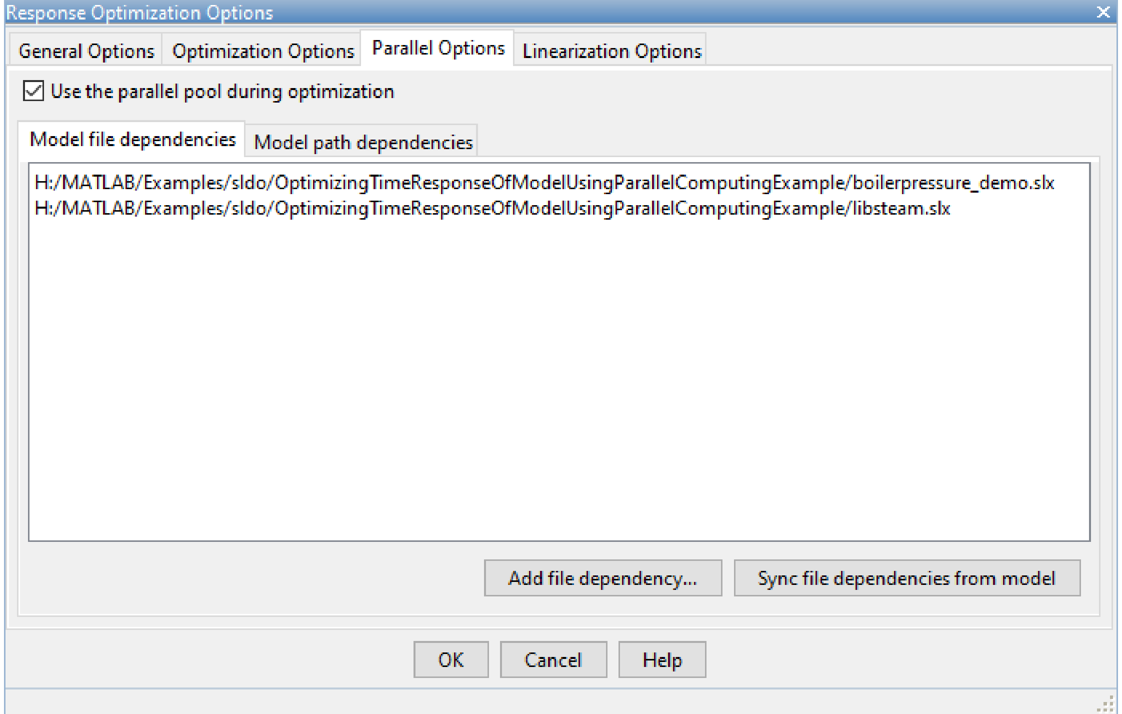
Click **Plot Model Response** to display the drum pressure variations with the initial controller.



Configuring and Running the Optimization in the GUI Using Parallel Computing

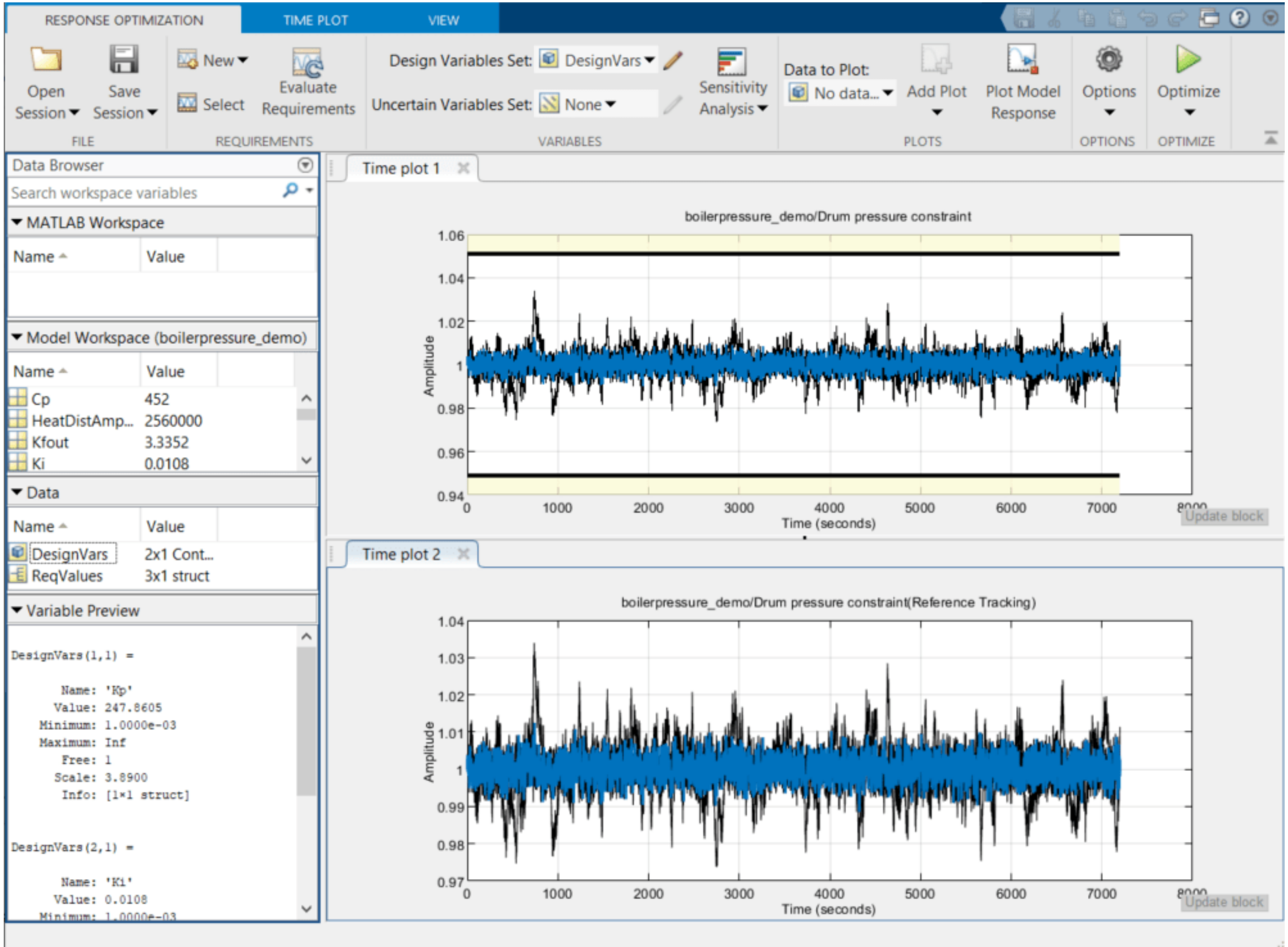
When computing the model response with the initial controller, this complex model took a long time to simulate. Using parallel computing can reduce the optimization time by simulating the model in parallel. For more information on parallel computing and optimization performance see the tutorial “Improving Optimization Performance Using Parallel Computing” on page 3-208.

To configure the optimization problem to use parallel computing click **Options** in the **Response Optimizer** and select the **Parallel Options** tab. Select the "Use the parallel pool during optimization" option. This triggers an automated search for any model dependencies. In this example, the Steam table library (`libsteam.slx`) is found as a model dependency (in addition to the `boilerpressure_demo` model itself), and is displayed in the Model file dependencies list box.



Clicking OK configures the optimization to use parallel computing.

To run the optimization click the **Optimize** button. A progress window opens displaying optimization progress and the plots update to show the optimized response.



The final response shows that the optimized regulator tracks the reference pressure much more closely and the drum pressure constraints are satisfied.

Configuring and Running the Optimization at the Command Line

You can also use the command line functions to configure the optimization to use parallel computing and run the optimization.

Select the model variables for optimization and set lower limits

```
p = sdo.getParameterFromModel('boilerpressure_demo',{'Kp','Ki'});
p(1).Minimum = 0.001;
p(2).Minimum = 0.001;
```

Select the model signal to bound and create a simulator to simulate the model.

```
nPressure = Simulink.SimulationData.SignalLoggingInfo;
nPressure.BlockPath               = 'boilerpressure_demo/1//y0';
nPressure.OutputPortIndex         = 1;
nPressure.LoggingInfo.NameMode    = 1;
nPressure.LoggingInfo.LoggingName = 'nPressure';
```

```
simulator = sdo.SimulationTest('boilerpressure_demo');
simulator.LoggingInfo.Signals = nPressure;
```

Get the optimization requirements defined by the check blocks in the model so that we can use them in the optimization problem.

```
bnds = getbounds('boilerpressure_demo/Drum pressure constraint');
PressureLimits = [bnds{:}];
bnds = getbounds('boilerpressure_demo/Drum pressure constraint(Reference Tracking)');
PressureRegulation = [bnds{:}];
requirements = struct(...
    'PressureLimits', PressureLimits, ...
    'PressureRegulation', PressureRegulation);
```

Define the function called during optimization. Notice that the function uses the simulator and requirements defined earlier to evaluate the design.

```
evalDesign = @(p) boilerpressure_design(p,simulator,requirements);
type boilerpressure_design
```

```
function design = boilerpressure_design(p,simulator,requirements)
%BOILERPRESSURE_DESIGN
%
% The boilerpressure_design function is used to evaluate a boiler
% controller design design.
%
% The |p| input argument is the vector of controller parameters.
%
% The |simulator| input argument is a sdo.SimulinkTest object used to
% simulate the |boilerpressure_demo| model and log simulation signals.
%
% The |requirements| input argument contains the design requirements used
% to evaluate the boiler controller design.
%
% The |design| return argument contains information about the design
% evaluation that can be used by the |sdo.optimize| function to optimize
% the design.
%
% see also sdo.optimize, sdoExampleCostFunction

% Copyright 2011 The MathWorks, Inc.

%% Simulate the model
%
% Use the simulator input argument to simulate the model and log model
% signals.
%
% First ensure that we simulate the model with the parameter values chosen
% by the optimizer.
%
simulator.Parameters = p;
%%
% Simulate the model and log signals.
%
simulator = sim(simulator);
%%
```

```
% Get the simulation signal log, the simulation log name is defined by the
% model |SignalLoggingName| property
%
logName = get_param('boilerpressure_demo','SignalLoggingName');
simLog = get(simulator.LoggedData,logName);

%% Evaluate the design requirements
%
% Use the requirements input argument to evaluate the design requirements
%
% Check the Pressure signal against the |PressureLimits| requirements.
%
nPressure = get(simLog,'nPressure');
c = [...
    evalRequirement(requirements.PressureLimits(1),nPressure.Values); ...
    evalRequirement(requirements.PressureLimits(2),nPressure.Values)];
%%
% Use the PressureLimits requirements as non-linear constraints for
% optimization.
design.Cleq = c(:);
%%
% Check the pressure signal against the |PressureRegulation| requirement.
%
f = evalRequirement(requirements.PressureRegulation,nPressure.Values);
%%
% Use the PressureRegulation requirement as an objective for optimization.
design.F = f;
end
```

Setup optimization options to use the parallel pool and specify the model and model files dependencies.

```
opt = sdo.OptimizeOptions;
opt.UseParallel               = true;
opt.OptimizedModel            = 'boilerpressure_demo';
[dirs,files]                  = sdo.getModelDependencies('boilerpressure_demo');
opt.ParallelFileDependencies = files;
```

To run the optimization using the parallel pool pass the optimization options, `opt`, to the `sdo.optimize` command.

```
>> [pOpt,info] = sdo.optimize(evalDesign,p,opt)
Starting parallel pool (parpool) using the 'local' profile ...
Connected to the parallel pool (number of workers: 6).
Configuring parallel workers for optimization...
Parallel workers configured for optimization.

 Optimization started 11-May-2021 17:56:00

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      5      17.5068            0
    1     10      11.6563            0         1.25         32.2
    2     15      8.29415            0         1.27         5.64
    3     20      5.67333            0         2.04         19.7
    4     25    0.0951198            0          477      0.00726
    5     30    0.0937752            0         1.22      0.00723
    6     39    0.0937752            0        0.392      0.00723
Local minimum possible. Constraints satisfied.

fmincon stopped because the size of the current step is less than
the value of the step size tolerance and constraints are
satisfied to within the value of the constraint tolerance.
Removing data from parallel workers...
Data removed from parallel workers.
```

Close the model.

```
bdclose('boilerpressure_demo')
```

Design Optimization to Meet Frequency-Domain Requirements (Code)

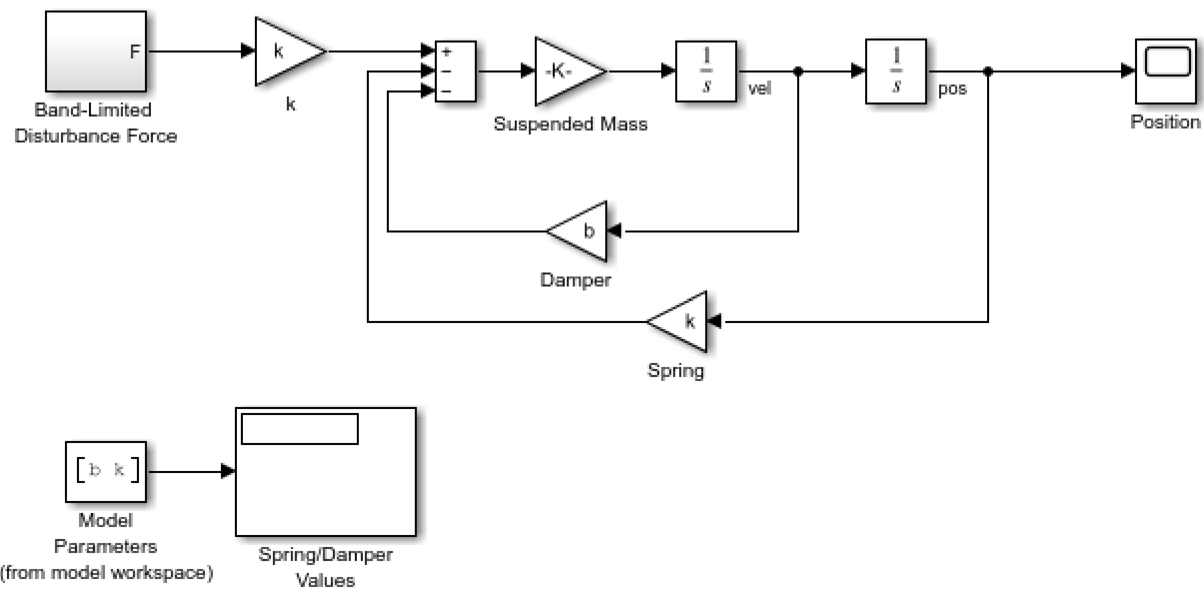
This example shows how to tune model parameters to meet frequency-domain requirements, using the `sdo.optimize` command.

This example requires Simulink® Control Design™.

Suspension Model

Open the Simulink model.

```
open_system('sdoSimpleSuspension')
```

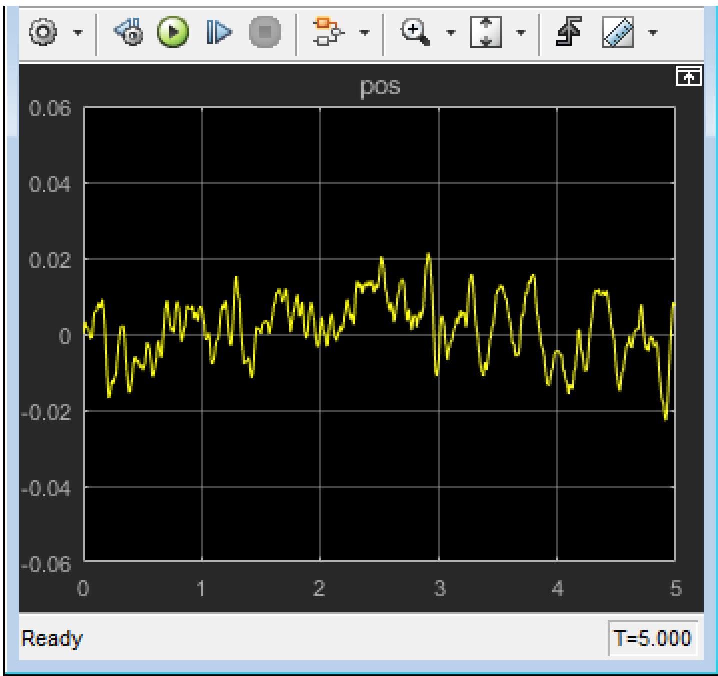


Mass-spring-damper models represent simple suspension systems and for this example we tune the system to meet typical suspension requirements. The model implements the second order system representing a mass-spring-damper using Simulink blocks and includes:

- a `Mass` gain block parameterized by the total suspended mass, `m0+mLoad`. The total mass is the sum of a nominal mass, `m0`, and a variable load mass, `mLoad`.
- a `Damper` gain block parameterized by the damping coefficient, `b`.
- a `Spring` gain block parameterized by the spring constant, `k`.
- two integrator blocks to compute the mass velocity and position.

- a `Band-Limited Disturbance Force` block applying a disturbance force to the mass. The disturbance force is assumed to be band-limited white noise.

Simulate the model to view the system response to the applied disturbance force.



Design Problem

The initial system has a bandwidth that is too high. This can be seen from the spiky position signal. You tune the spring and damper values to meet the following requirements:

- The -3dB system bandwidth must not exceed 10 rad/s.
- The damping ratio of the system must be less than 1/sqrt(2). This ensures that no frequencies in pass band are amplified by the system.
- Minimize the expected failure rate of the system. The expected failure rate is described by a Weibull distribution dependent on the mass, spring, and damper values.
- These requirements must all be satisfied as the load mass ranges from 0 to 20 kg.

Specify Design Variables

```
DesignVars = sdo.getParameterFromModel('sdoSimpleSuspension',{'b','k'});
DesignVars(1).Minimum = 100;
DesignVars(1).Maximum = 10000;
DesignVars(2).Minimum = 10000;
DesignVars(2).Maximum = 100000;
```

Specify Uncertain Variables

Specify `mLoad`, the load mass, as an uncertain variable. This will ensure the optimal solution is robust to variations in load mass.

```
UncVars = sdo.getParameterFromModel('sdoSimpleSuspension','mLoad');
UncVars_Values = {...
    10; ...
    20};
```

Specify Design Requirements

Specify design requirements to satisfy during optimization.

```
Requirements = struct;
Requirements.Bandwidth = sdo.requirements.BodeMagnitude(...
    'BoundFrequencies', [10 100], ...
    'BoundMagnitudes', [-3 -3]);
Requirements.DampingRatio = sdo.requirements.PZDampingRatio;
```

The reliability requirement will be specified in the optimization objective function described below. The reliability requirement is used to tune the spring and damper values to minimize the expected failure rate over a lifetime of 100e3 miles. The failure rate is computed using a Weibull distribution on the damping ratio of the system. As the damping ratio increases, the failure rate is expected to increase.

Linearization Definition

The design requirements use the bandwidth and damping ratio of the system, these frequency domain characteristics require linearizing the model. Create a simulator for the model and use the simulator to compute the linear systems used by the requirements.

```
Simulator = sdo.SimulationTest('sdoSimpleSuspension');
```

Specify linear systems to compute by specifying the linearization inputs and outputs of the system. The linear system input is the output of the `Band-Limited Disturbance Force` block and the linear system output is the output of the `x_dot` block (the `position` signal).

```
IOs(1) = linio('sdoSimpleSuspension/Band-Limited  Disturbance Force',1,'input');
IOs(2) = linio('sdoSimpleSuspension/x_dot',1,'output');
```

Add the linearization IOs to a `sdo.SystemLoggingInfo` object with a logging name, and linearization snapshot time. In this case, the snapshot time is set to 0, the model initial condition.

```
sys1 = sdo.SystemLoggingInfo;
sys1.Source = 'IOs';
sys1.LoggingName = 'IOs';
sys1.LinearizationIOs = IOs;
sys1.SnapshotTimes = 0;
```

Add the system logging info to the simulator. When the simulator is used to run the model, the linear system defined by the specified linearization IOs is computed and added to the simulation log with the specified logging name.

```
Simulator.SystemLoggingInfo = sys1;
```

Create Optimization Objective Function

Create a function that is called at each optimization iteration to evaluate the design requirements.

Use an anonymous function with one argument that calls `sdoSimpleSuspension_Design`. The `sdoSimpleSuspension_Design` function has arguments for the design parameters, the simulator, the design requirements, the uncertain variables, and uncertain variable values.

```
optimfcn = @(P) sdoSimpleSuspension_Design(P,Simulator,Requirements,UncVars,UncVars_Values);
type sdoSimpleSuspension_Design


function Vals = sdoSimpleSuspension_Design(P,Simulator,Requirements,UncVars,UncVars_Values)
%SDOSIMPLESUSPENSION_DESIGN
%
%    The sdoSimpleSuspension_Design function is used to evaluate a simple
%    suspension system design.
%
%    The |P| input argument is the vector of suspension design parameters.
%
%    The |Simulator| input argument is a sdo.SimulinkTest object used to
%    simulate the |sdoSimpleSuspension| model and log simulation signals.
%
%    The |Requirements| input argument contains the design requirements
%    used to evaluate the suspension design.
%
%    The |UncVars| and |UncVars_Values| arguments specify the uncertain
%    variable and uncertain variable values.
%
%    The |Vals| return argument contains information about the design
%    evaluation that can be used by the |sdo.optimize| function to optimize
%    the design.
%
% See also sdoSimpleSuspension_cmddemo

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%% Evaluate the suspension reliability
%
%Get the spring and damper design values
allVarNames = {P.Name};
idx         = strcmp(allVarNames,'k');
k           = P(idx).Value;
idx         = strcmp(allVarNames,'b');
b           = P(idx).Value;

%Get the nominal mass from the model workspace
wksp = get_param('sdoSimpleSuspension','ModelWorkspace');
m    = evalin(wksp,'m0');

%The expected failure rate is defined by the Weibull cumulative
%distribution function, 1-exp(-(x/l)^k), where k=3, l is a function of the
%mass, spring and damper values, and x the lifetime.
d        = b/2/sqrt(m*k);
pFailure = 1-exp(-(100e3*d/250e3)^3);

%% Nominal Evaluation
%
% Evaluate the model and requirements with uncertain parameters set to their
% nominal values.

% Simulate the model.
Simulator.Parameters = [P(:);UncVars(:)];
Simulator = sim(Simulator);

% Retrieve logged linearizations.
```

```
Sys = find(Simulator.LoggedData,'IOs');

% Evaluate the design requirements.
Cleq_Bandwidth = evalRequirement(Requirements.Bandwidth,Sys.values);
Cleq_DampingRatio = evalRequirement(Requirements.DampingRatio,Sys.values);

%% Uncertain Evaluation
%
% Evaluate the model and requirements for all combinations of uncertain
% parameter values.
for ct=1:size(UncVars_Values,1)
    UncVars(1).Value = UncVars_Values{ct,1};

    % Simulate the model.
    Simulator.Parameters = [P(:);UncVars(:)];
    Simulator = sim(Simulator);

    % Retrieve logged linearizations.
    Sys = find(Simulator.LoggedData,'IOs');

    % Evaluate the design requirements.
    Cleq_Bandwidth_UncVars = evalRequirement(Requirements.Bandwidth,Sys.values);
    Cleq_DampingRatio_UncVars = evalRequirement(Requirements.DampingRatio,Sys.values);

    Cleq_Bandwidth = [Cleq_Bandwidth; Cleq_Bandwidth_UncVars]; %#ok<AGROW>
    Cleq_DampingRatio = [Cleq_DampingRatio; Cleq_DampingRatio_UncVars]; %#ok<AGROW>
end

%% Return Values.
%
% Collect the evaluated design requirement values in a structure to
% return to the optimization solver.
Vals.F = pFailure;
Vals.Cleq = [...
    Cleq_Bandwidth(:); ...
    Cleq_DampingRatio(:)];
end
```

Optimization Options

Specify optimization options.

```
Options = sdo.OptimizeOptions;
Options.MethodOptions.Algorithm = 'active-set';
Options.MethodOptions.TolGradCon = 1e-06;
```

Optimize the Design

Call sdo.optimize with the objective function handle, parameters to optimize, and options.

```
[Optimized_DesignVars,Info] = sdo.optimize(optimfcn,DesignVars,Options);
```

```
 Optimization started 01-Sep-2022 13:53:44

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      5    0.0619897       0.7642
    1     10     0.351266      -0.1277        0.461         1.22
```

```
    2     15     0.189345     -0.03881        0.188        0.312
    3     20    0.0829063      0.01312         0.51        0.425
    4     24    0.0365398            0        0.308         1.55
    5     28    0.0294977            0       0.0143        0.733
    6     32    0.0293065            0     0.000417      0.00142
Local minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the value of the optimality tolerance,
and constraints are satisfied to within the  value of the constraint tolerance.
```

Related Examples

To learn how to optimize the suspension system using the **Response Optimizer**, see "Design Optimization to Meet Frequency-Domain Requirements (GUI)" on page 3-136.

Close the model.

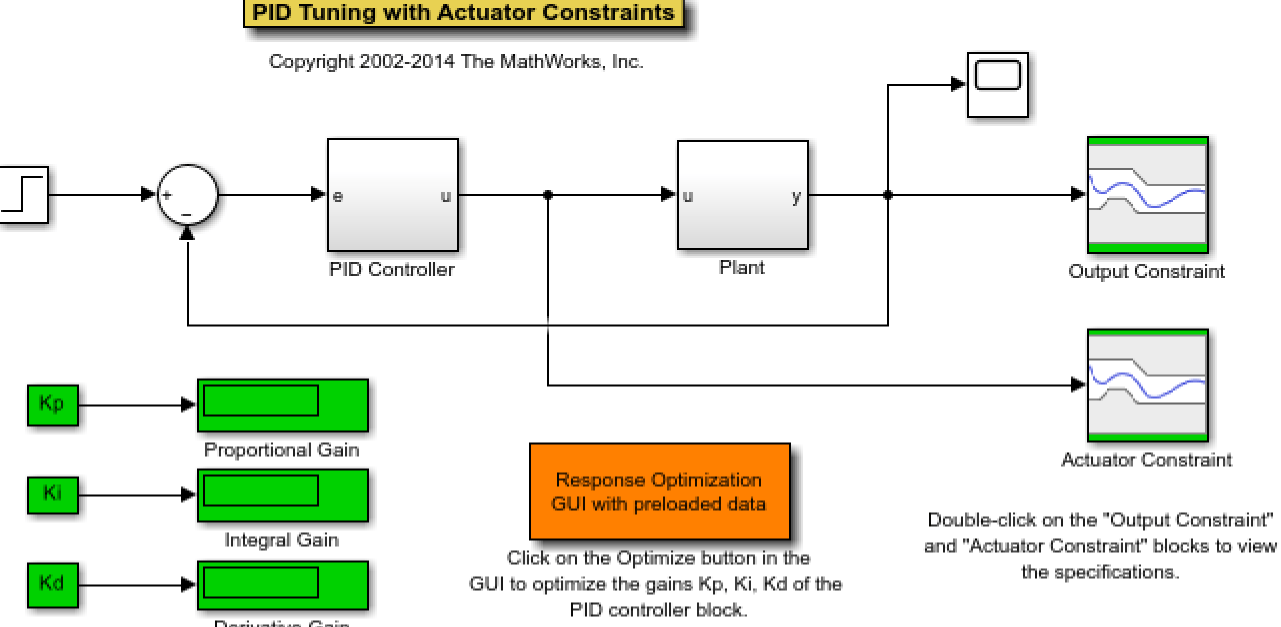
```
bdclose('sdoSimpleSuspension')
```

PID Tuning with Actuator Constraints

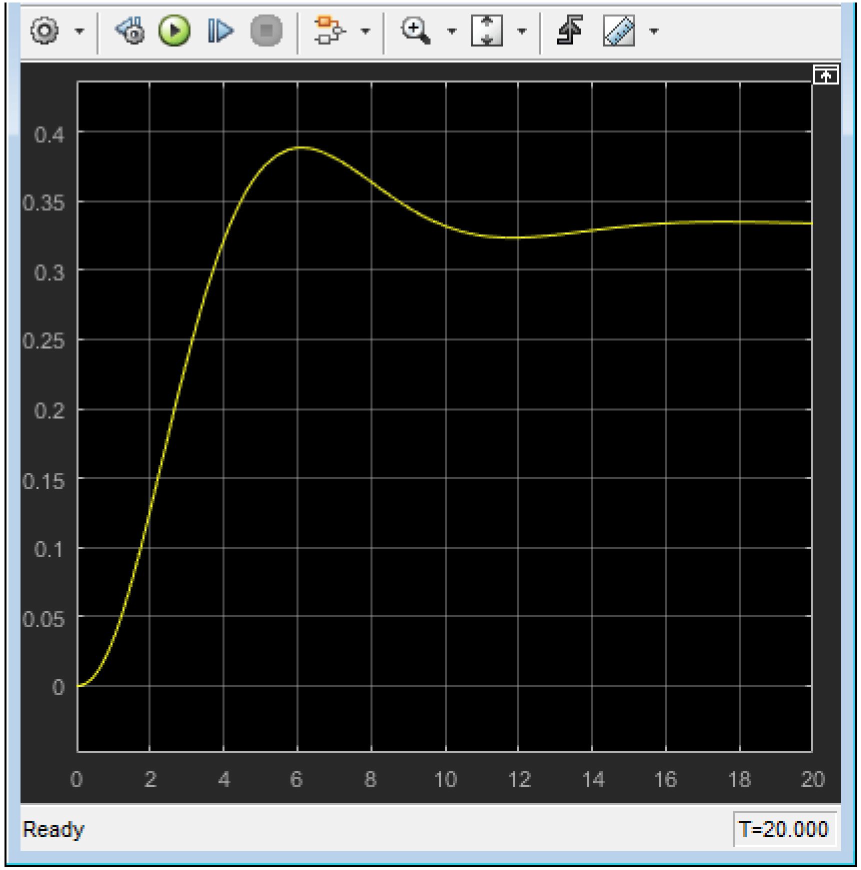
This example shows how to use Simulink® Design Optimization™ to tune the gains of the PID controller (Kp, Ki, and Kd) and optimize the step response of the plant. To view the results, use the following steps.

Open the `pidtune_demo` model using the command below and run the simulation. The simulation produces an unoptimized step response and the initial data for optimization.

```
open_system('pidtune_demo')
```



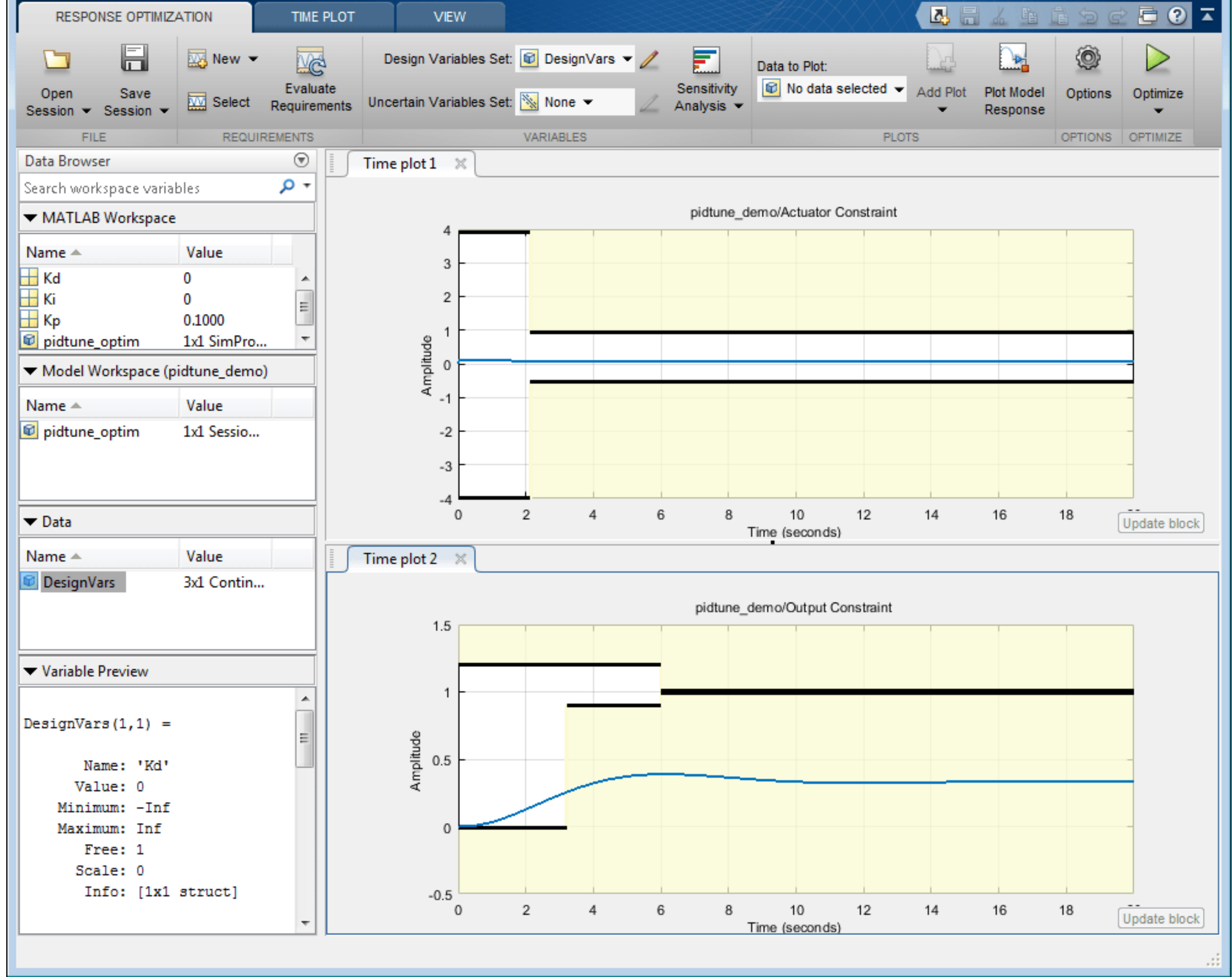
Double-click the `Scope` block to view the unoptimized step response.



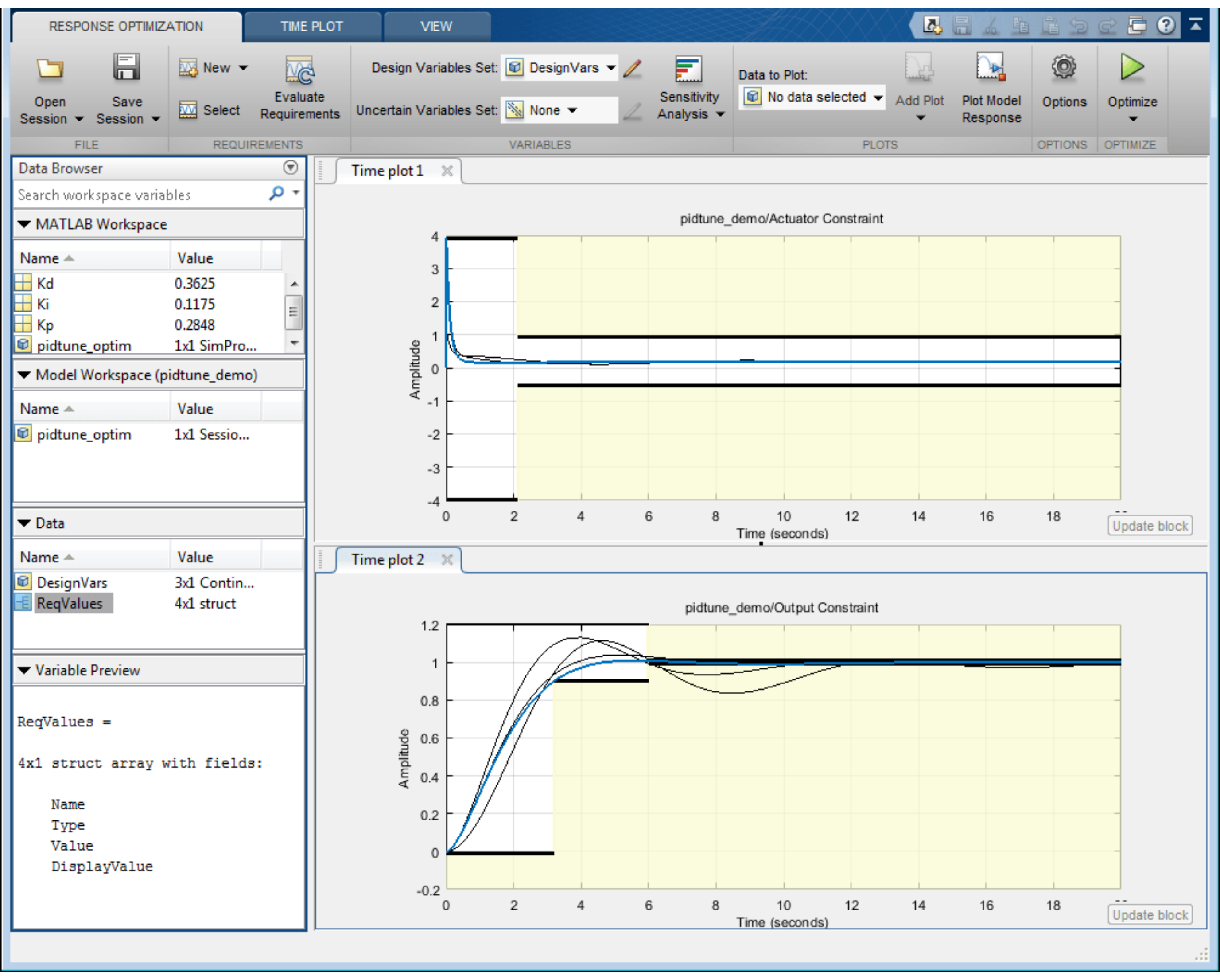
Double-click the `Output Constraint` block to view constraints on the plant response, including rise time, settling time and maximum overshoot.

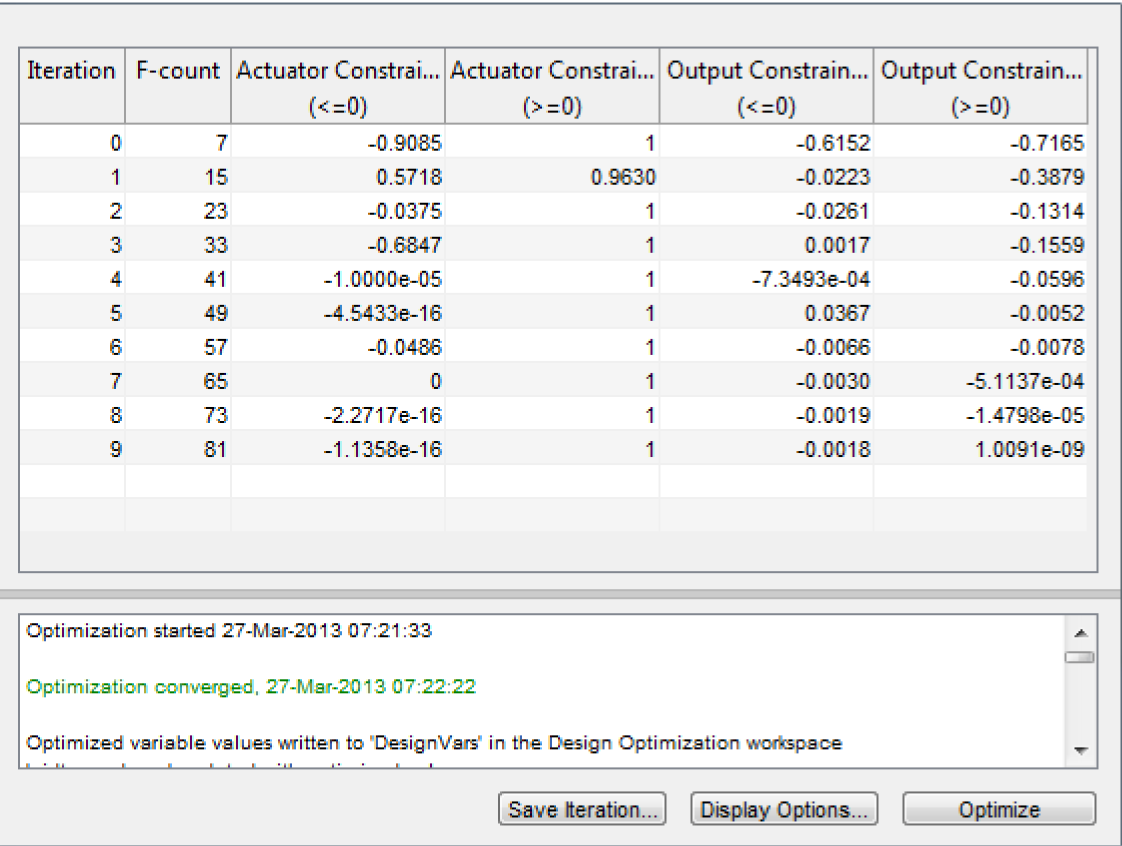
Double-click the `Actuator Constraint` block to view constraints on the actuator signal of the controller.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
New
Select
Evaluate Requirements
Design Variables Set: DesignVars
Uncertain Variables Set: None
Sensitivity Analysis
Data to Plot: No data selected
Add Plot
Plot Model Response
Options
Optimize
FILE
REQUIREMENTS
VARIABLES
PLOTS
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
Kd 0.3625
Ki 0.1175
Kp 0.2848
pidtune_optim 1x1 SimPro...
Model Workspace (pidtune_demo)
pidtune_optim 1x1 Sessio...
Data
DesignVars 3x1 Contin...
ReqValues 4x1 struct
Variable Preview
ReqValues =
4x1 struct array with fields:
Name
Type
Value
DisplayValue
Time plot 1
pidtune_demo/Actuator Constraint
Amplitude
Time (seconds)
Update block
Time plot 2
pidtune_demo/Output Constraint



Iteration	F-count	Actuator Constrai... (<=0)	Actuator Constrai... (>=0)	Output Constrain... (<=0)	Output Constrain... (>=0)
0	7	-0.9085	1	-0.6152	-0.7165
1	15	0.5718	0.9630	-0.0223	-0.3879
2	23	-0.0375	1	-0.0261	-0.1314
3	33	-0.6847	1	0.0017	-0.1559
4	41	-1.0000e-05	1	-7.3493e-04	-0.0596
5	49	-4.5433e-16	1	0.0367	-0.0052
6	57	-0.0486	1	-0.0066	-0.0078
7	65	0	1	-0.0030	-5.1137e-04
8	73	-2.2717e-16	1	-0.0019	-1.4798e-05
9	81	-1.1358e-16	1	-0.0018	1.0091e-09

Close the model.

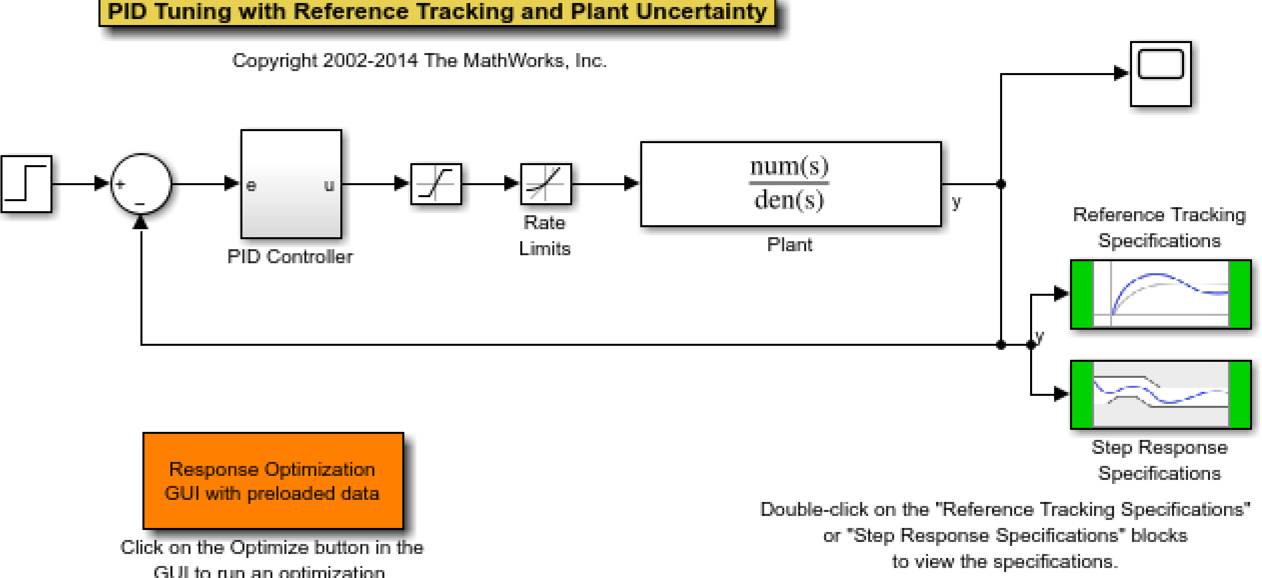
```
bdclose('pidtune_demo')
```

PID Tuning with Reference Tracking and Plant Uncertainty

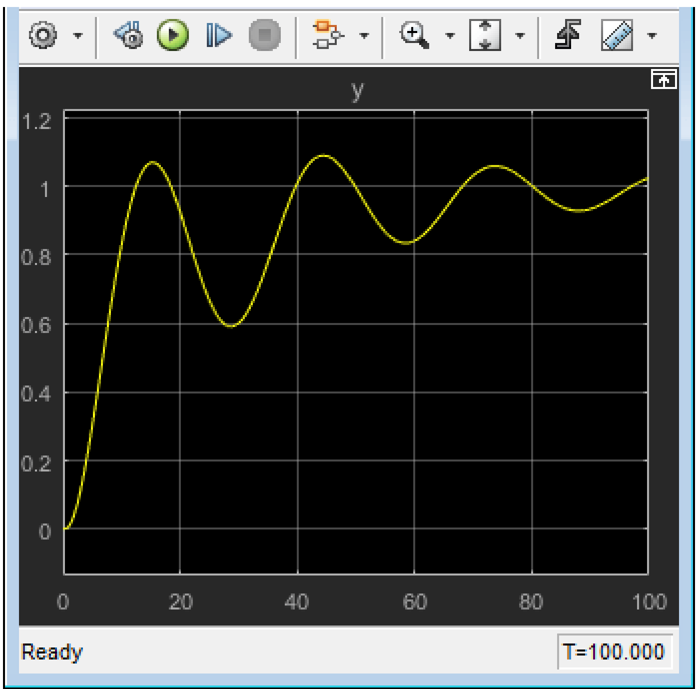
This example shows how to use Simulink® Design Optimization™ to track a reference signal and optimize the response with uncertainties in the plant model. The plant model consists of the plant transfer function and includes a Saturation block and a Rate Limits block. To view the results, use the following steps.

Open the `pidtrack_demo` model using the command below and run the simulation. The simulation produces an unoptimized step response and the initial data for optimization.

```
open_system('pidtrack_demo')
```



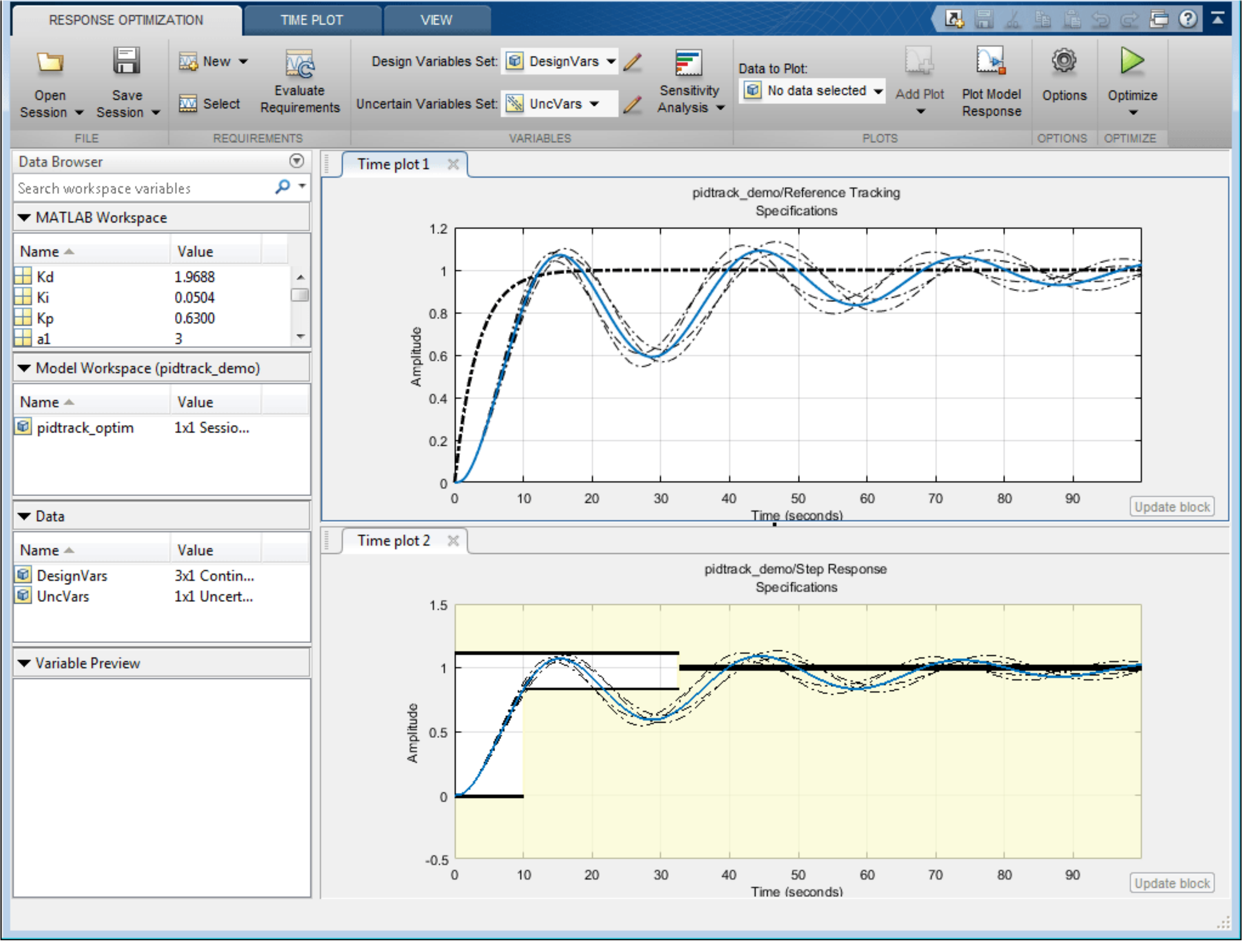
Double-click the `Scope` block to view the unoptimized step response.



Double-click the `Step Response Specifications` block to view constraints on the plant response, including rise time, settling time and maximum overshoot.

Double-click the `Reference Tracking Specifications` block to view the reference signal that the controller has to track.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



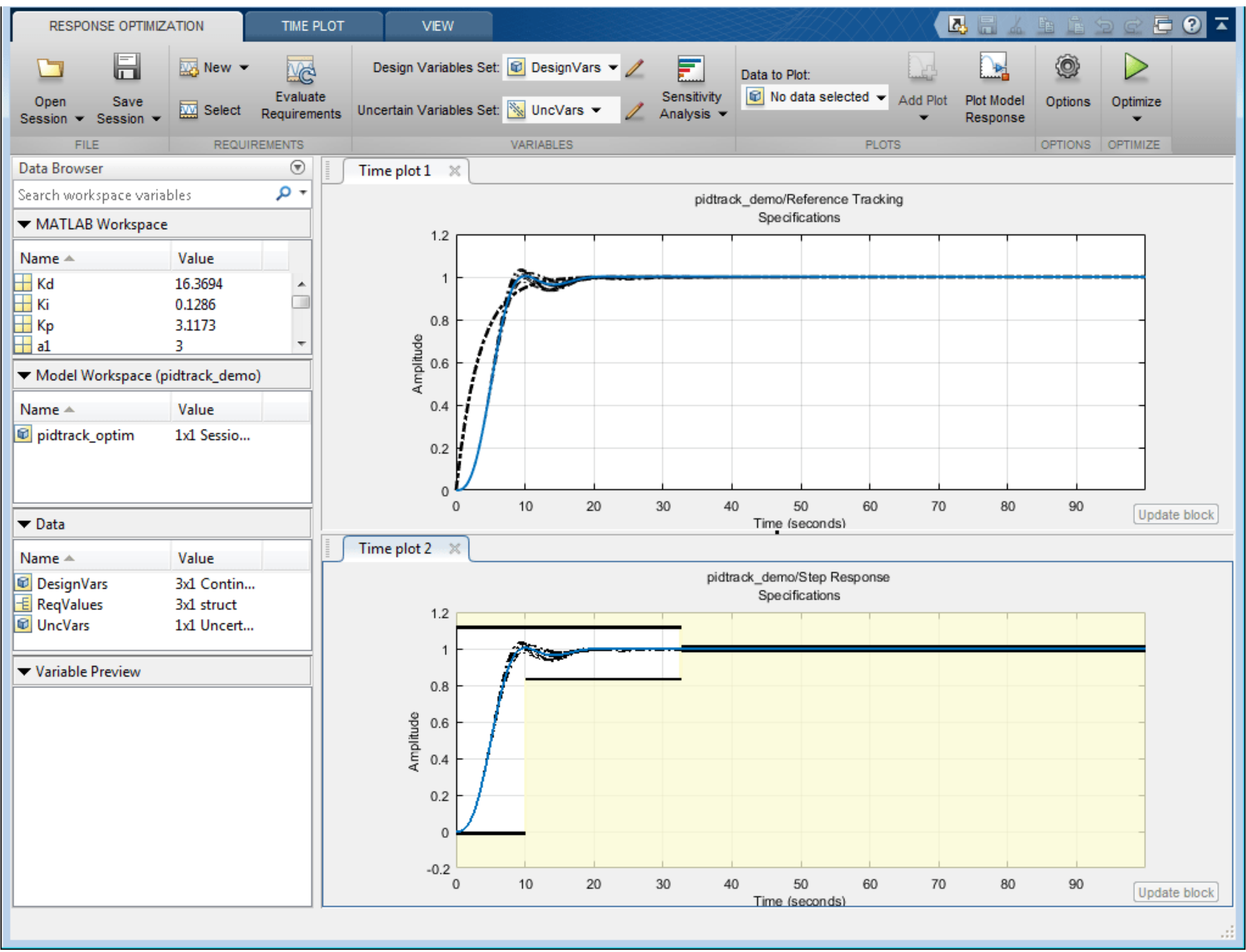
The solid lines in the plots indicate the plant response without considering the uncertainties and the dashed lines indicate the uncertain responses.

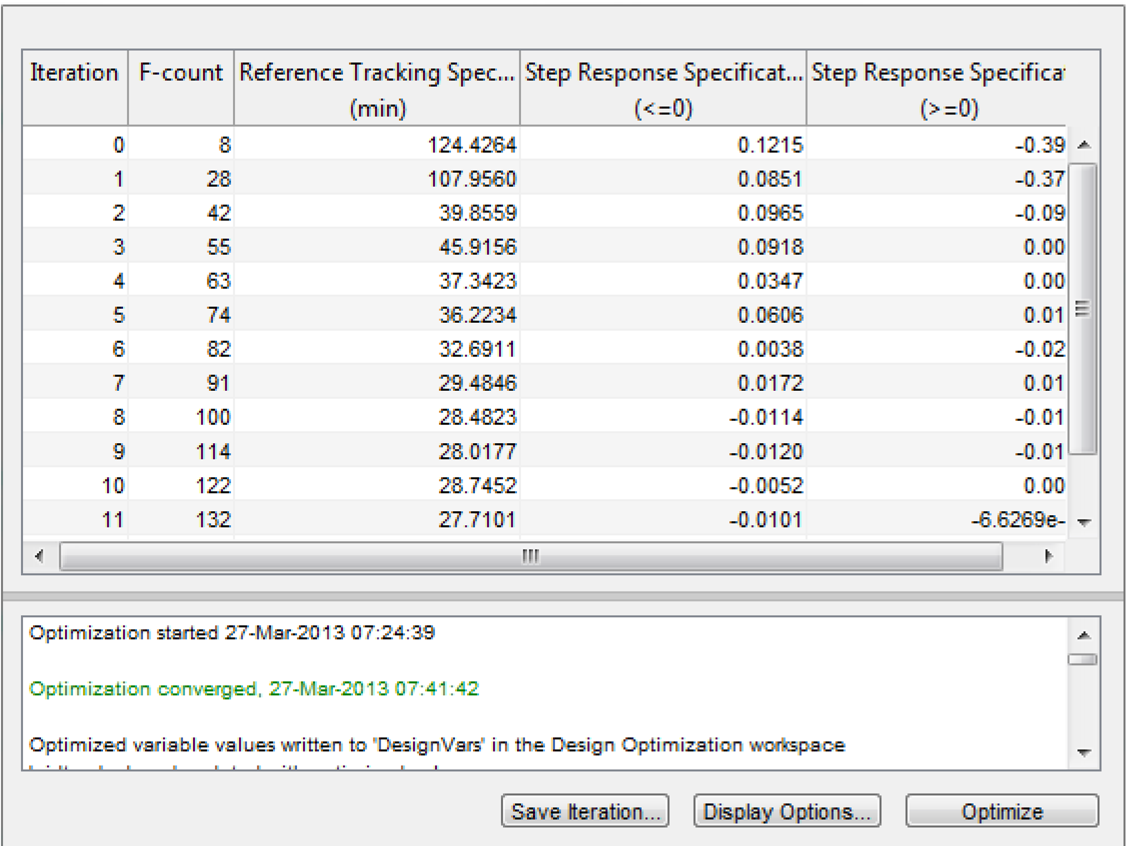
Start the optimization by pressing the **Optimize** button from the **Response Optimizer**.

The tuned parameters are the PID Controller gains `Kp`, `Ki`, and `Kd`. The plant parameters `a1` and `a2` are only known within 10% (uncertainty).

The optimization seeks to minimize the gap between the actual and ideal responses for the nominal values (solid lines) and min/max values (dotted lines) of `a1` and `a2`.

The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set: DesignVars
Uncertain Variables Set: UncVars
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
Kd
16.3694
Ki
0.1286
Kp
3.1173
a1
3
Model Workspace (pidtrack_demo)
pidtrack_optim
1x1 Sessio...
Data
DesignVars
3x1 Contin...
ReqValues
3x1 struct
UncVars
1x1 Uncert...
Variable Preview
Time plot 1
pidtrack_demo/Reference Tracking
Specifications
Amplitude
Time (seconds)
Update block
Time plot 2
pidtrack_demo/Step Response
Specifications
Amplitude
Time (seconds)
Update block



Iteration	F-count	Reference Tracking Spec... (min)	Step Response Specificat... (<=0)	Step Response Specifica (>=0)
0	8	124.4264	0.1215	-0.39
1	28	107.9560	0.0851	-0.37
2	42	39.8559	0.0965	-0.09
3	55	45.9156	0.0918	0.00
4	63	37.3423	0.0347	0.00
5	74	36.2234	0.0606	0.01
6	82	32.6911	0.0038	-0.02
7	91	29.4846	0.0172	0.01
8	100	28.4823	-0.0114	-0.01
9	114	28.0177	-0.0120	-0.01
10	122	28.7452	-0.0052	0.00
11	132	27.7101	-0.0101	-6.6269e-


```
% Close the model.
bdclose('pidtrack_demo')
```

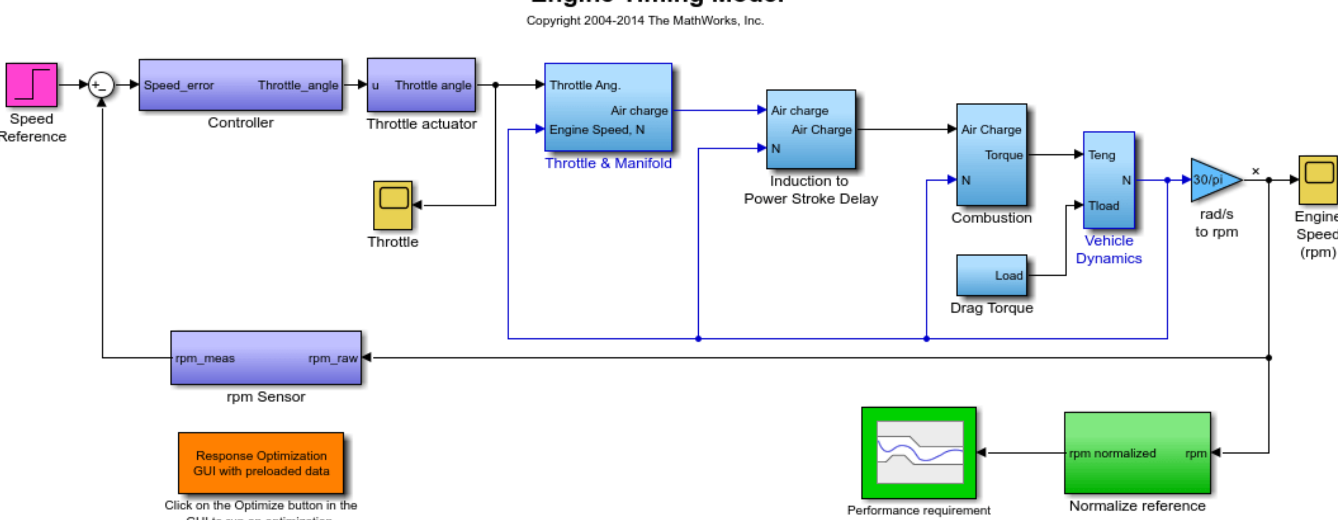
Engine Design and Cost Tradeoffs

This example shows how to use Simulink® Design Optimization™ to optimize a design for performance and cost. In this example, you tune an automotive engine speed controller while reducing controller costs by tuning sensor accuracy and actuator response time.

Opening the Model

Open the automotive engine model using the command below. The following subsystems model the engine response: `Throttle & Manifold`, `Induction to Power Stroke Delay`, `Combustion`, `Drag Torque` and `Vehicle Dynamics`. The main signal of interest in the model is the engine speed in rpm. The control system consists of the lead-lag `Controller`, `rpm Sensor`, and `Throttle actuator` blocks. The model is driven by a step change in speed reference.

```
open_system('enginetradeoff_demo')
```



Design Overview

The design has the following objectives:

Engine performance objective:

The engine must respond to step changes in the speed reference with the following characteristics:

- Maximum overshoot of 2%
- Rise time of 4 seconds to reach 90% of the reference speed
- Settling time of 7.5 seconds to reach within 2% of the reference speed

This objective is included as a constraint in the `Performance requirement` block. The input to this block is the engine speed, which is normalized by the speed reference value. This means that although the speed reference changes, the performance requirement remains the same.

Cost minimization objective:

The design cost of the controller is to be minimized. This objective uses sensor and actuator parameterization to compute a design cost. The design cost is computed so that it is always greater than 1 and the optimization attempts to drive the cost to 1.

We use a custom requirement to minimize this cost. The `enginetradeoff_cost` function used by the custom requirement simply returns the cost value to be minimized.

```
type enginetradeoff_cost
```

```
function Cost = enginetradeoff_cost(u)
%Compute controller cost based on sensor accuracy, actuator response, and
%controller sampling time.

% Copyright 2013 The MathWorks, Inc.

%Cost constants
min_cost       = 1;       %Minimum cost > 0
sensor_var_min = 1e-3;    %Minimum sensor variance (most expensive)
sampling_min   = 1e-2;    %Minimum controller sampling time (most expensive)
throttle_max   = 2*pi*10; %Maximum actuator response frequency (most expensive)

%Get variable names
varnames = {u.DesignVars.Name};

%Form cost
Cost = min_cost;
%Add sensor cost
index = strcmp(varnames, 'sensor_std');
if any(index)
  Cost = Cost + sensor_var_min./max(u.DesignVars(index).Value,sensor_var_min);
end

%Add sampling cost
index = strcmp(varnames, 'Ts');
if any(index)
  Cost = Cost+ sampling_min./max(u.DesignVars(index).Value,sampling_min);
end

%Add throttle cost
index = strcmp(varnames, 'Tthrottle');
if any(index)
  Cost = Cost + u.DesignVars(index).Value/throttle_max;
end
```

Model parameterization:

To achieve the performance and cost objectives, we parameterize the following in the model:

- Final step value of the speed reference: This ensures that the design works over a range of operating points, from low speed to high speed values.
- Gain, pole and zero values of the controller: This allows us to change the controller performance. We tune these values using optimization.
- Response time of the throttle actuator: The response time is optimized to minimize controller cost. The actuator cost is inversely proportional to the response time, i.e., a faster response time implies a more expensive actuator.

- Accuracy of the rpm sensor: The accuracy is specified by a standard deviation value and optimized to minimize controller cost. The sensor cost is inversely proportional to standard deviation, i.e., a smaller standard deviation implies a more accurate sensor, which is more expensive.

Running the Optimization

Optimizing the engine controller for performance and cost involves:

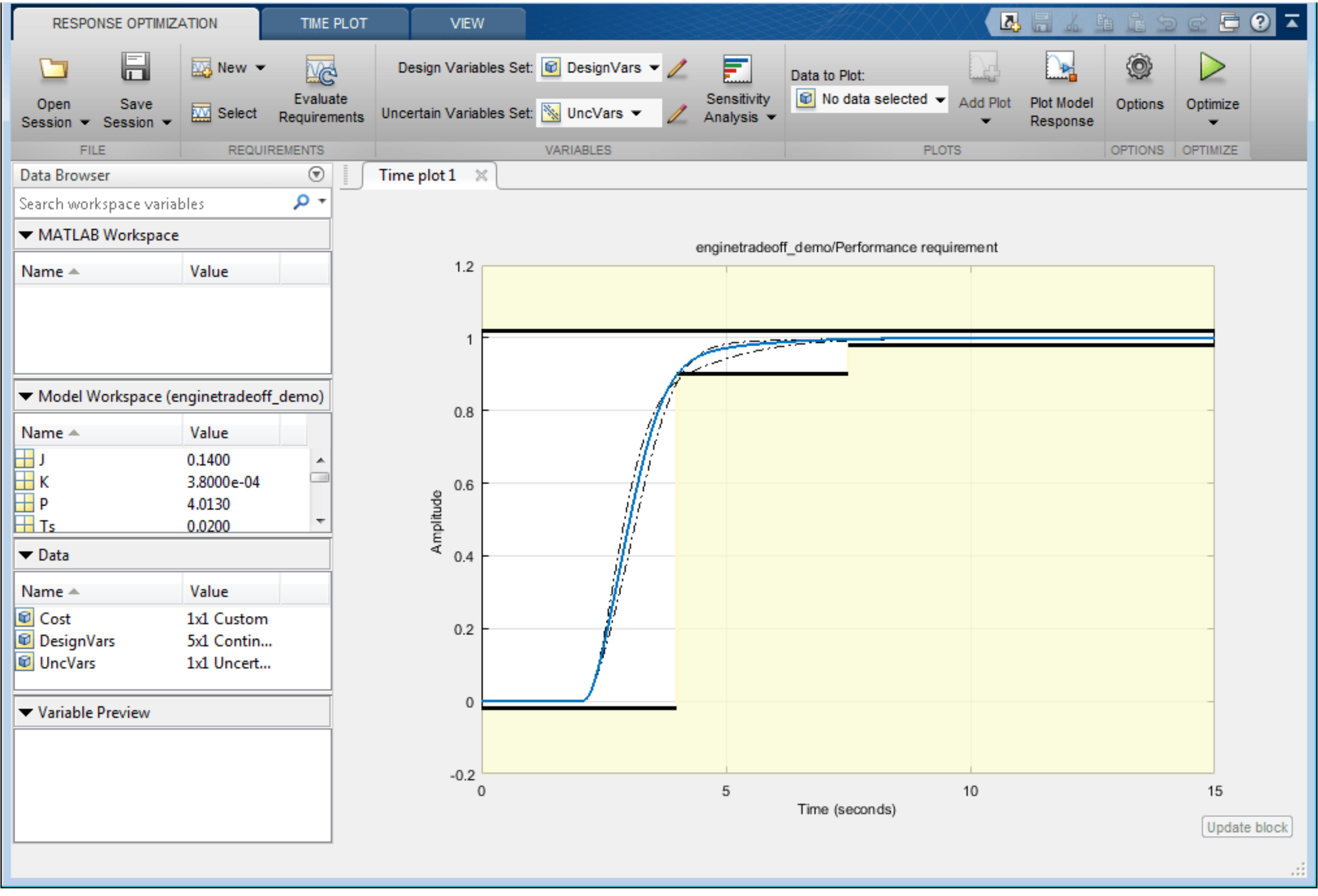
- Optimizing the controller, sensor, and actuator parameters.

- Optimizing the response over different operating conditions.

With problems of this type, it is a good practice to build the design iteratively rather than optimizing for all objectives together. Here, we use the divide and conquer strategy as shown in the table below. The idea is to use the optimized parameter values from one stage as the initial guess for the next stage.

	Tune controller parameters	Sweep model over the operating range	Tune sensor accuracy	Tune throttle response time
Stage 1	X			
Stage 2	X	X		
Stage 3	X		X	
Stage 4	X		X	X
Stage 5	X	X	X	X

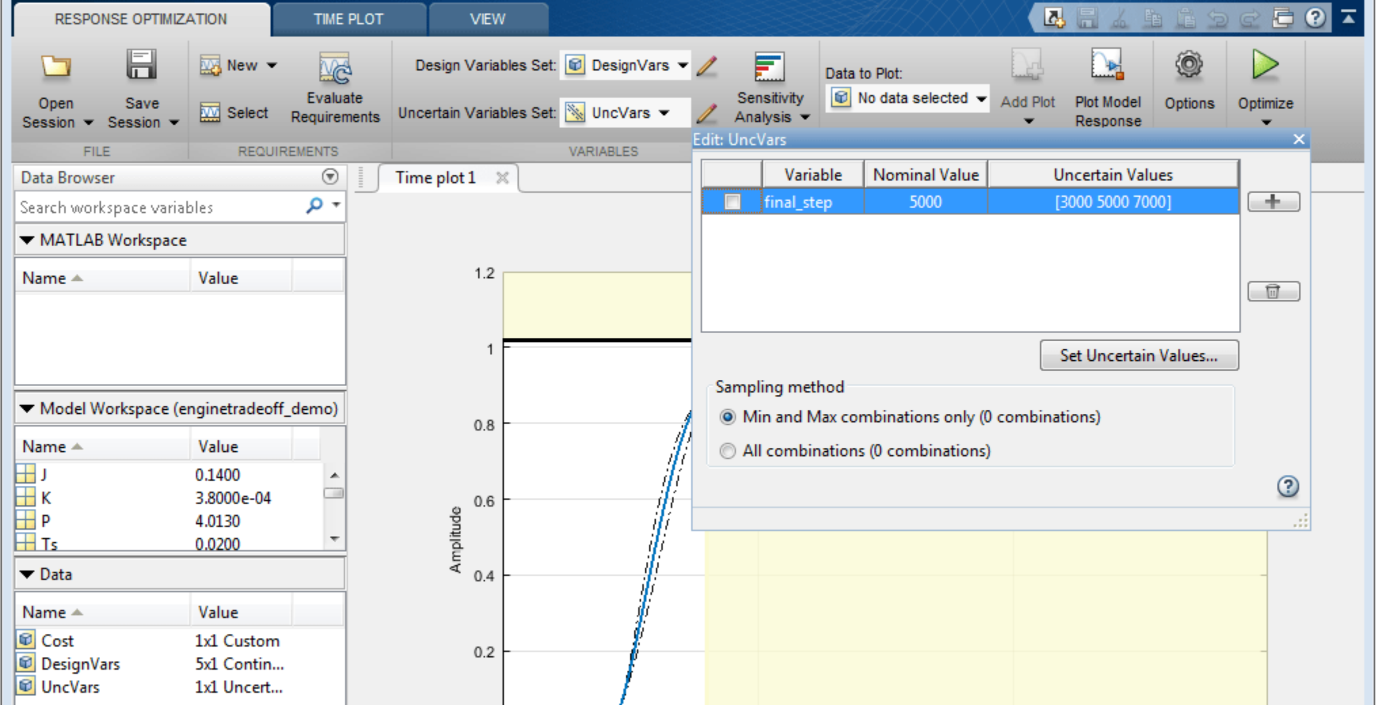
You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



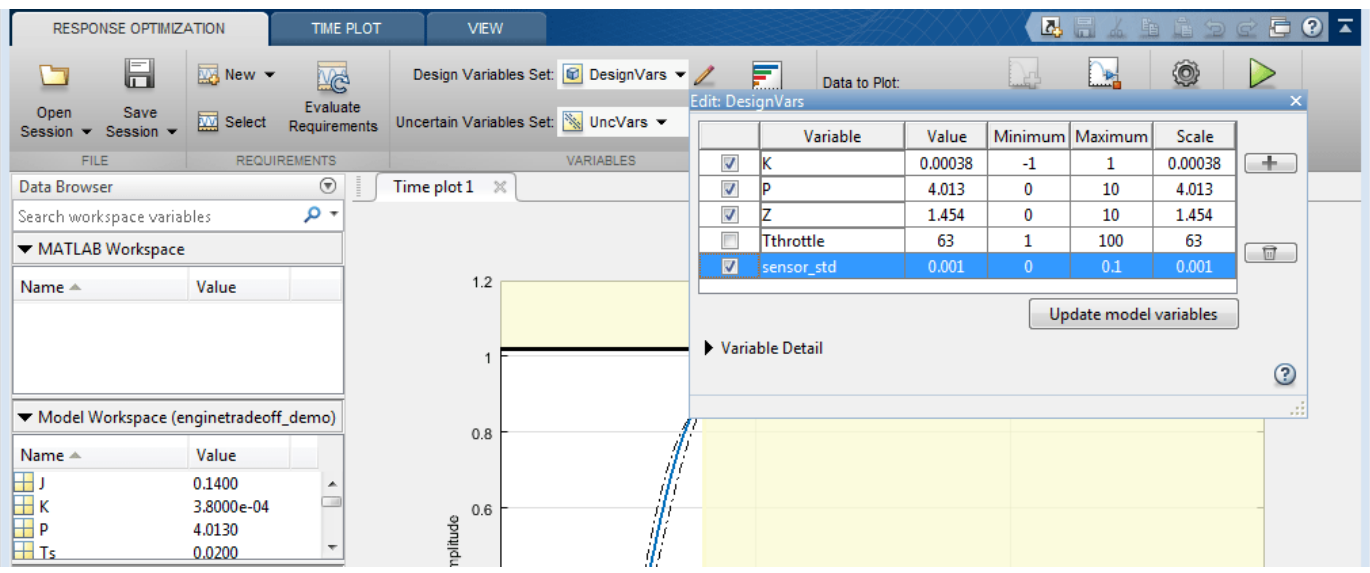
The optimization project saved with the example corresponds to stage 2. In this stage, we optimize the controller parameters over the operating range. To do so, we specify `K`, `P` and `Z` as tuned parameters and the final step value, `final_step`, of the reference signal as an uncertain parameter. At this stage, the custom controller cost objective is not included in the optimization problem.

We introduce the controller cost objective in stage 3 by configuring the model as follows:

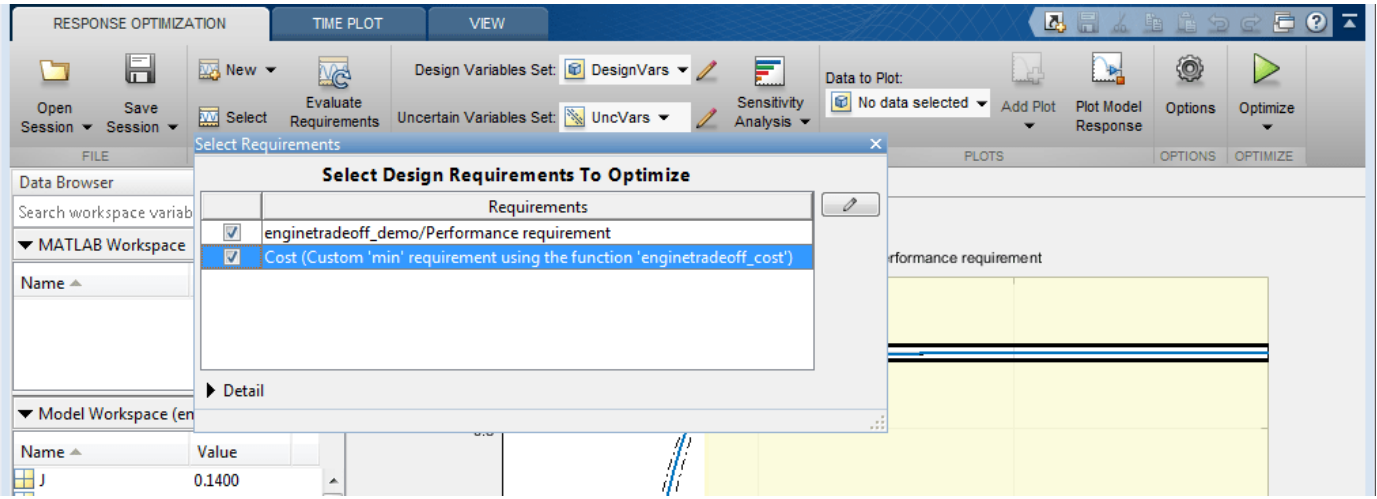
- Open the `Uncertain Variables` editor from the **Response Optimizer** and then unselect the check box for `final_step`. This removes sweeping the model over different operating points from the optimization problem and thus reduces computational load.



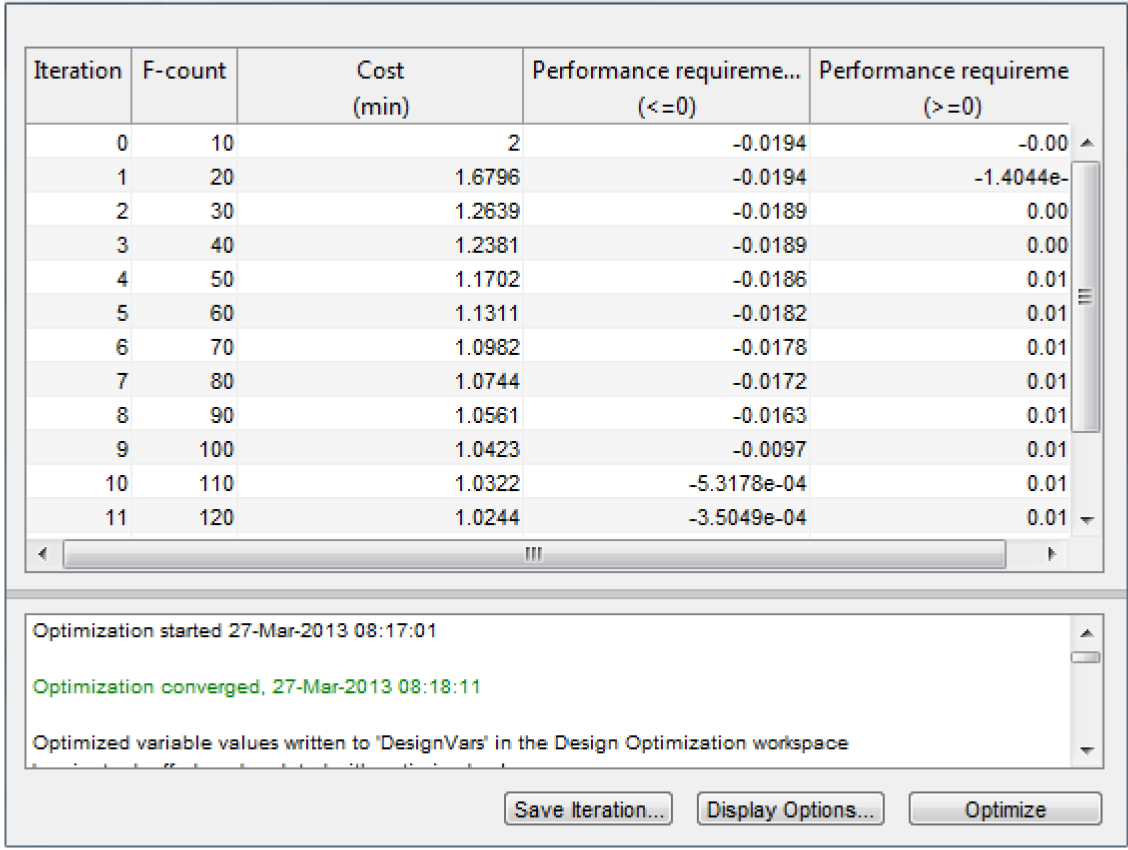
- Open the `Design Variables` editor from the **Response Optimizer** and then select the check box for `sensor_std` to tune this parameter.



- Click the **Select** button in the **Response Optimizer** to open the `Design Requirements` editor, and then select the check box for custom `Cost`. This accounts for the cost minimization objective during optimization.

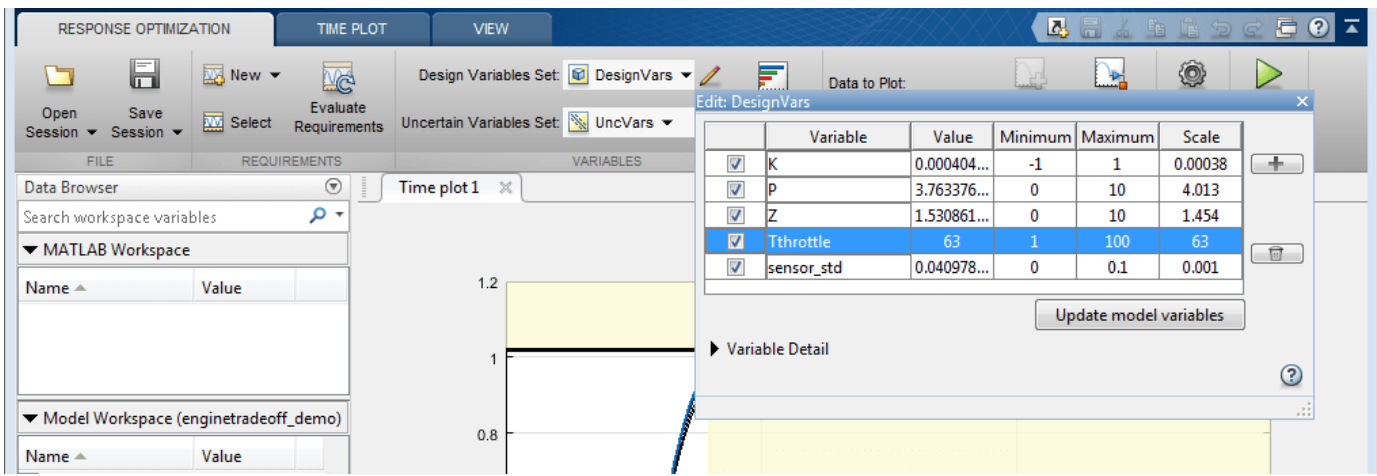


We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.



To configure the optimization for Stage 4:

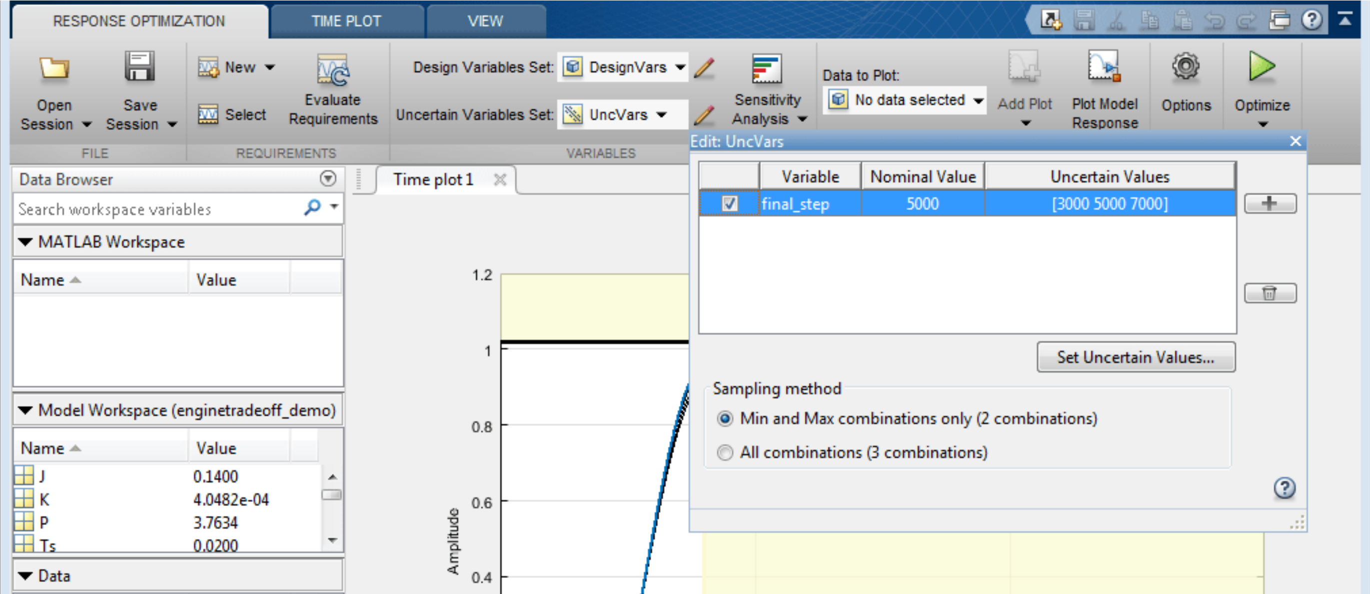
- Open the `Design Variables` editor from the **Response Optimizer** and then select the check box for `Tthrottle` to tune this parameter.



You can start the optimization by pressing the **Optimize** button from **Response Optimizer**.

To configure the optimization for stage 5:

- Open the `Uncertain Variables` editor from the **Response Optimizer** and then select the check box for `final_step` to sweep the model over the operating range.



You can start the optimization by pressing the **Optimize** button from the **Response Optimizer**.

```
% Close the model
bdclose('enginetradeoff_demo')
```

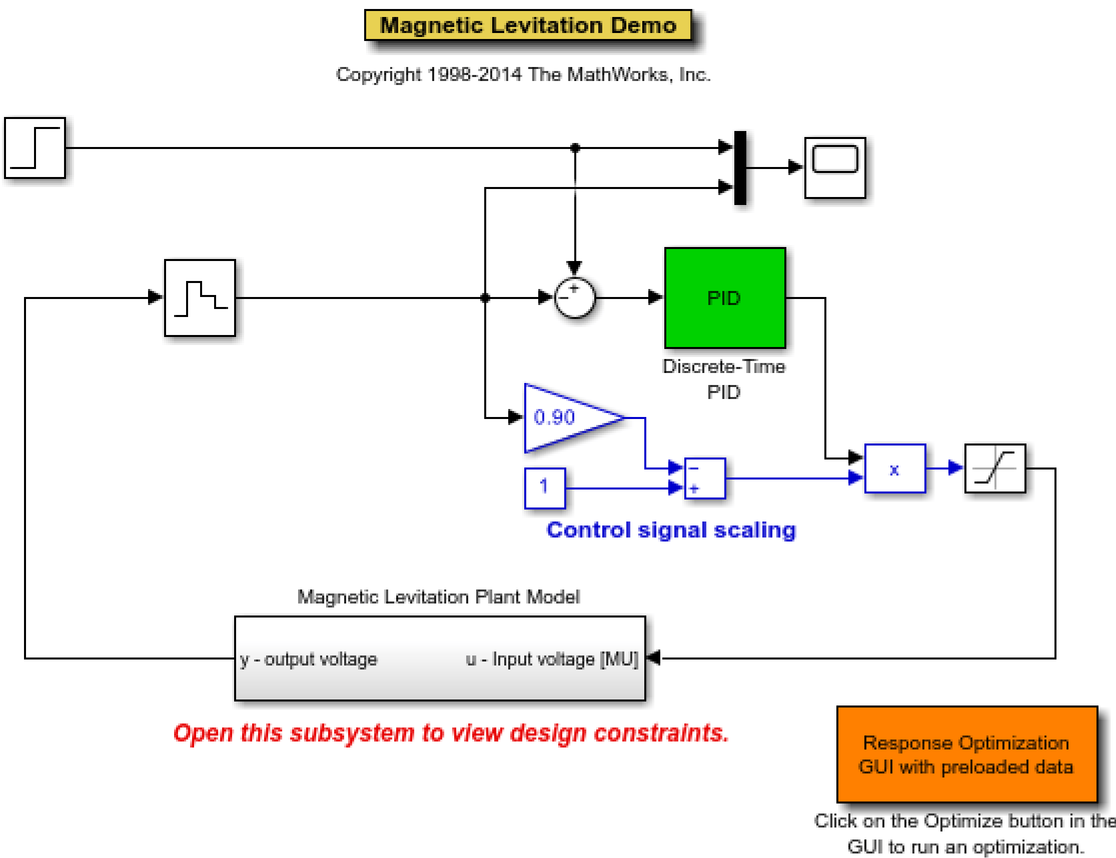
Magnetic Levitation Controller Tuning

This example shows how to use numerical optimization to tuning the controller parameters of a nonlinear system. In this example, we model a CE 152 Magnetic Levitation system where the controller is used to position a freely levitating ball in a magnetic field. The control structure for this model is fixed and the required controller performance can be specified in terms of an idealized time response.

Earnshaw's Theorem

Earnshaw's theorem proved that it is not possible to achieve stable levitation using static, macroscopic, classical electromagnetic fields. However the CE 152 system works around this by creating a potential well around the point at which the ball is to be suspended, thereby creating a non-inverse square law force. This is achieved by an inductive coil that generates a time varying electromagnetic field. The electromagnetic field is controlled through the use of feedback to keep the ball at the required location.

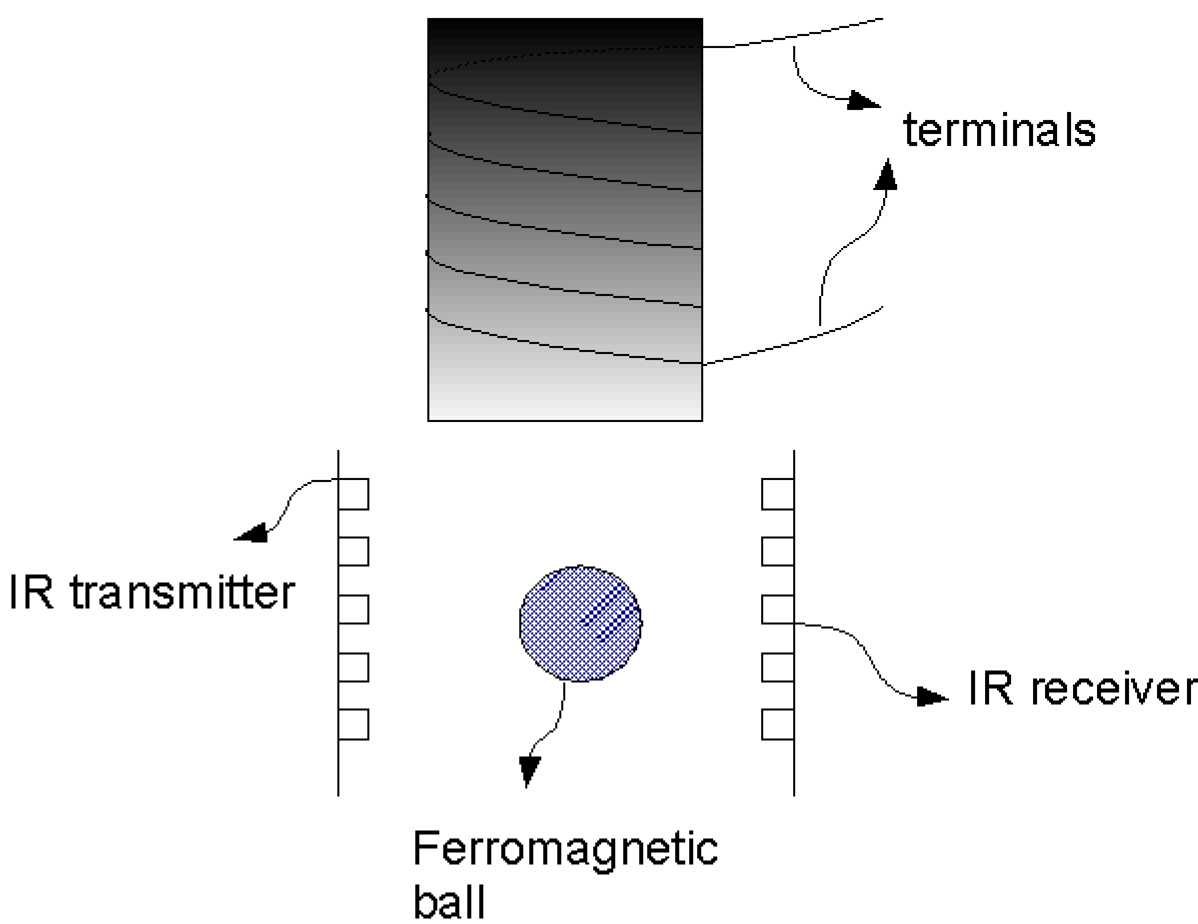
```
open_system('maglev_demo')
```



Model Description

The magnetic levitation system is a nonlinear dynamic system with one input and one output. Double-click the `Magnetic Levitation Plant Model` to open this subsystem. The input voltage is

applied to a coil that creates the electromagnetic field. The output voltage is measured by an IR receiver and represents the position of the ball in the magnetic field. The diagram below outlines this system.

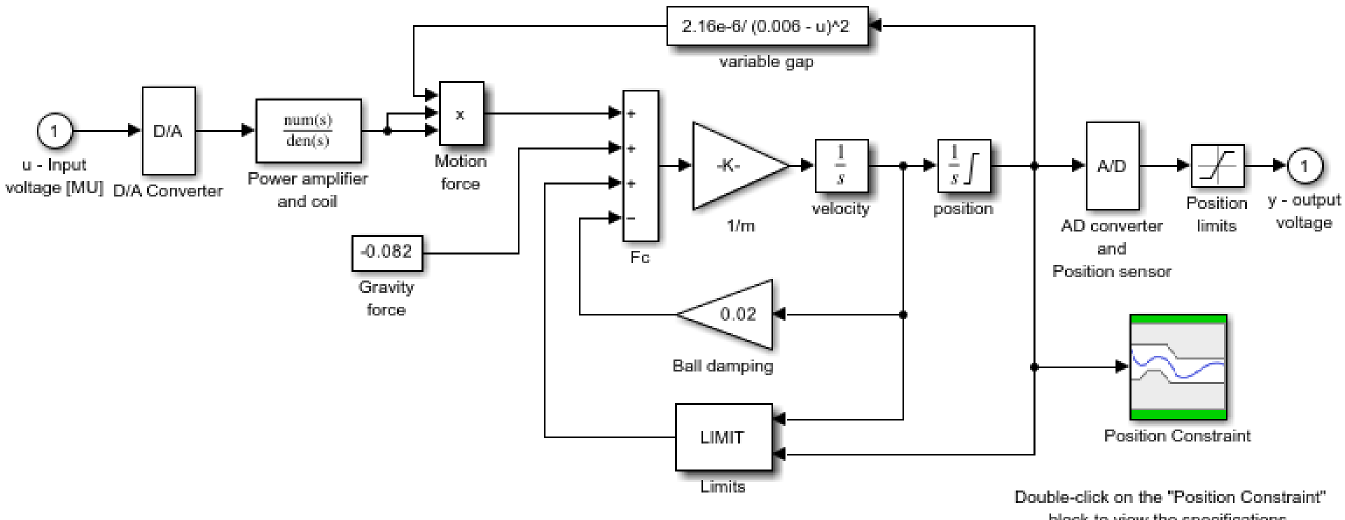


The physical system consists of a ball (with mass 0.00837 kg) which is under the influence of three forces:

- The magnetic field produced by an inductive coil. This is modeled by the `Power amplifier and coil` block in the Simulink® model. The input to the inductor is a voltage signal and the output a current. The force from the coil depends on the square of the current, the air-gap between the coil and the ball, and the physical properties of the ball. This produces an upward acting force on the ball.
- The gravitational force acting downwards
- A damping force which acts in a direction opposite to the velocity at any instant of time

These three forces cause the resulting motion of the ball and are modeled in Simulink as shown.

```
open_system('maglev_demo/Magnetic Levitation Plant Model')
```



Non-linearities arising from saturation of the coil and changes in dynamics outside the limits of the magnetic field are also modeled in the Simulink Model. As the force from the coil decays according to an inverse square law larger voltages are required the further the ball is from the coil. The control signal is scaled to account for this and the scaling is included in the *Control signal scaling* blocks.

Control Problem Description

The requirement for the controller is that it be able to position the ball at any arbitrary location in the magnetic field and that it move the ball from one position to another. These requirements are captured by placing step response bounds on the position measurement. Specifically we require the following constraints on the ball:

- Position constraint: within 20% of the desired position in less than 0.5 second
- Settling Time Constraint: within 2% of the desired position within 1.5 second

To meet the control requirements we implement a Proportional-Integral-Derivative (PID) controller. For convenience the controller uses a normalized position measurement with a range from 0 to 1, representing the bottom-most and top-most positions of the ball respectively.

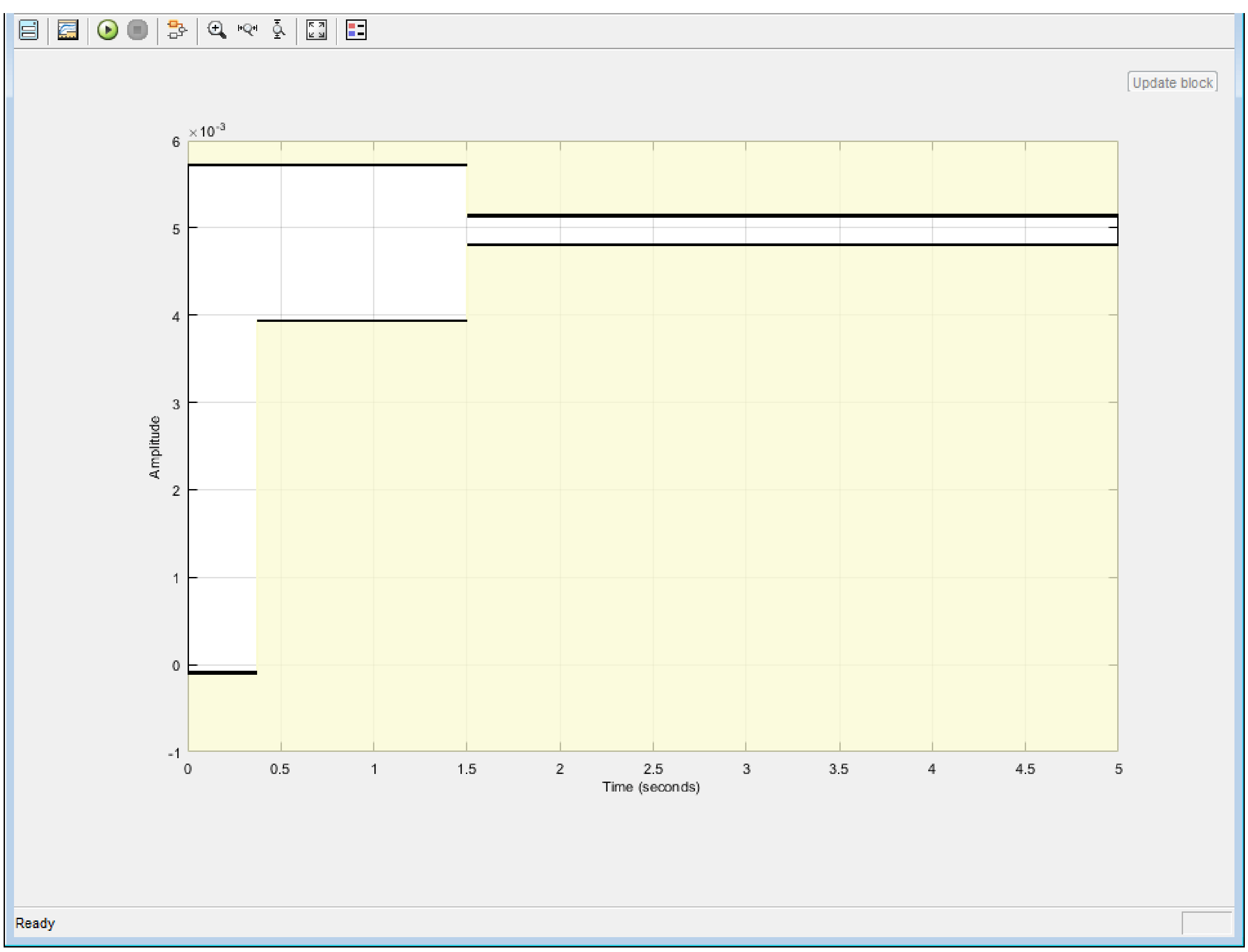
Simulink® Design Optimization™ and numerical optimization is ideally suited to tune the PID coefficients because:

- The system dynamics are complex enough to require effort and time for analysis if we approach the problem using conventional control design techniques.
- The controller structure is fixed.

- We have knowledge of the step response we require from the system.

Setting Constraint Values

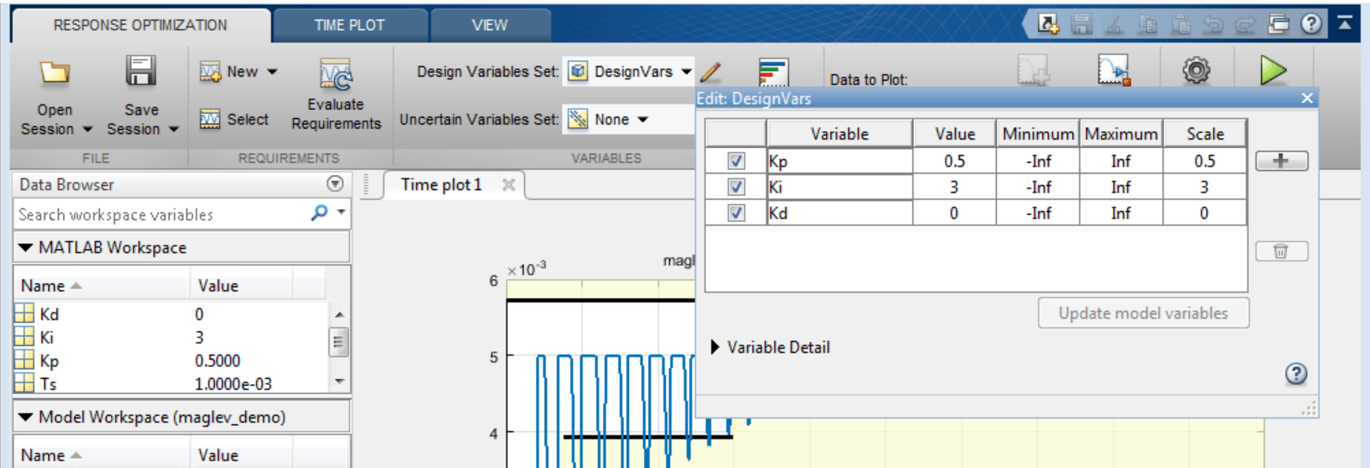
Given the step response characteristic we desire, it is simple to specify the upper and lower bounds of the response. Double-click the `Position Constraint` block in the `Magnetic Levitation Plant Model` subsystem to view constraints on the position of the ball. The constraint lines may be moved using the mouse.



You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.

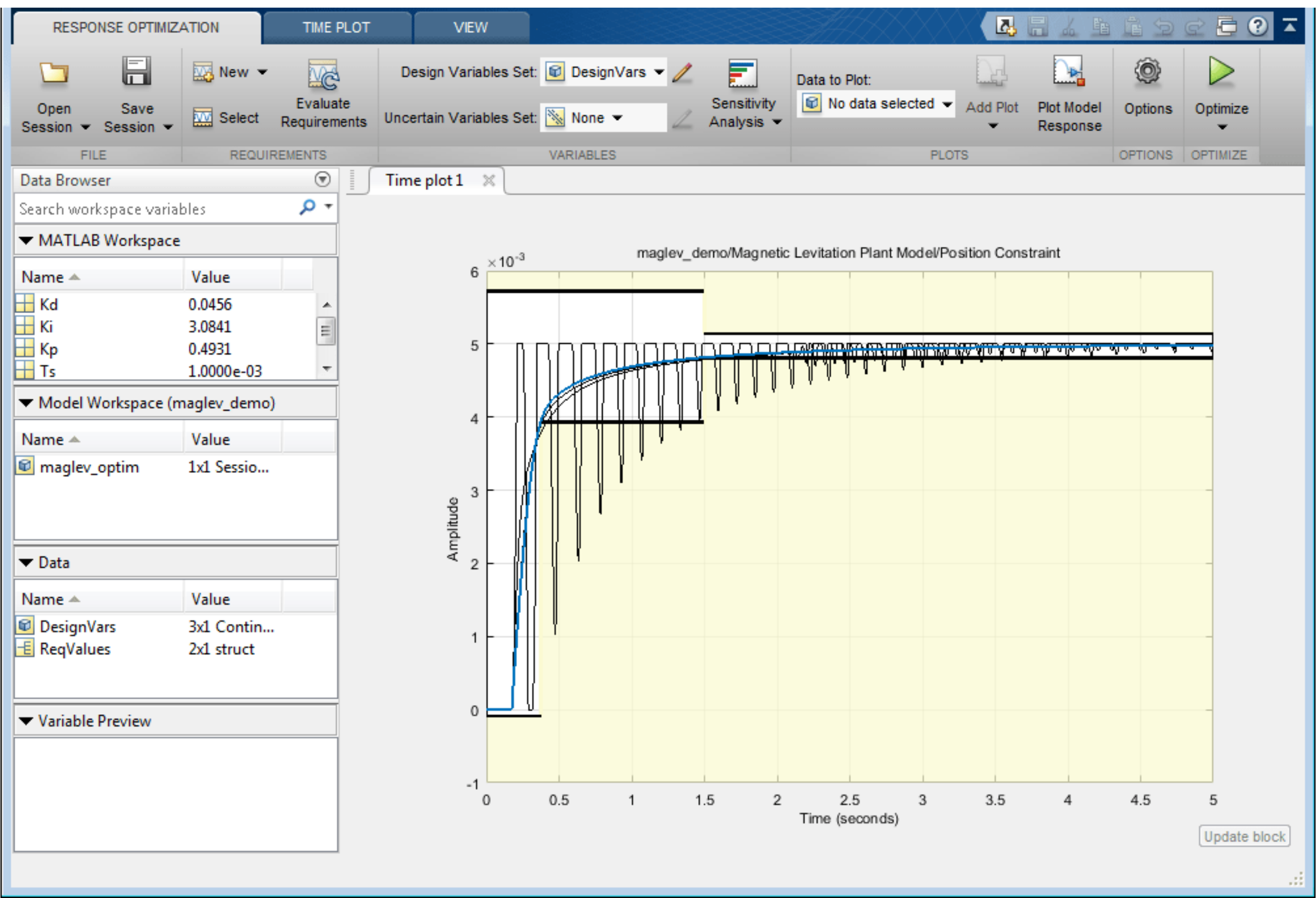
Defining Tuned Parameters

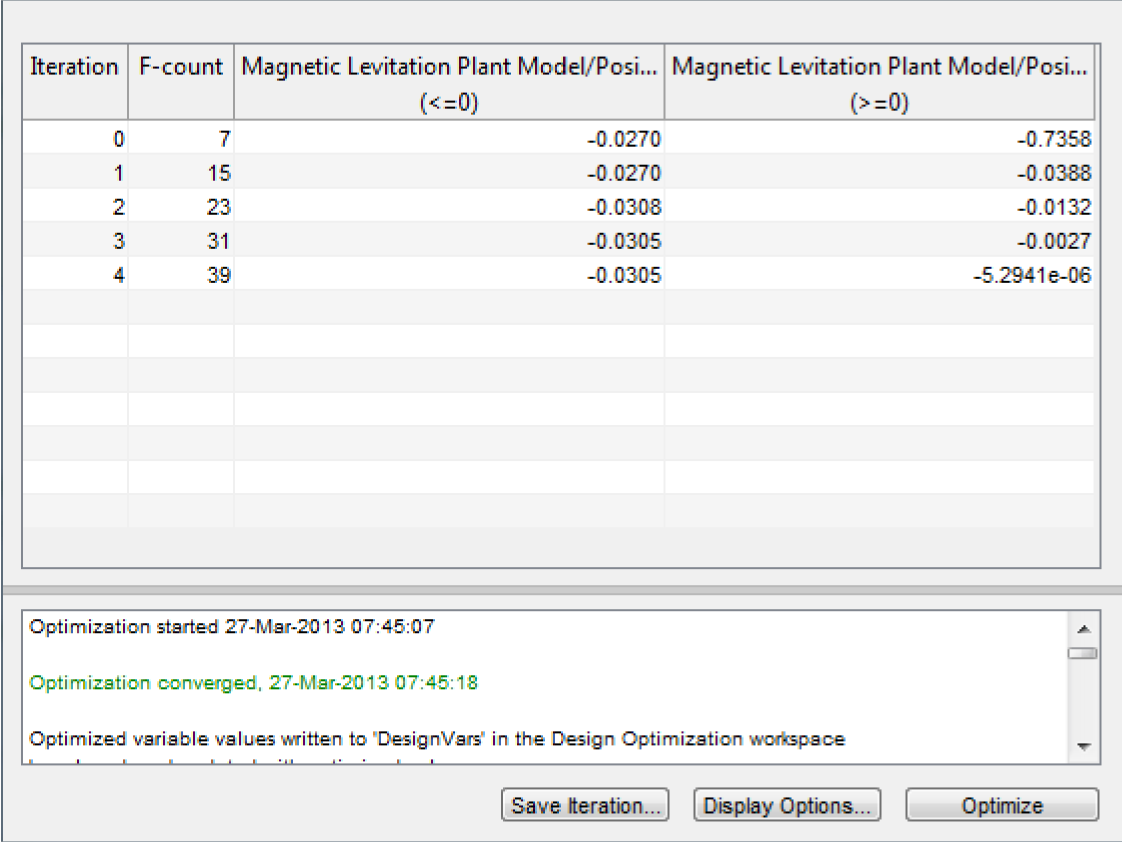
We select the PID controller parameters to tune by opening the `Design Variables` editor, as shown below.



Running the Optimization

After specifying the optimization parameters and the required step response bounds we start the optimization by pressing the **Optimize** button from the **Response Optimizer**. During optimization, the plots are updated with the position of the ball for each iteration and the dark curve shows the final optimized trajectory of the ball (as shown below).

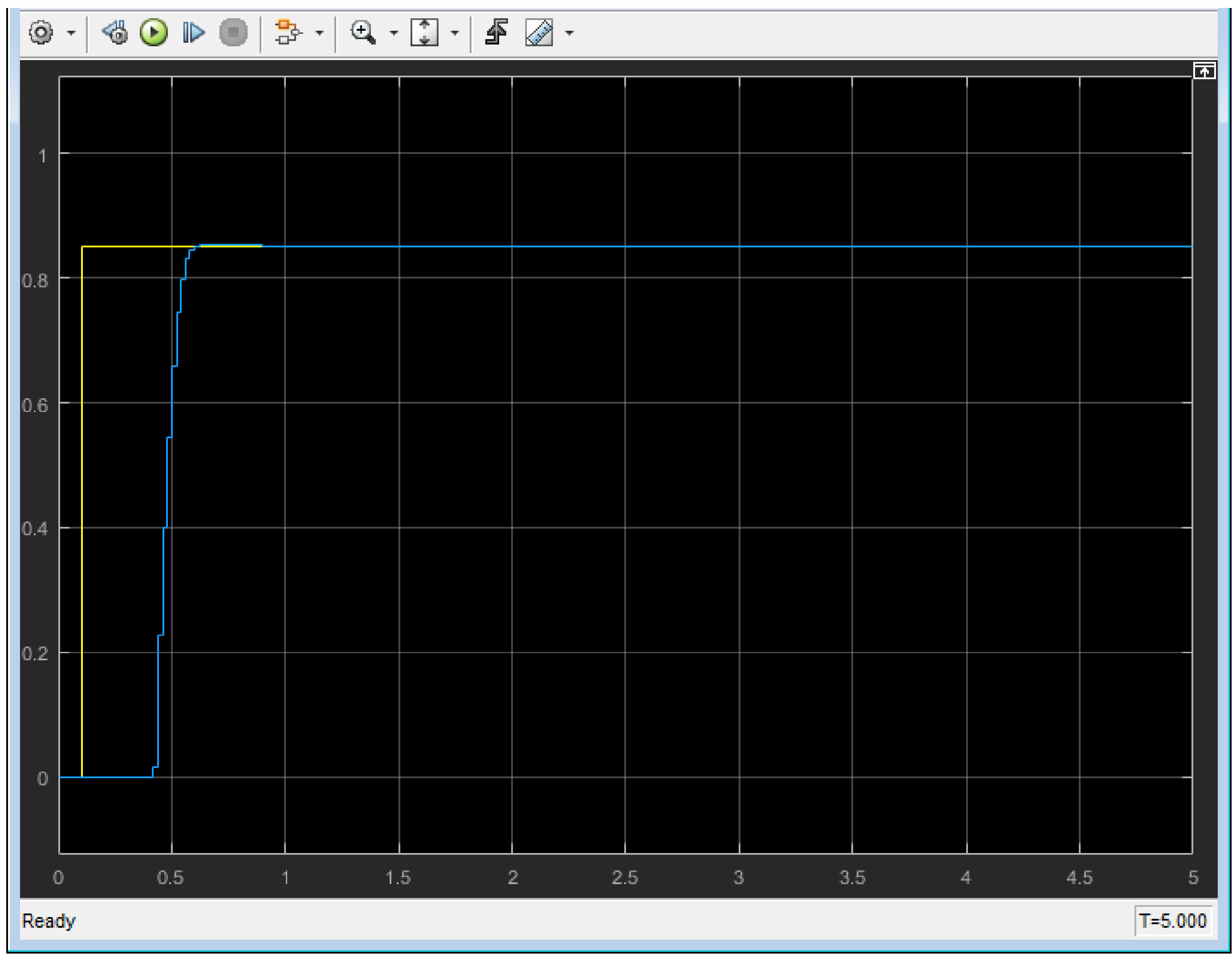




Iteration	F-count	Magnetic Levitation Plant Model/Posi... (<=0)	Magnetic Levitation Plant Model/Posi... (>=0)
0	7	-0.0270	-0.7358
1	15	-0.0270	-0.0388
2	23	-0.0308	-0.0132
3	31	-0.0305	-0.0027
4	39	-0.0305	-5.2941e-06

Verifying the Results

Once we complete the optimization, it is important to validate the results against other step sizes. A successful parameter optimization should be able to provide good control for all steps sizes close to the tuned step size of 1. Step sizes from .7 to 1 should be tested to confirm the controller's performance. The following plot shows the response to a step input from 0 to 0.85 at 0.1 seconds.



Conclusion

The verification step shows that controller's performance satisfies the requirements specified and the tuned parameter values are suitable for control. The tuned parameters could be used to provide baseline performance against which other control schemes can be compared, or a baseline for controllers for different operating regions.

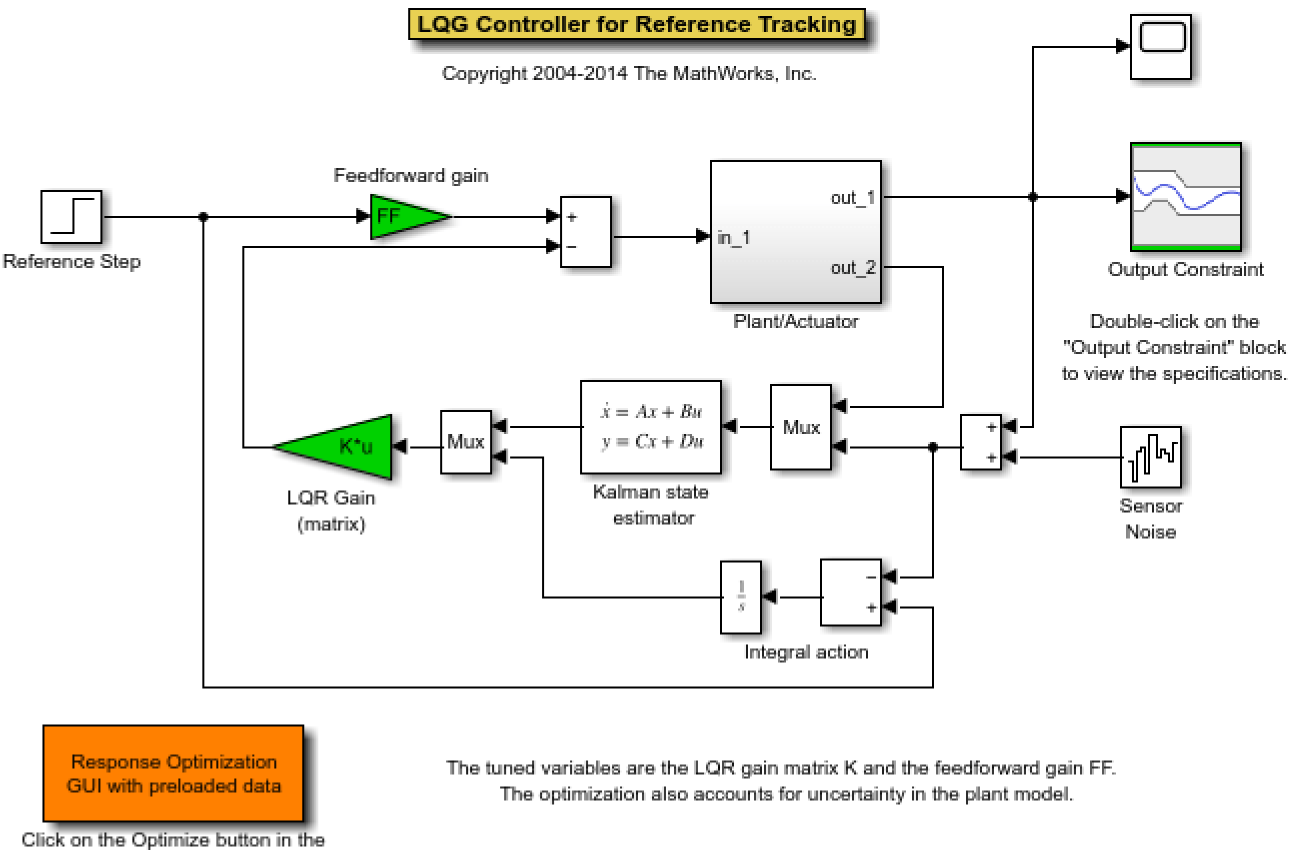
```
% Close the model.
bdclose('maglev_demo')
```

LQG Controller Tuning

This example shows how to use Simulink® Design Optimization™ to optimize the output response of a plant by tuning the LQR gain matrix and feed-forward gain. This model includes uncertainty in the plant model and accounts for this uncertainty in the optimization process.

Open the `lqg_demo` model using the command below and run the simulation. The simulation produces an unoptimized response of the plant and the initial data for optimization. Double-click the Scope block to view the unoptimized response of the plant.

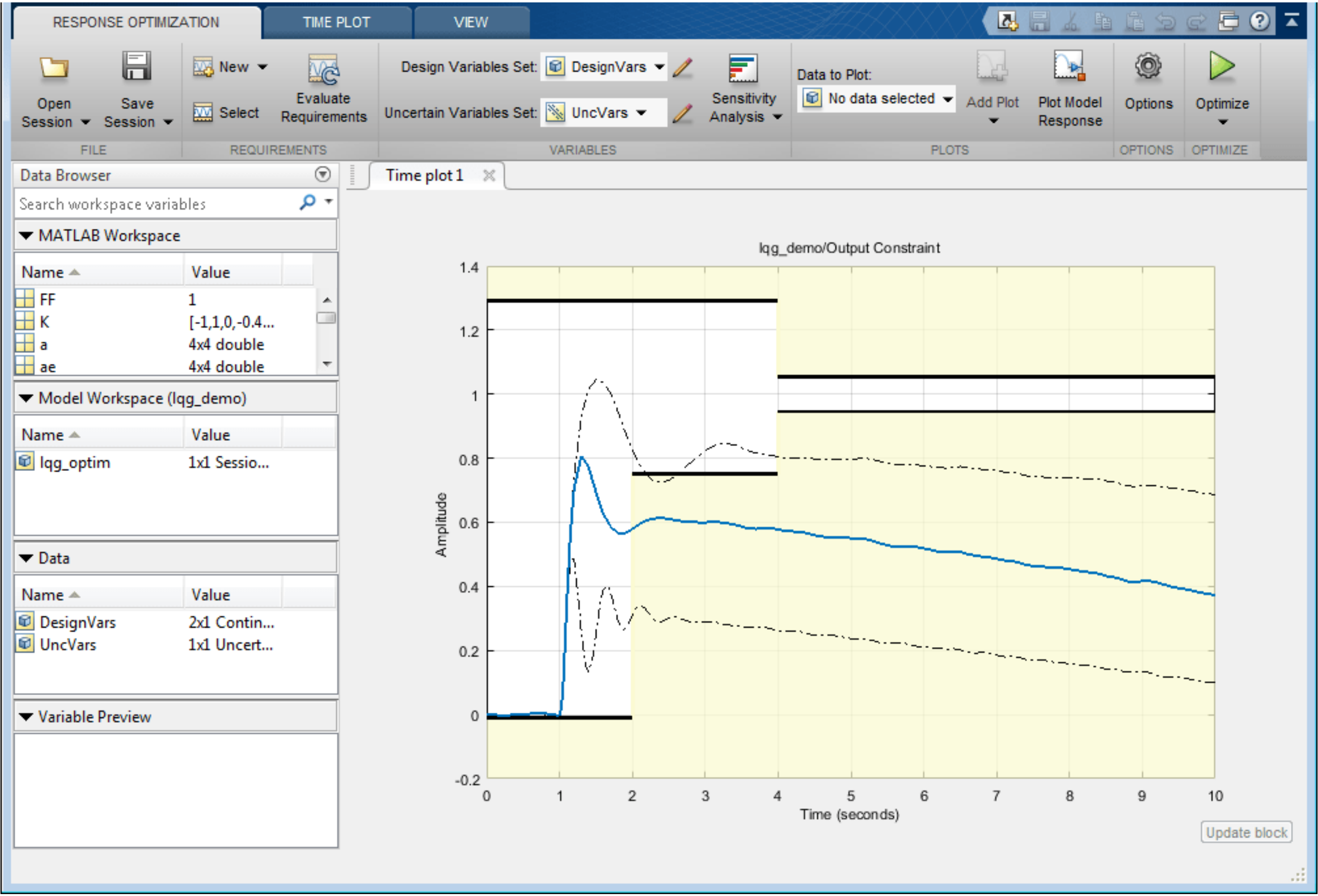
```
open_system('lqg_demo')
```



Double-click the `Plant/Actuator` block to view the details of the subsystem. Note that the plant is represented in State-Space form in this model and includes Rate Limiter and Saturation blocks.

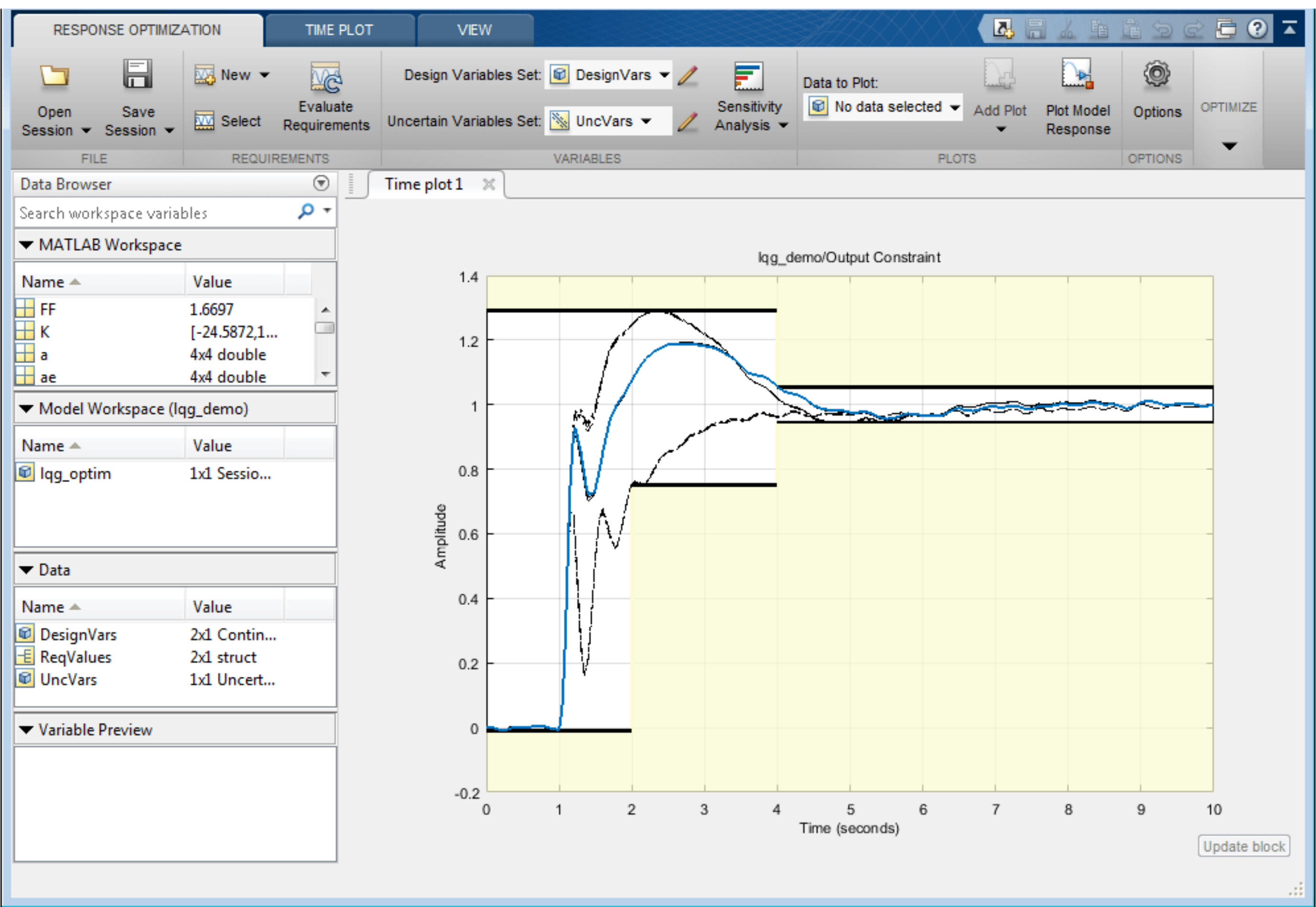
Double-click the `Output Constraint` block to view constraints on the step response of the plant.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



The solid line in the plot indicates the plant response without considering the uncertainties and the dashed lines indicate the uncertain responses.

We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
UncVars
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
FF
1.6697
K
[-24.5872,1...
a
4x4 double
ae
4x4 double
Model Workspace (lqg_demo)
lqg_optim
1x1 Sessio...
Data
DesignVars
2x1 Contin...
ReqValues
2x1 struct
UncVars
1x1 Uncert...
Variable Preview
Time plot 1
lqg_demo/Output Constraint
Amplitude
Time (seconds)
Update block

Iteration	F-count	Output Constraint (Upper) (<=0)	Output Constraint (Lower) (>=0)
0	13	-0.1922	-0.8926
1	27	-0.0592	-0.4918
2	42	0.1625	-0.3928
3	71	0.1519	-0.3909
4	85	0.0188	-0.2274
5	99	0.2201	-0.0731
6	113	0.1944	-0.0845
7	127	0.0301	-0.0323
8	141	0.0146	-0.0093
9	155	-0.0015	-3.6894e-04
10	169	-0.0015	-1.2161e-04

Optimization started 27-Mar-2013 07:47:22

Optimization converged, 27-Mar-2013 07:48:33

Optimized variable values written to 'DesignVars' in the Design Optimization workspace

Save Iteration... Display Options... Optimize

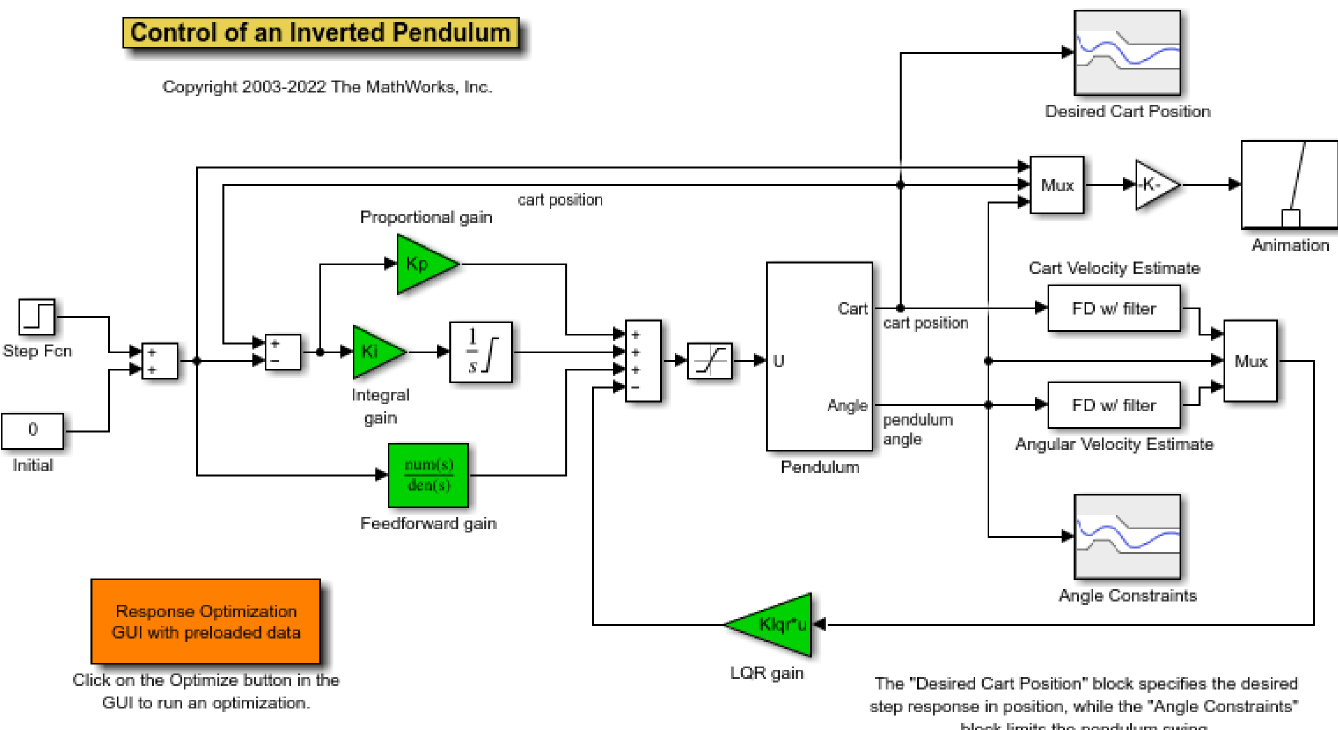
```
% Close the model.
bdclose('lqg_demo')
```

Inverted Pendulum Controller Tuning

This example shows how to use Simulink® Design Optimization™ to optimize the controller of an inverted pendulum. The inverted pendulum is on a cart and the motion of the cart is controlled. The controller's Proportional, Integral and Feed-forward gains are tuned to limit pendulum angle variations and respond to step changes in cart position optimally.

Open the `pendulum_demo` model using the command below and run the simulation. The simulation produces an unoptimized position and angle of the inverted pendulum and the initial data for optimization. An animation window shows the cart position and inverted pendulum angle.

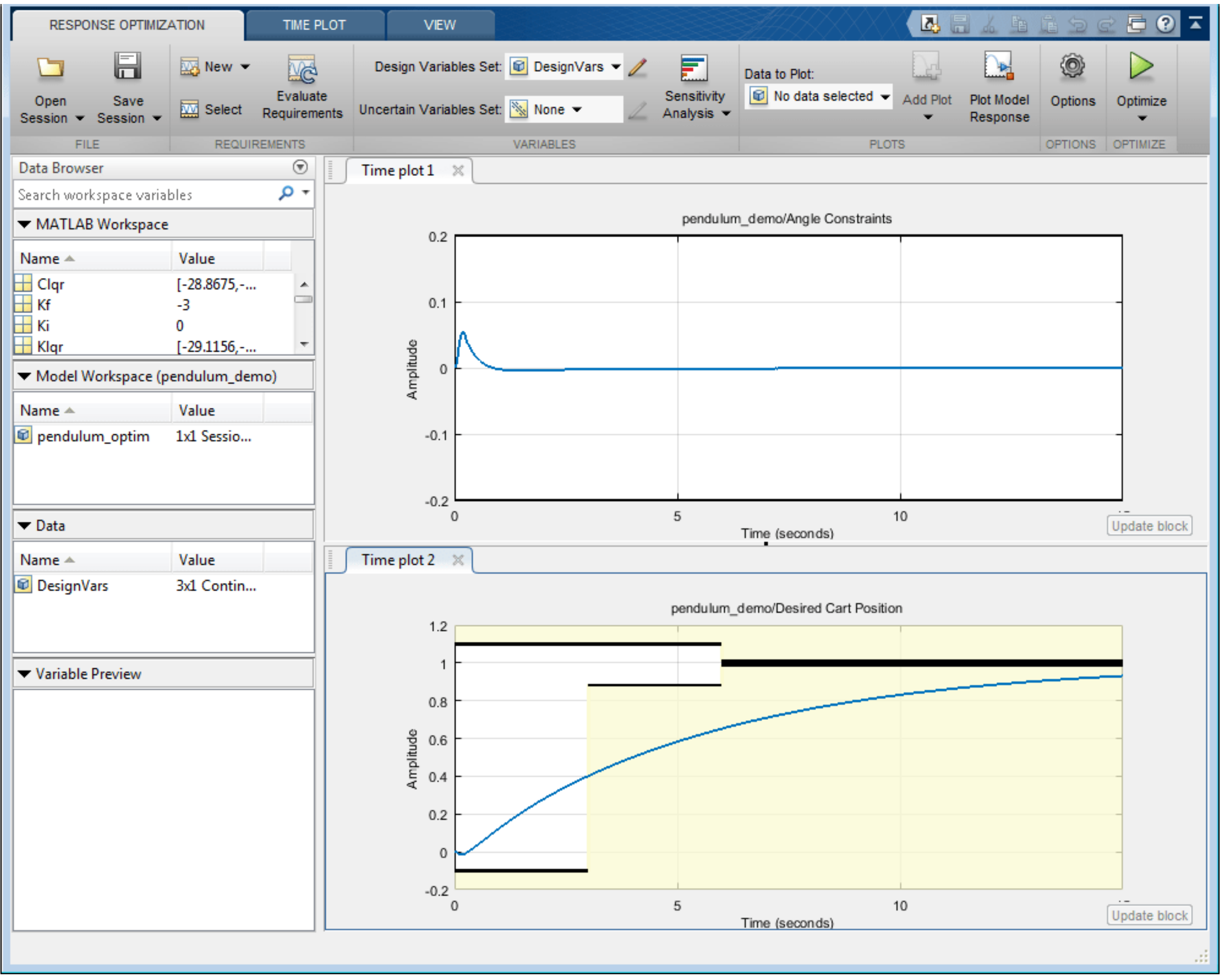
```
open_system('pendulum_demo')
```



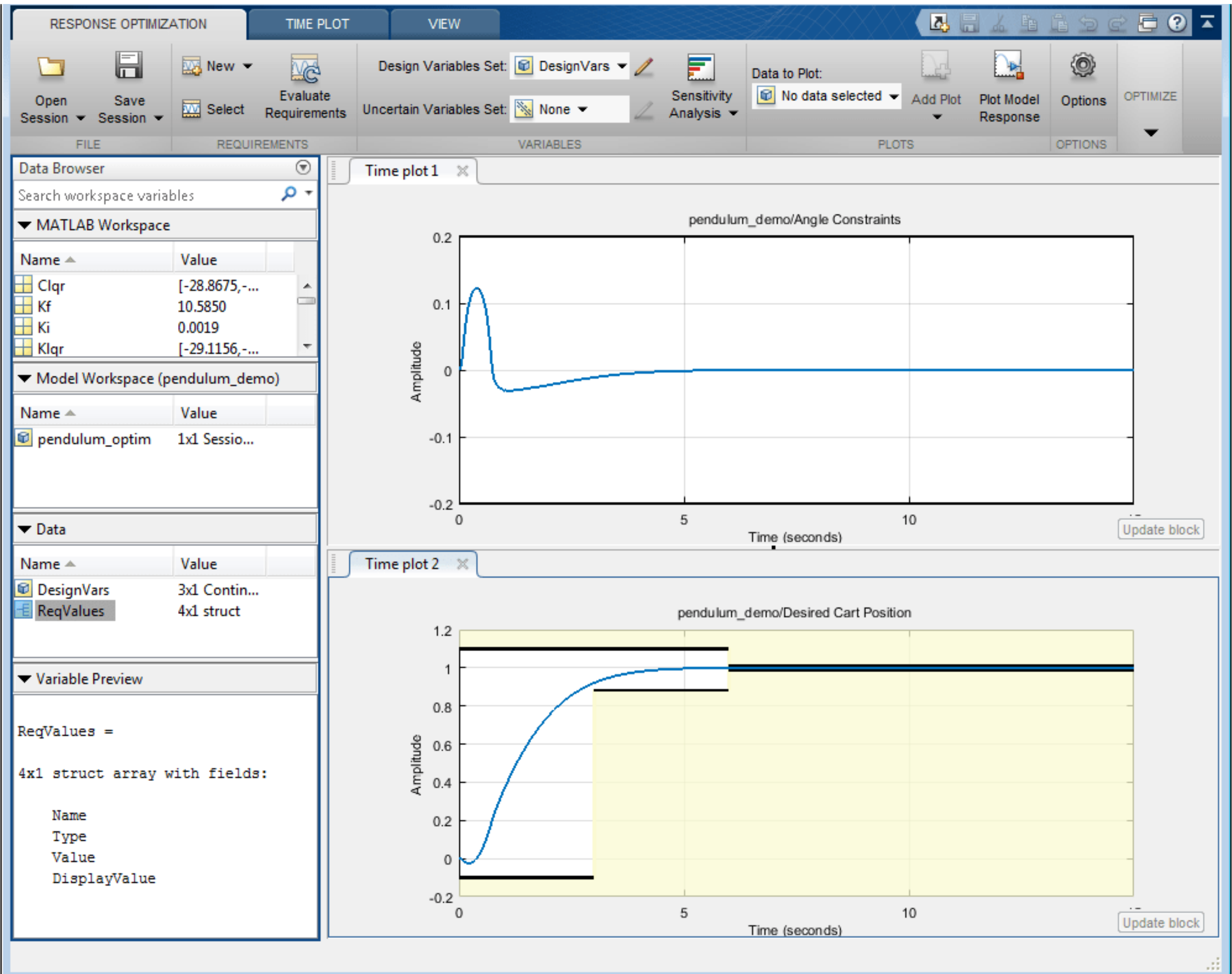
Double-click the `Desired Cart Position` block to view constraints on the cart position of the inverted pendulum.

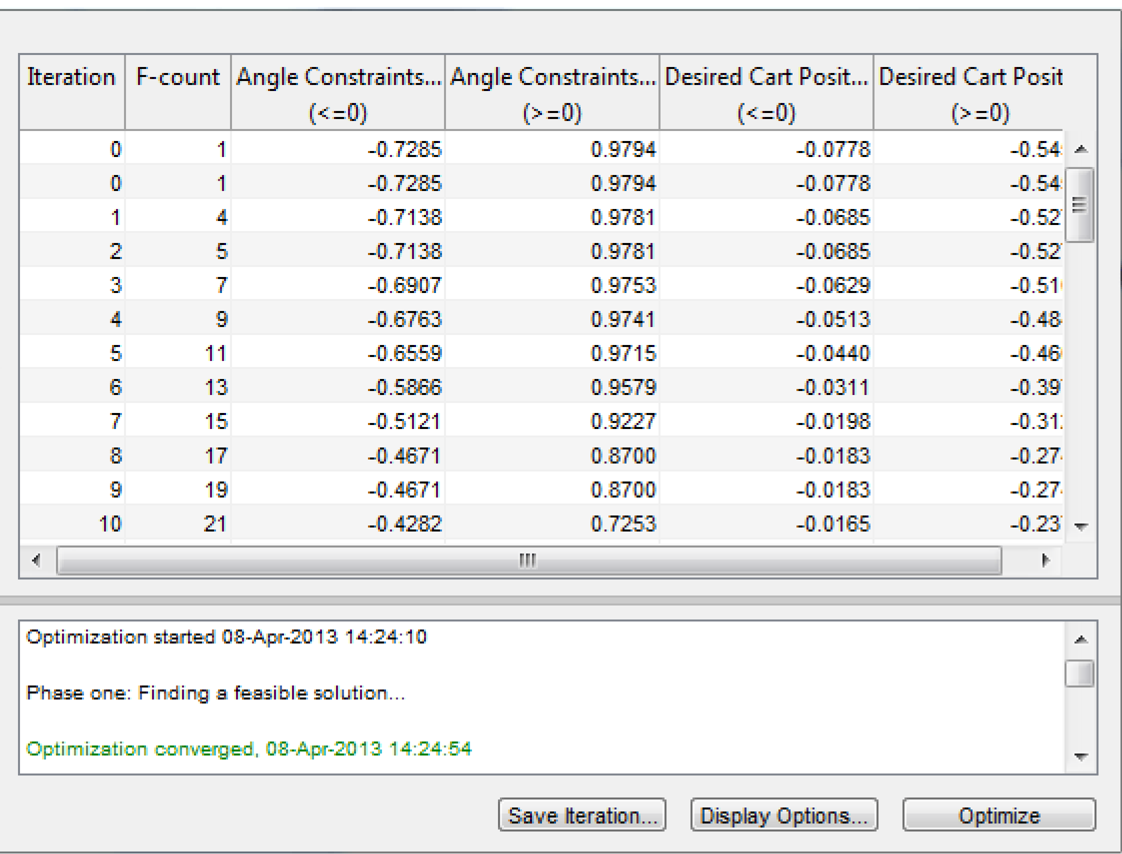
Double-click the `Angle Constraints` block to view constraints on the angle of the inverted pendulum.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
Clqr
[-28.8675,-...
Kf
10.5850
Ki
0.0019
Klqr
[-29.1156,-...
Model Workspace (pendulum_demo)
pendulum_optim
1x1 Sessio...
Data
DesignVars
3x1 Contin...
ReqValues
4x1 struct
Variable Preview
ReqValues =
4x1 struct array with fields:
Name
Type
Value
DisplayValue
Time plot 1
pendulum_demo/Angle Constraints
Amplitude
Time (seconds)
Update block
Time plot 2
pendulum_demo/Desired Cart Position
Amplitude
Time (seconds)
Update block



Iteration	F-count	Angle Constraints... (<=0)	Angle Constraints... (>=0)	Desired Cart Posit... (<=0)	Desired Cart Posit (>=0)
0	1	-0.7285	0.9794	-0.0778	-0.54
0	1	-0.7285	0.9794	-0.0778	-0.54
1	4	-0.7138	0.9781	-0.0685	-0.52
2	5	-0.7138	0.9781	-0.0685	-0.52
3	7	-0.6907	0.9753	-0.0629	-0.51
4	9	-0.6763	0.9741	-0.0513	-0.48
5	11	-0.6559	0.9715	-0.0440	-0.46
6	13	-0.5866	0.9579	-0.0311	-0.39
7	15	-0.5121	0.9227	-0.0198	-0.31
8	17	-0.4671	0.8700	-0.0183	-0.27
9	19	-0.4671	0.8700	-0.0183	-0.27
10	21	-0.4282	0.7253	-0.0165	-0.23

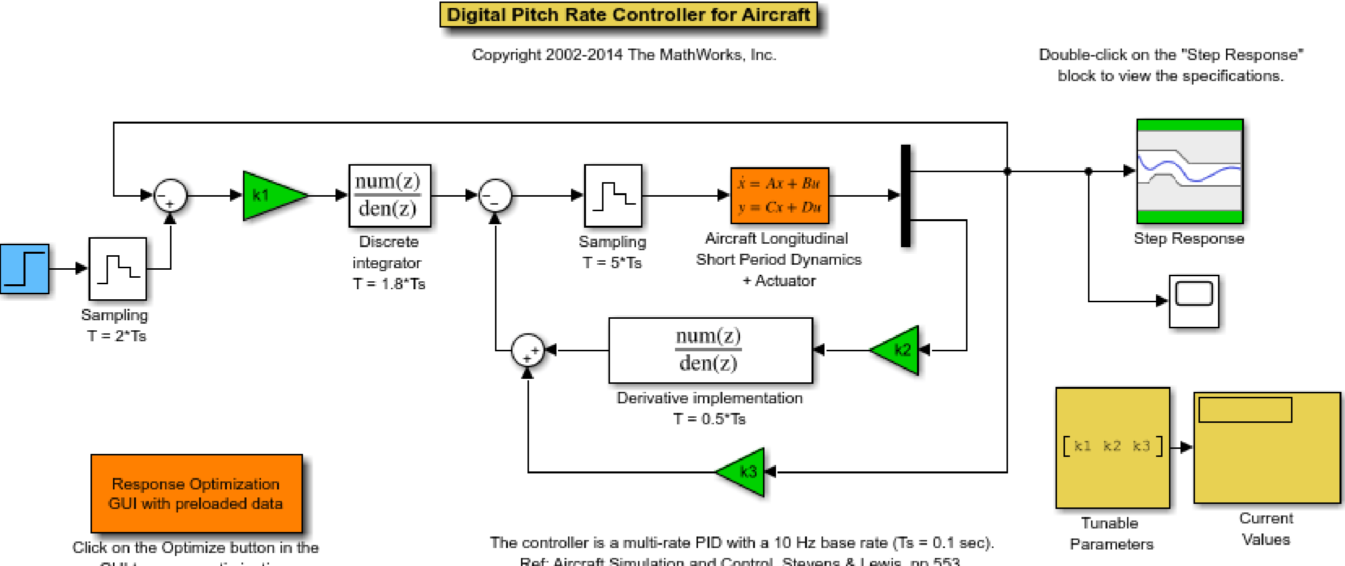

```
% Close the model.
bdclose('pendulum_demo')
```

Pitch Rate Controller Tuning

This example shows how to use Simulink® Design Optimization™ to tune the gains of a Digital Pitch Rate Controller and optimize the response of an Aircraft to a step altitude change. The controller includes state derivative and integral feedback. The controller is tuned to satisfy a 10 percent overshoot and 0.9 second rise time step response characteristic.

Open the `pitchrate_demo` model using the command below and run the simulation. The simulation produces an unoptimized response of the aircraft and the initial data for optimization.

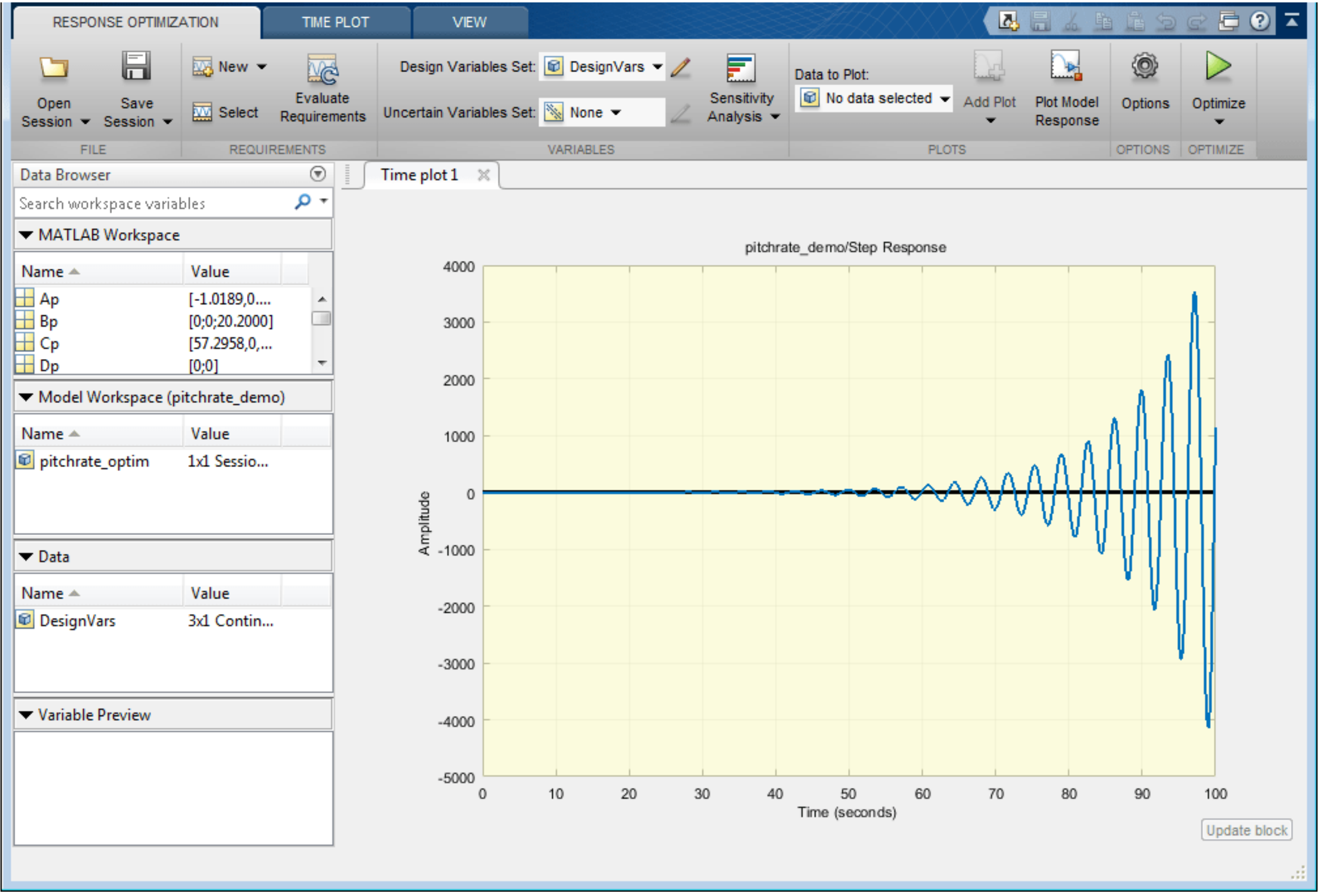
```
open_system('pitchrate_demo')
```



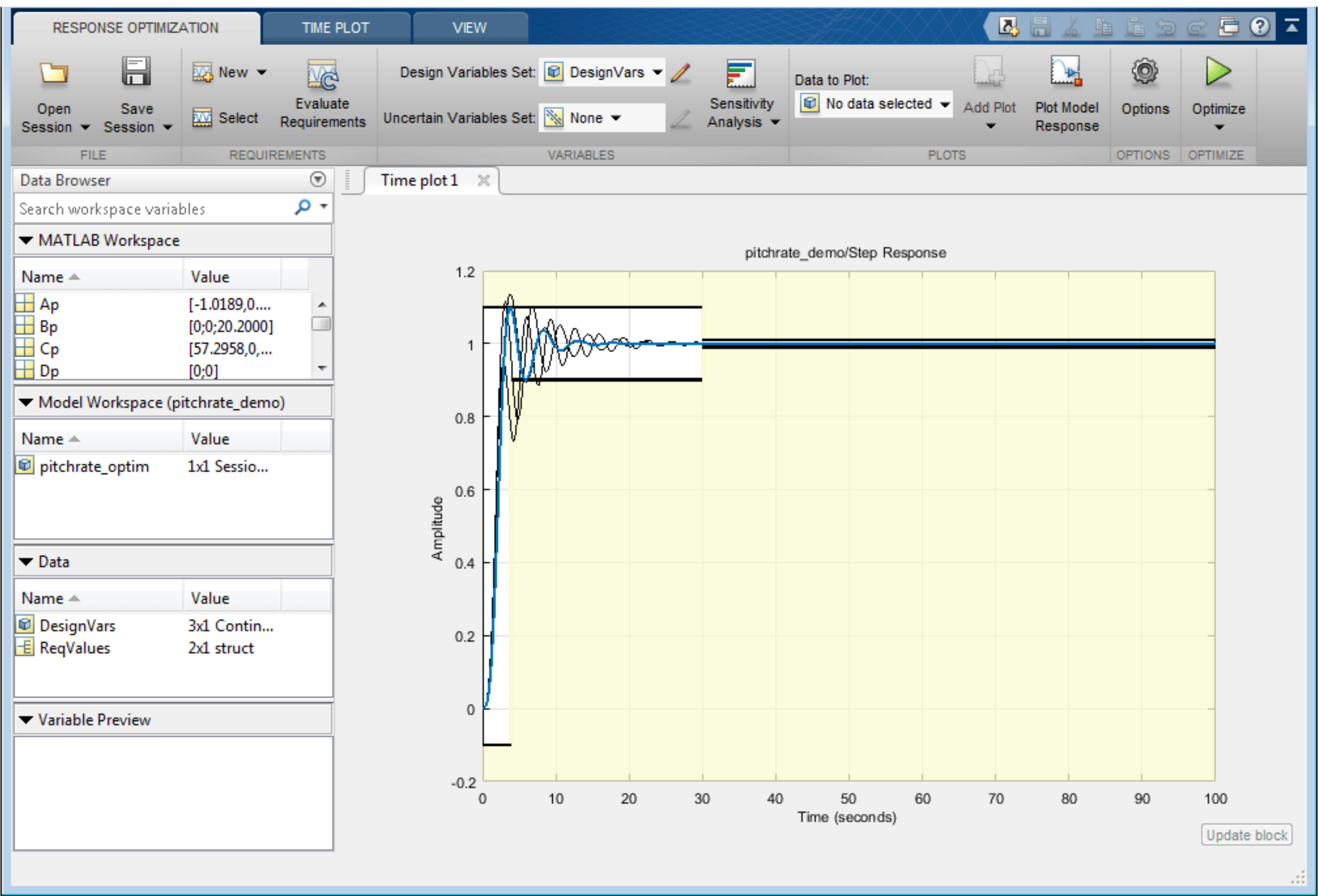
Double-click the Scope block to view the unoptimized response of the aircraft.

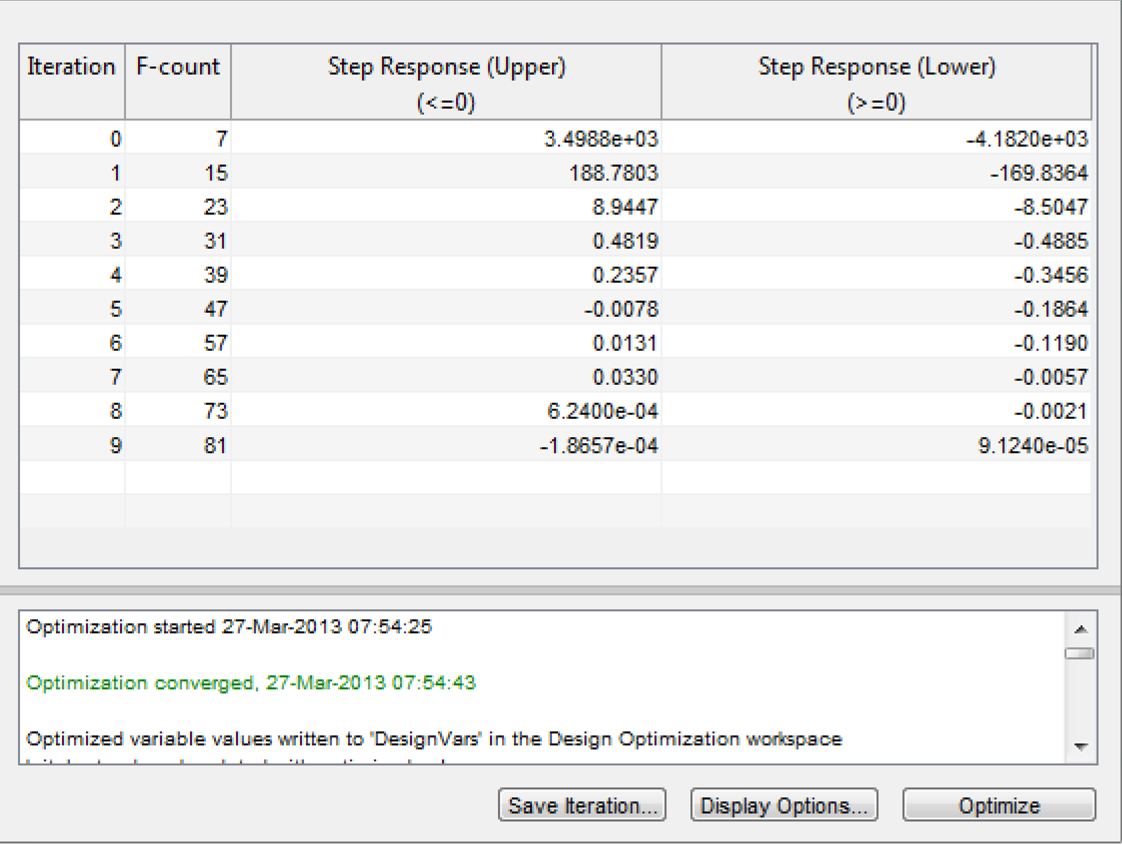
Double-click the `Step Response` block to view constraints on the step response of the aircraft.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
Ap
[-1.0189,0....
Bp
[0;0;20.2000]
Cp
[57.2958,0,...
Dp
[0;0]
Model Workspace (pitchrate_demo)
pitchrate_optim
1x1 Sessio...
Data
DesignVars
3x1 Contin...
ReqValues
2x1 struct
Variable Preview
Time plot 1
pitchrate_demo/Step Response
Amplitude
Time (seconds)
Update block



Iteration	F-count	Step Response (Upper) (<=0)	Step Response (Lower) (>=0)
0	7	3.4988e+03	-4.1820e+03
1	15	188.7803	-169.8364
2	23	8.9447	-8.5047
3	31	0.4819	-0.4885
4	39	0.2357	-0.3456
5	47	-0.0078	-0.1864
6	57	0.0131	-0.1190
7	65	0.0330	-0.0057
8	73	6.2400e-04	-0.0021
9	81	-1.8657e-04	9.1240e-05


```
bdclose('pitchrate_demo')
```

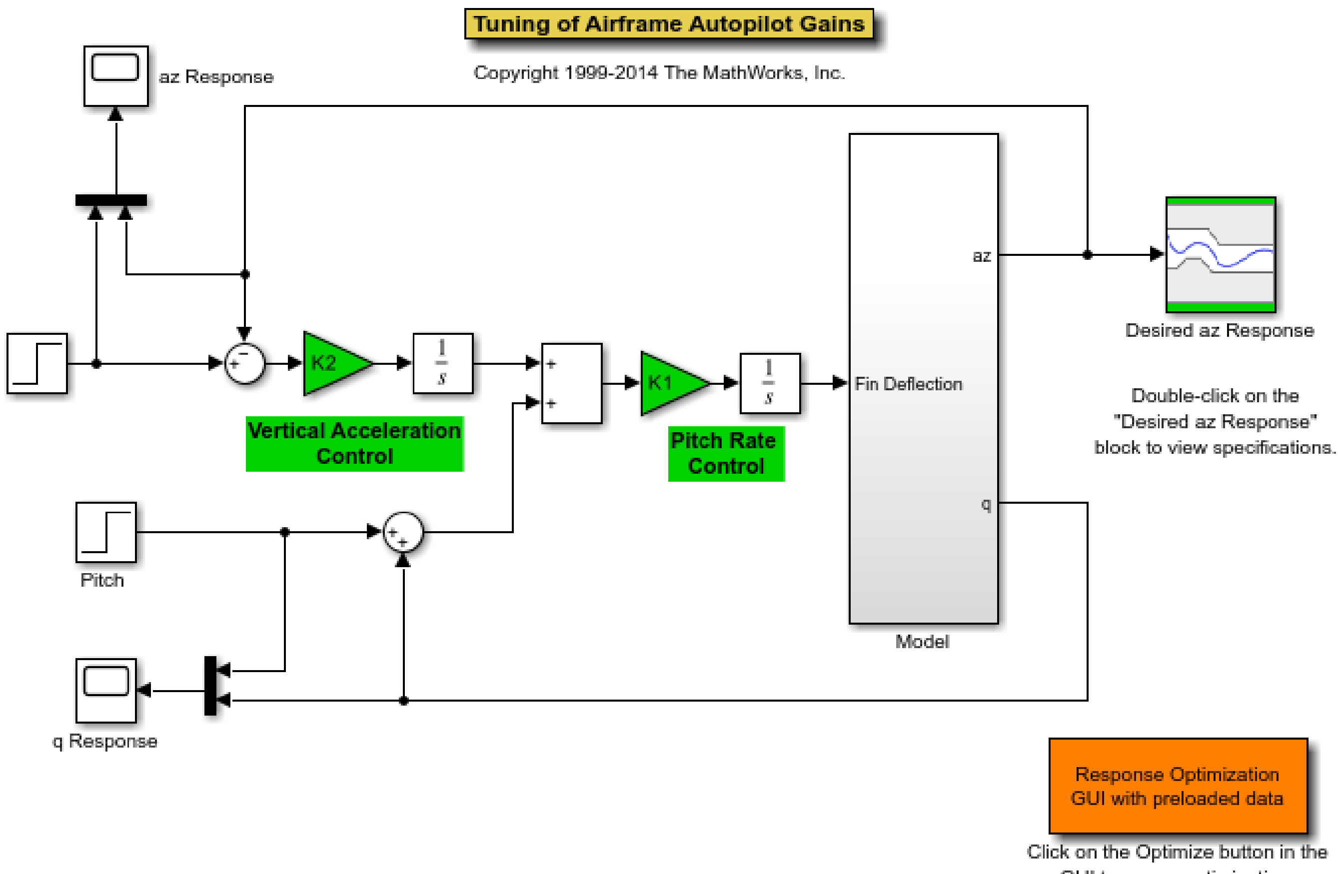
Tuning of Airframe Autopilot Gains

This example shows how to apply Simulink® Design Optimization™ to optimize the autopilot gains of an airframe to control its fin deflection. The model uses blocks from Aerospace Blockset™.

The autopilot controller consists of an inner pitch loop and outer vertical acceleration loop. Both controllers are integral only controllers. The gains of both the controllers are tuned to satisfy a 2 second rise-time step response characteristic.

Open the `nlairframe_demo` model using the command below and run the simulation. The simulation produces an unoptimized vertical acceleration of the airframe and the initial data for optimization.

```
open_system('nlairframe_demo')
```



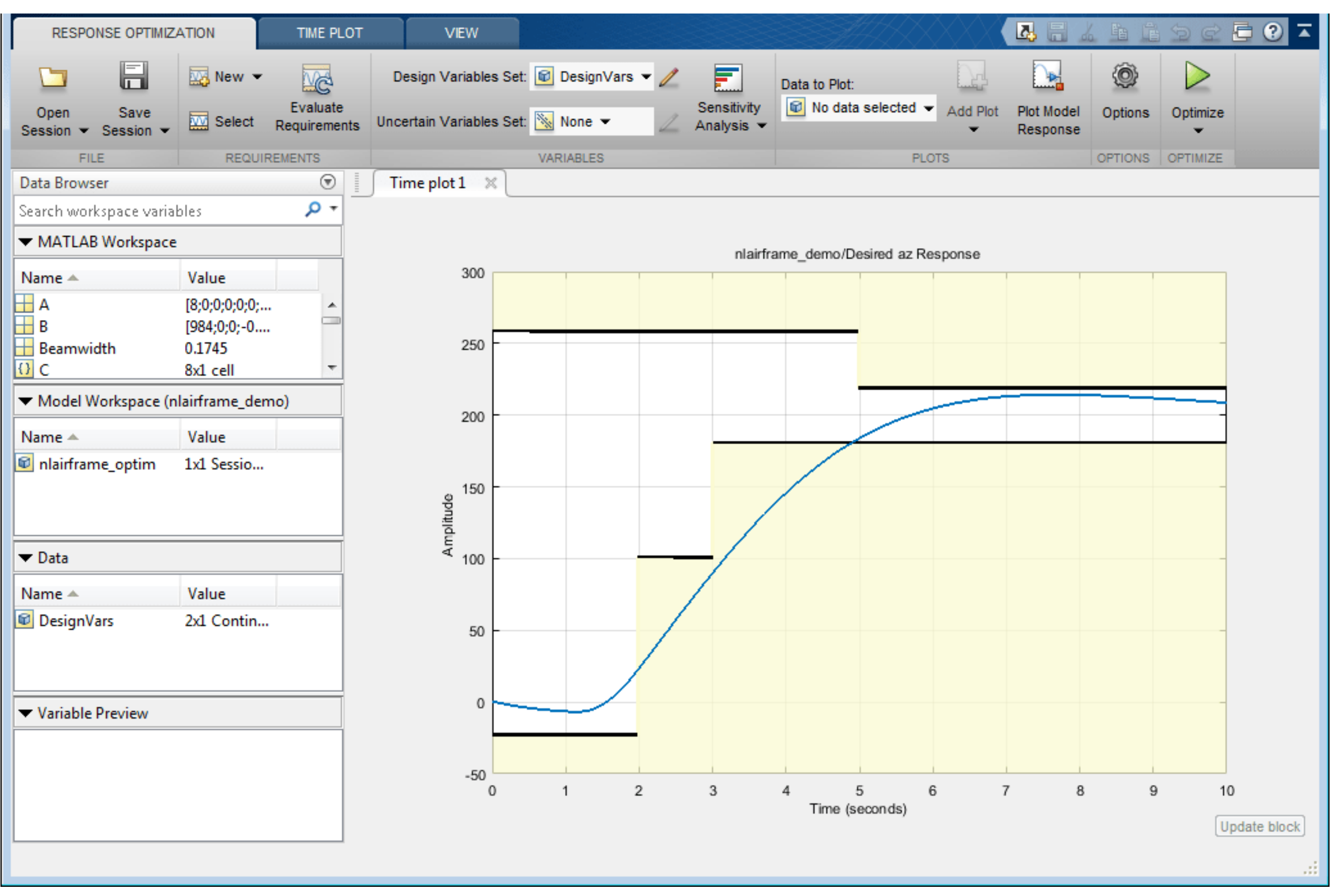
Double-click the `az Response` Scope block to view the unoptimized vertical acceleration az of the airframe.

Double-click the `q Response` Scope block to view the unoptimized rotation rate q of the airframe.

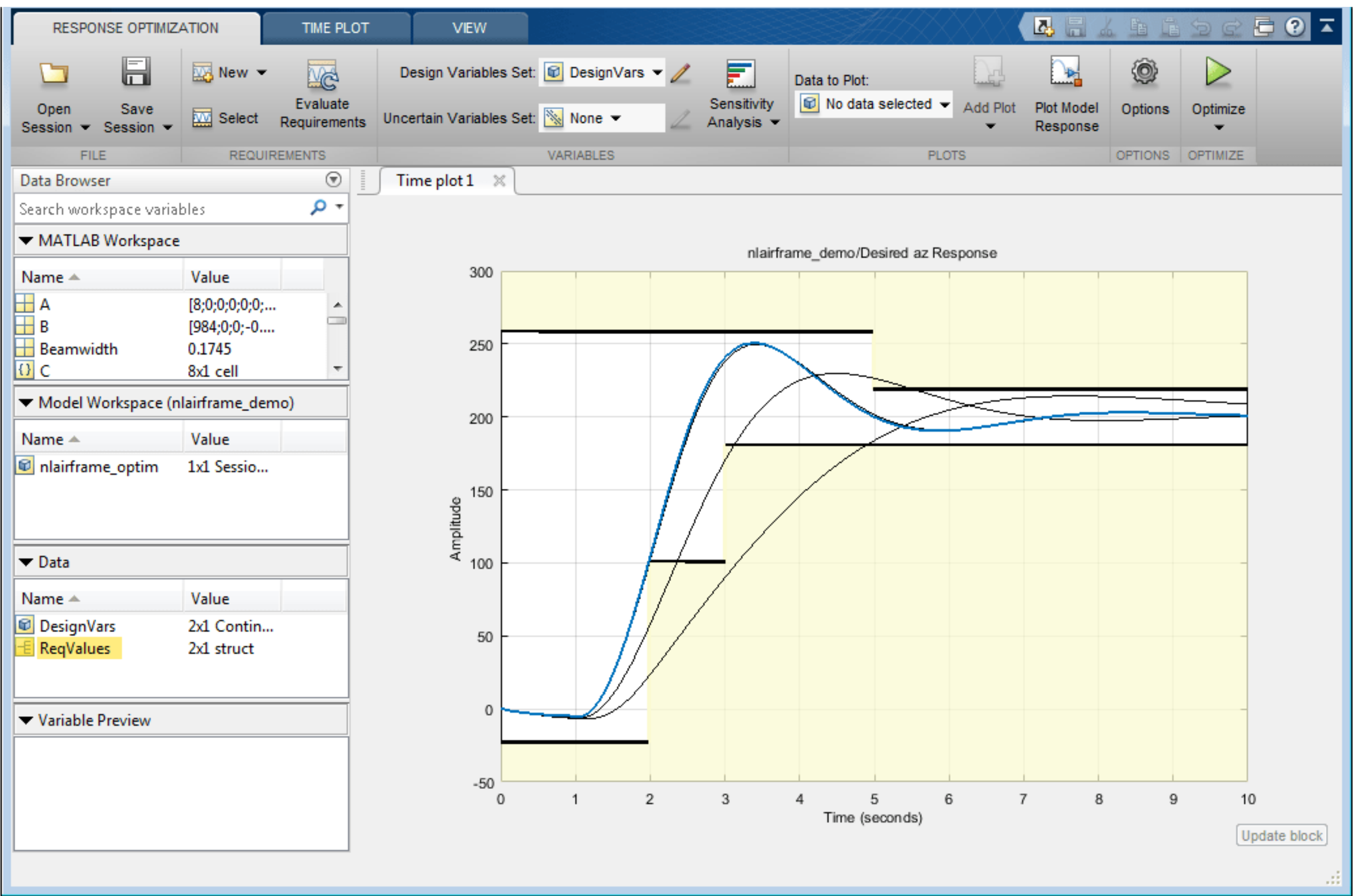
Double-click the `Model` block to view the details of the subsystem. It includes an Atmosphere model and Aerodynamics and Equations of Motion model.

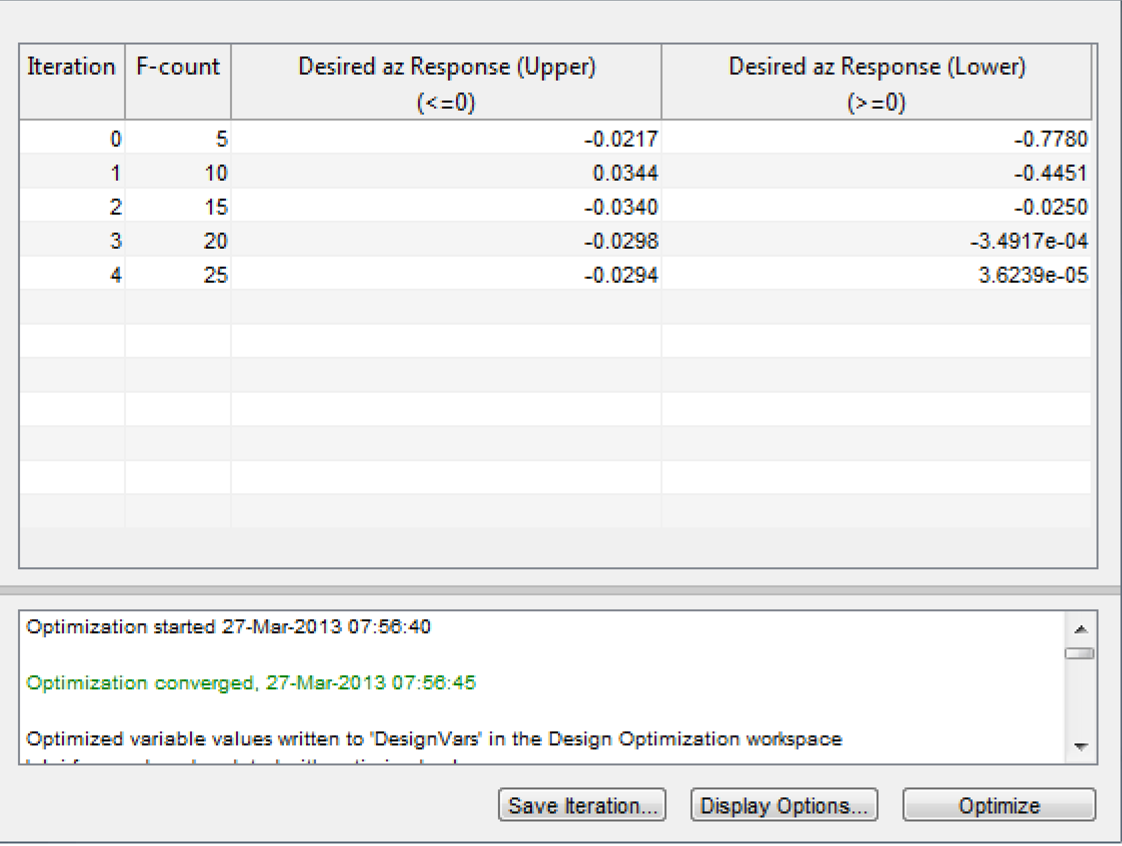
Double-click the `Desired az Response` block to view constraints on the vertical acceleration of the airframe. These constraints are used to simultaneously tune the gains of the two integral controllers. The first segment of the upper bound constraint represents an overshoot. Note that this is a soft constraint and can be violated.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
New
Select
Evaluate Requirements
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
Options
Optimize
FILE
REQUIREMENTS
VARIABLES
PLOTS
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
A
[8;0;0;0;0;0;...
B
[984;0;0;-0....
Beamwidth
0.1745
C
8x1 cell
Model Workspace (nlairframe_demo)
nlairframe_optim
1x1 Sessio...
Data
DesignVars
2x1 Contin...
ReqValues
2x1 struct
Variable Preview
Time plot 1
nlairframe_demo/Desired az Response
Amplitude
Time (seconds)
Update block



Iteration	F-count	Desired az Response (Upper) (<=0)	Desired az Response (Lower) (>=0)
0	5	-0.0217	-0.7780
1	10	0.0344	-0.4451
2	15	-0.0340	-0.0250
3	20	-0.0298	-3.4917e-04
4	25	-0.0294	3.6239e-05

The darker curve shows the final optimized response of the airframe.

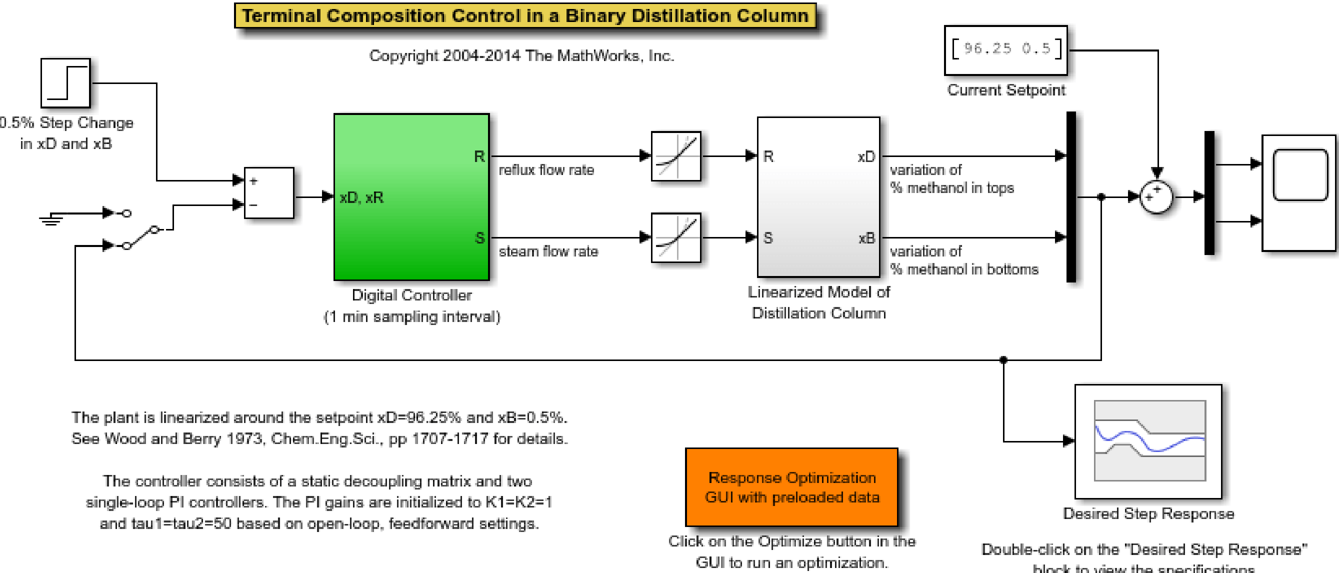
```
% Close the model.
bdclose('nlairframe_demo')
```

Distillation Controller Tuning

This example shows how to use Simulink® Design Optimization™ to optimize the multi-loop controller parameters of a distillation column. The Distillation column produces methanol and is represented as a linear model with delays. The digital multi-loop controller consists of a decoupling matrix and two single-loop PI controllers. The parameters of both the single-loop controllers are tuned simultaneously to satisfy a 14 percent overshoot and 13 minute rise-time step response characteristics.

Open the `distillation_demo` model using the command below and run the simulation. The simulation produces the unoptimized composition of methanol in the column and the initial data for optimization.

```
open_system('distillation_demo')
```

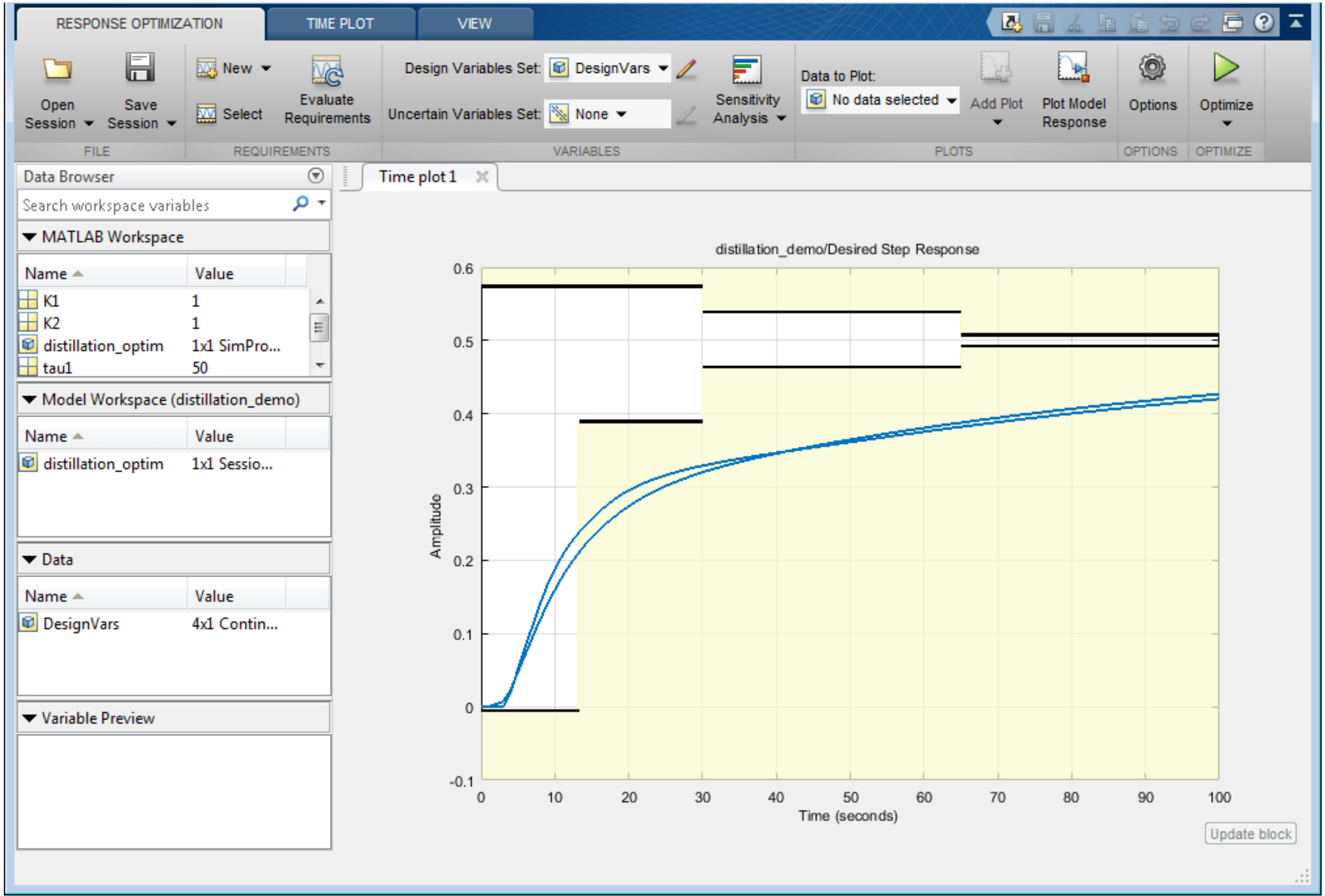


Double-click the Scope block to view the unoptimized methanol composition in the top and bottom of the column.

Double-click the `Linearized Model of Distillation Column` block. Note that this is a subsystem and shows the model for variation of methanol in the top and bottom of the distillation column.

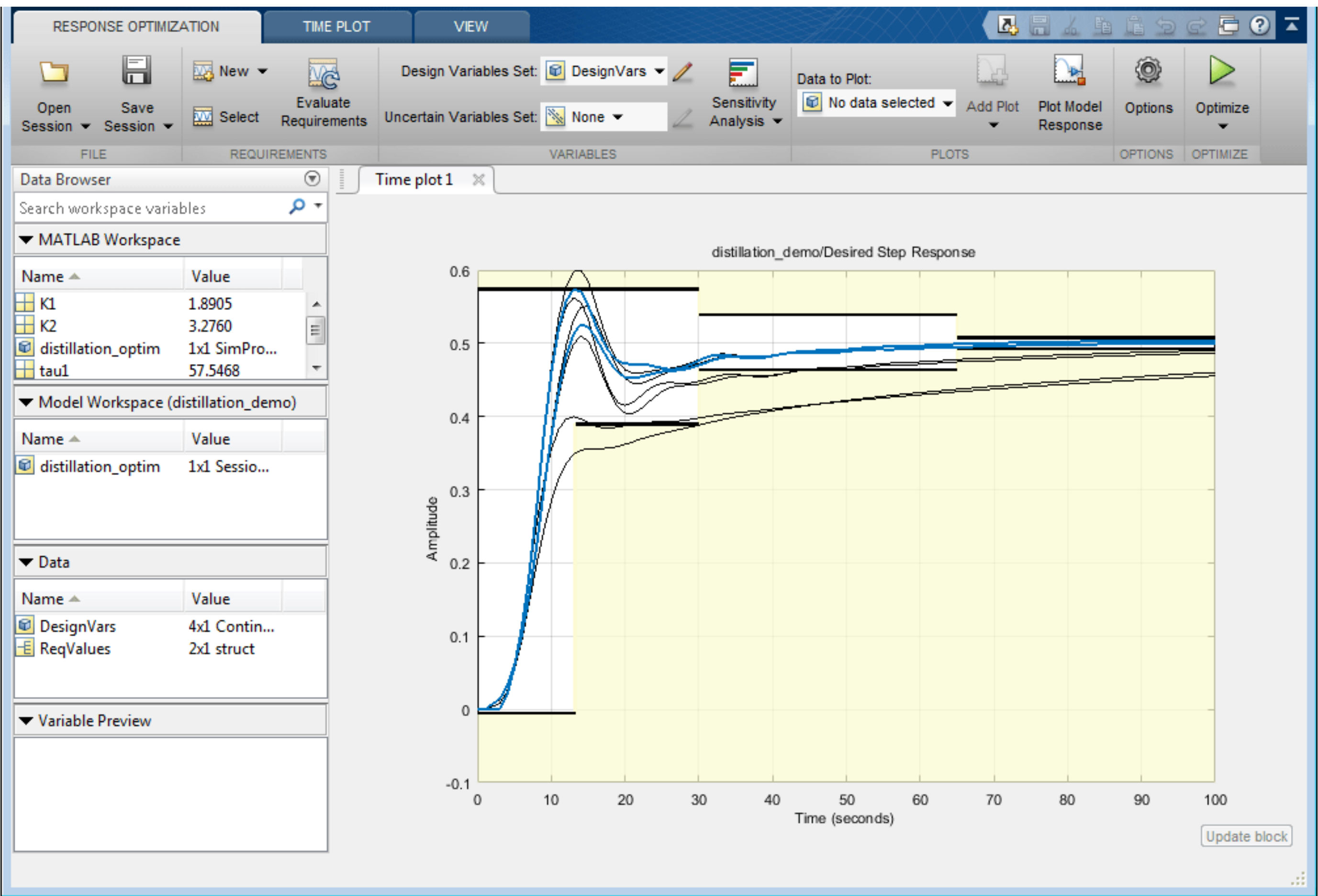
Double-click the `Desired Step Response` block to view constraints on the step response of the distillation column. These constraints are used to simultaneously tune both of the single-loop controller parameters.

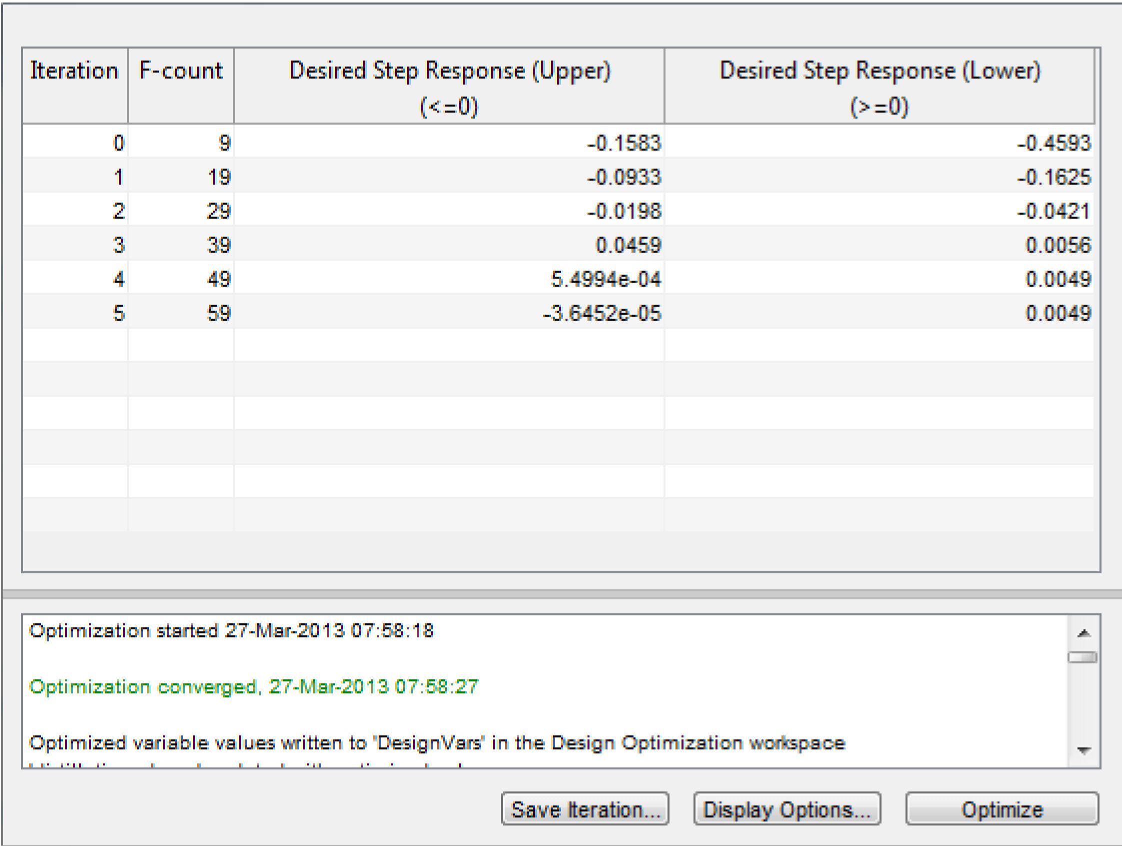
You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



There are two curves in the plot representing the methanol composition in the top and bottom of the column.

We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
K1
1.8905
K2
3.2760
distillation_optim
1x1 SimPro...
tau1
57.5468
Model Workspace (distillation_demo)
distillation_optim
1x1 Sessio...
Data
DesignVars
4x1 Contin...
ReqValues
2x1 struct
Variable Preview
Time plot 1
distillation_demo/Desired Step Response
Amplitude
Time (seconds)
Update block



Iteration	F-count	Desired Step Response (Upper) (<=0)	Desired Step Response (Lower) (>=0)
0	9	-0.1583	-0.4593
1	19	-0.0933	-0.1625
2	29	-0.0198	-0.0421
3	39	0.0459	0.0056
4	49	5.4994e-04	0.0049
5	59	-3.6452e-05	0.0049

The two solid curves show the final optimized methanol composition in the top and bottom of the distillation column.

```
% Close the model
bdclose('distillation_demo')
```

Heat Exchanger Controller Tuning

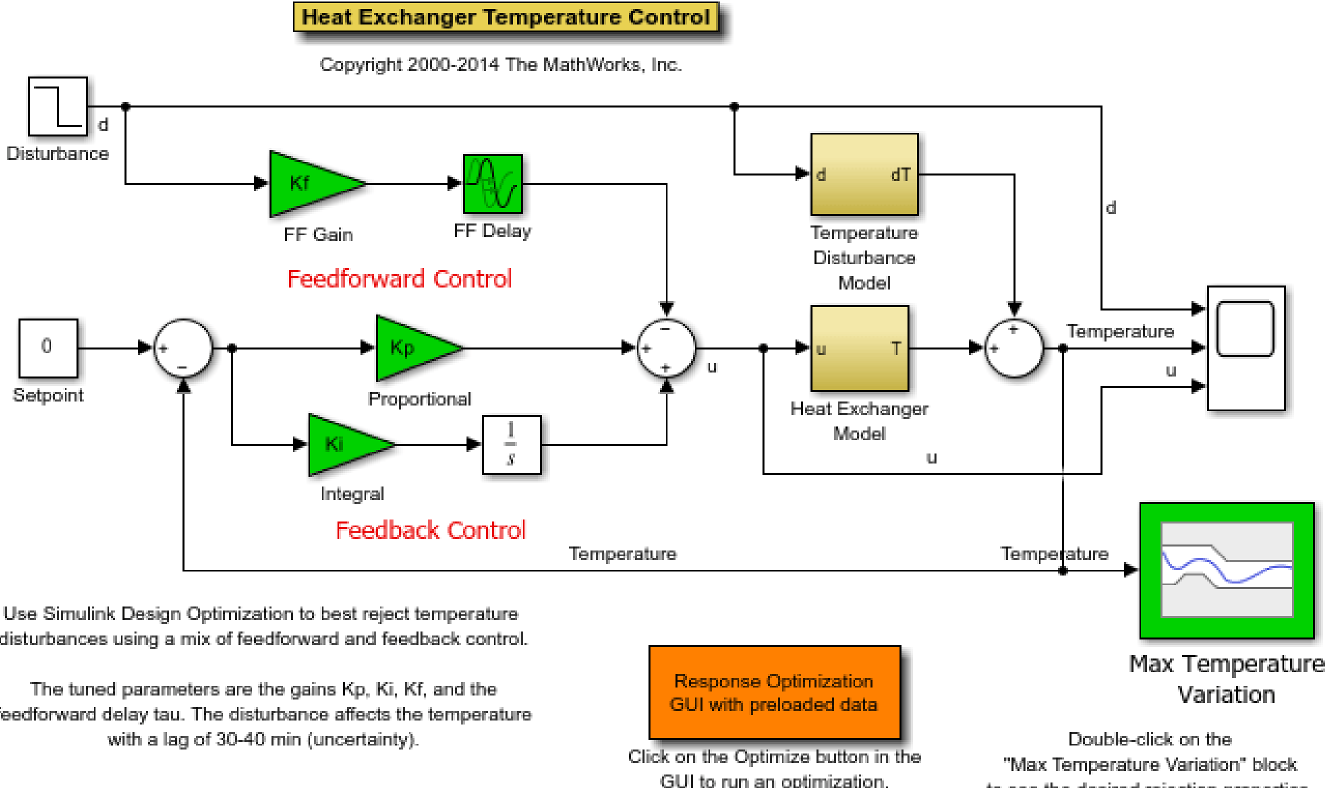
This example shows how to use Simulink® Design Optimization™ to optimize the temperature control of a heat exchanger around a temperature set-point.

The controller regulates the temperature around a setpoint in response to external temperature disturbances. The effect of this disturbance is modeled with an uncertain delay introduced in the `Temperature Disturbance Model` block.

The temperature controller includes a PI controller along with a feed-forward external temperature measurement. The controller gains are tuned to reduce the effect of external temperature variations by a factor of 50.

Open the `heatex_demo` model using the command below and run the simulation. The simulation produces an unoptimized temperature variation of the heat exchanger and the initial data for optimization.

```
open_system('heatex_demo')
```

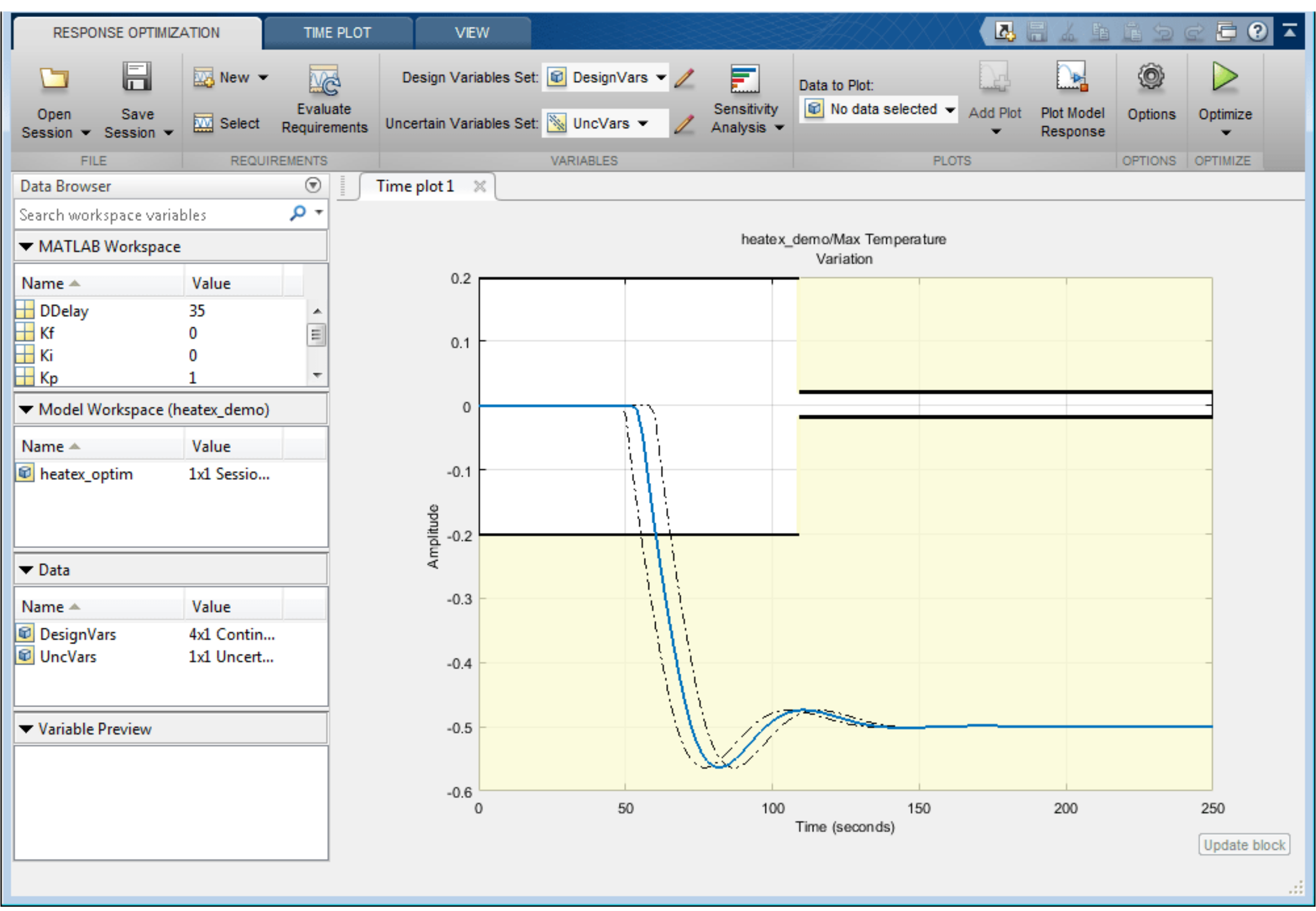


Double-click the Scope block to view the unoptimized temperature response, the disturbance signal and the control signal.

Double-click the `Heat Exchanger Model` block to view the model details. The exchanger is modeled as a first-order system with delay.

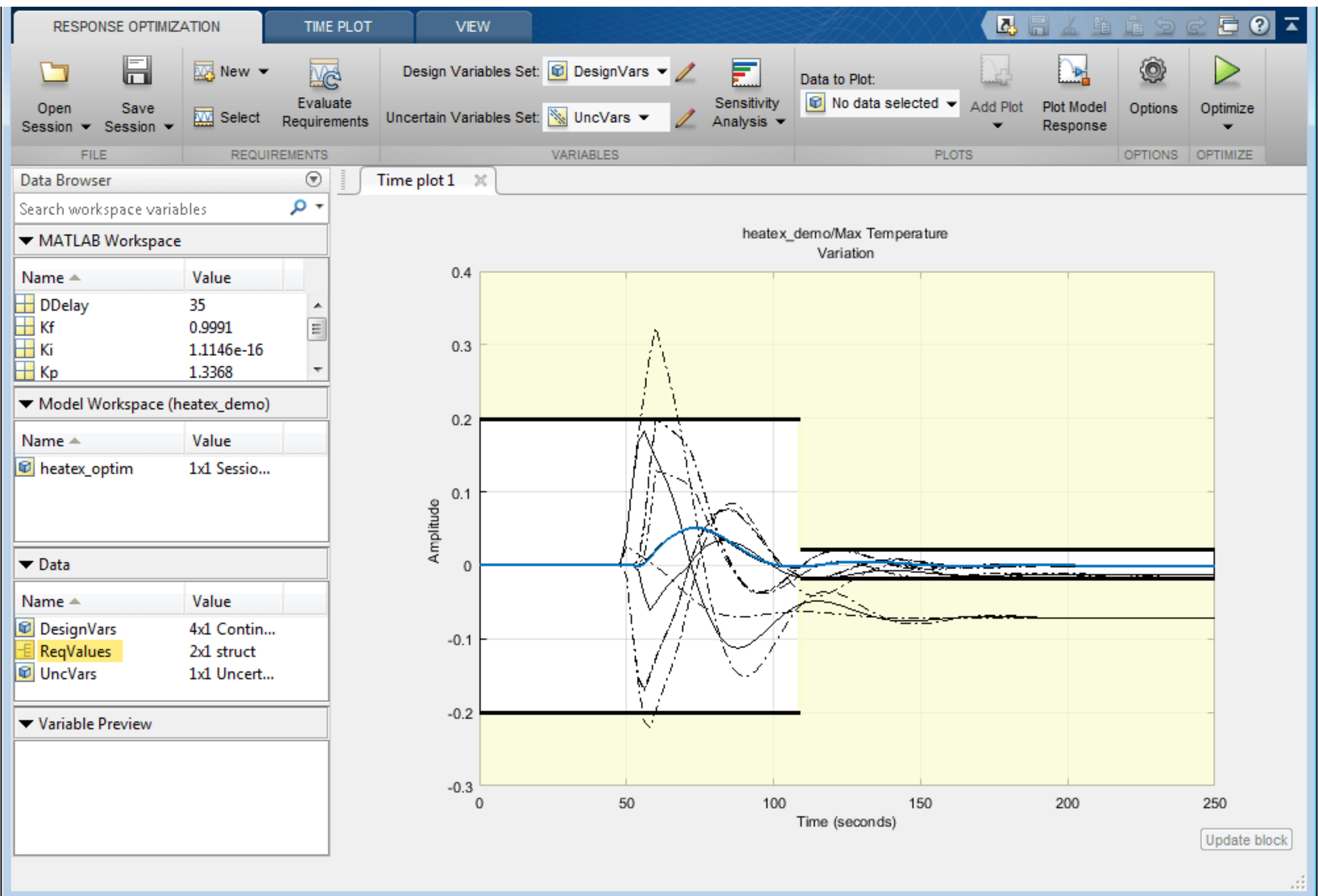
Double-click the `Max Temperature Variation` block to view constraints on the temperature variation of the heat exchanger. This constraint is used to tune the controller parameters.

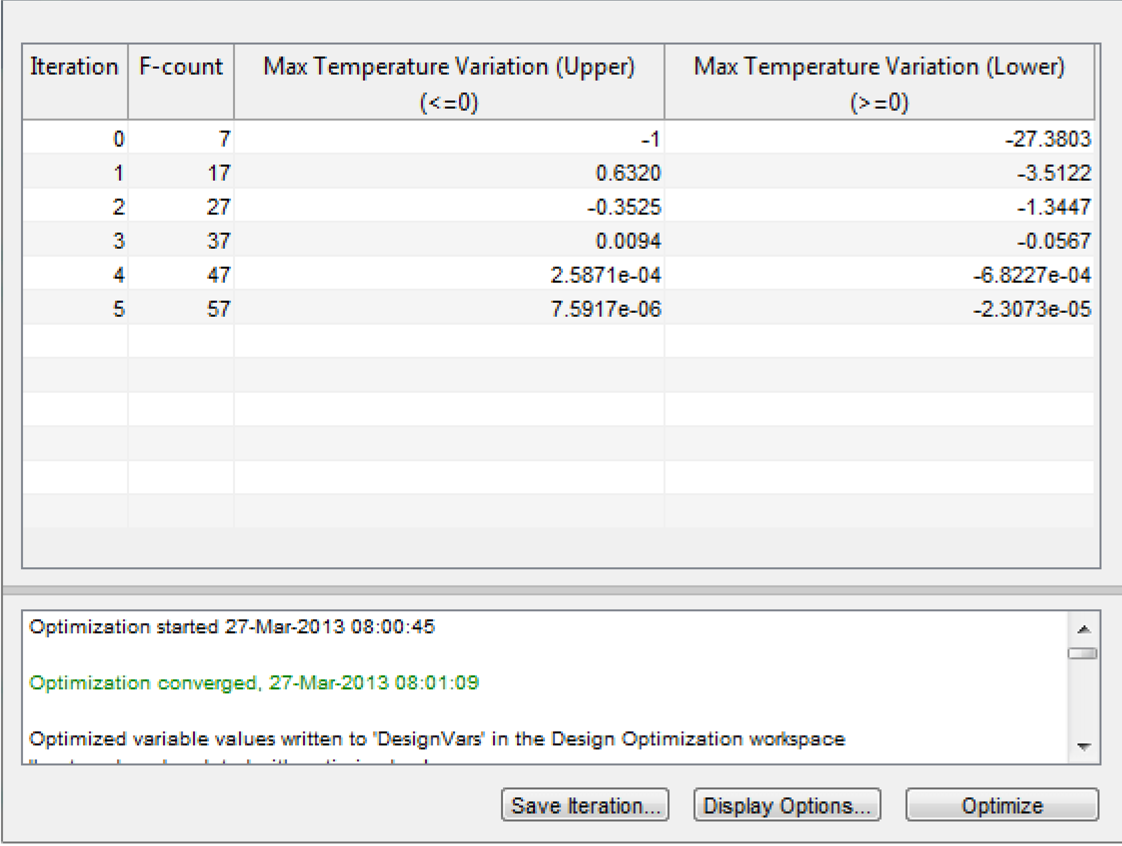
You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



The solid line represents the current response with the mean `Disturbance Delay` as specified in the constraint block. The dashed lines represent the response with the maximum and minimum `Disturbance Delay`.

We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
UncVars
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
DDelay
35
Kf
0.9991
Ki
1.1146e-16
Kp
1.3368
Model Workspace (heatex_demo)
heatex_optim
1x1 Sessio...
Data
DesignVars
4x1 Contin...
ReqValues
2x1 struct
UncVars
1x1 Uncert...
Variable Preview
Time plot 1
heatex_demo/Max Temperature
Variation
Amplitude
Time (seconds)
Update block



Iteration	F-count	Max Temperature Variation (Upper) (<=0)	Max Temperature Variation (Lower) (>=0)
0	7	-1	-27.3803
1	17	0.6320	-3.5122
2	27	-0.3525	-1.3447
3	37	0.0094	-0.0567
4	47	2.5871e-04	-6.8227e-04
5	57	7.5917e-06	-2.3073e-05

The solid curve shows the final optimized temperature variation of the heat exchanger.

```
% Close the model
bdclose('heatex_demo')
```

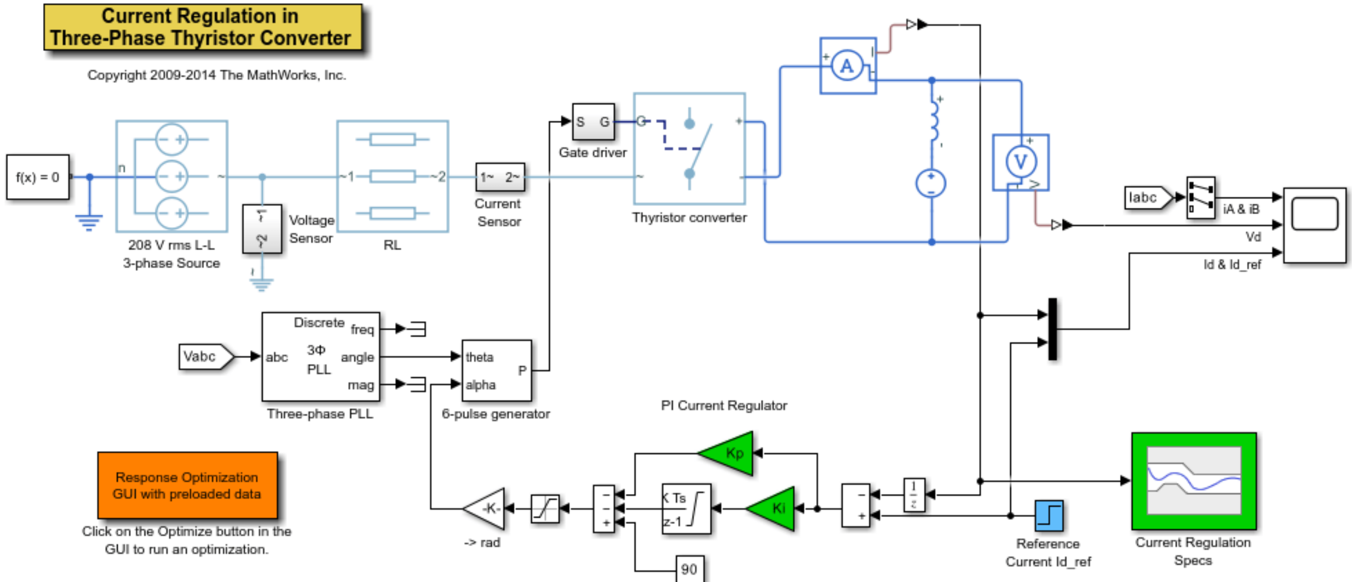
Power Converter Tuning

This example shows how to use Simulink® Design Optimization™ to optimize the current controller parameters of a 3-phase thyristor converter. The model uses blocks from Simscape™ and Simscape™ Electrical™.

The 3-phase thyristor is controlled by a pulse-width modulator with variable phase angle computed by a PI controller. The PI Current Regulator gains are tuned to track the reference DC current and limit oscillations.

Open the `power_demo` model using the command below and run the simulation. The simulation produces an unoptimized current variation of the DC motor and the initial data for optimization.

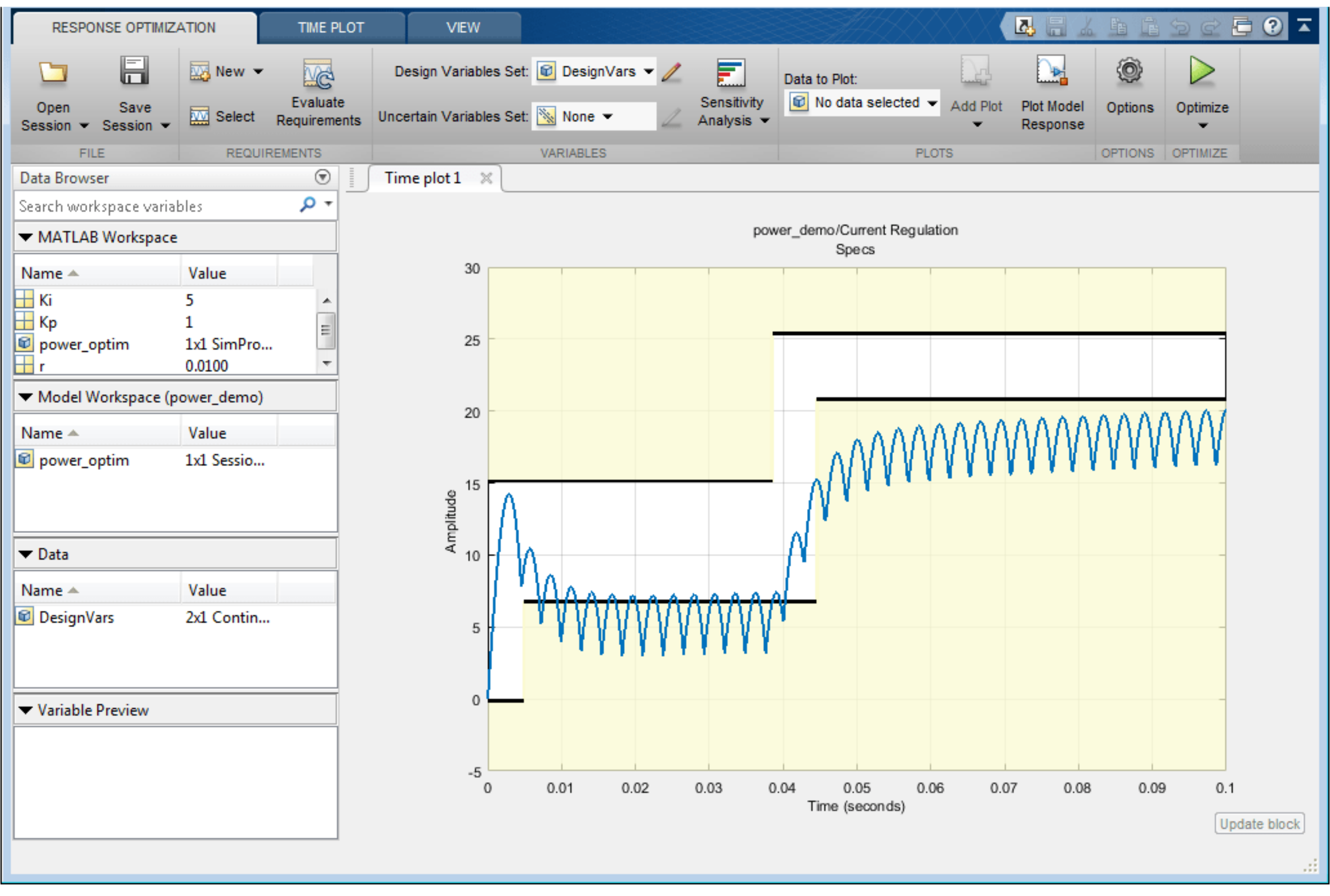
```
open_system('power_demo')
```



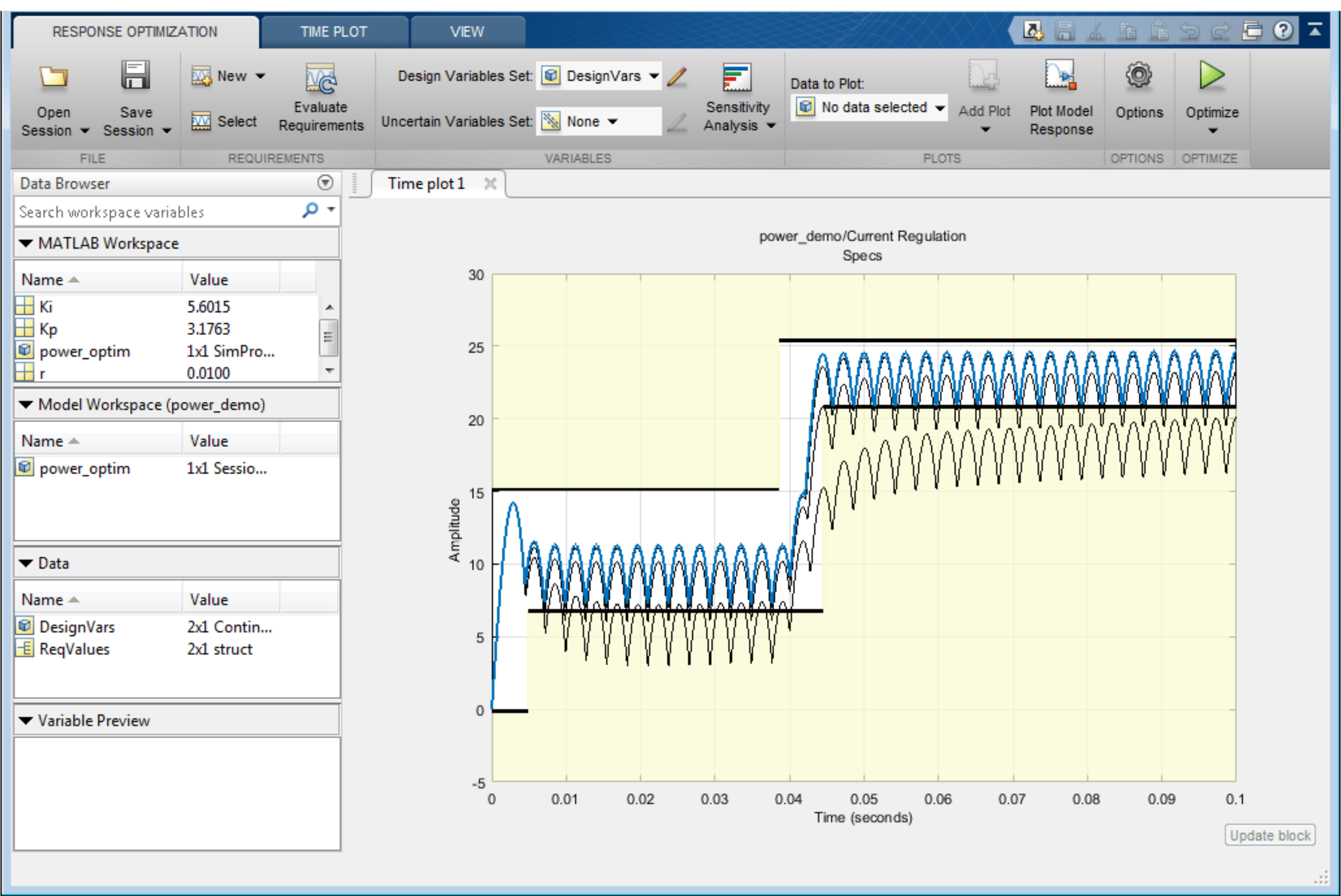
Double-click the Scope block to view the unoptimized current response. Note that two phases of the 3-phase source current and the output voltage of the DC motor are also displayed in this block.

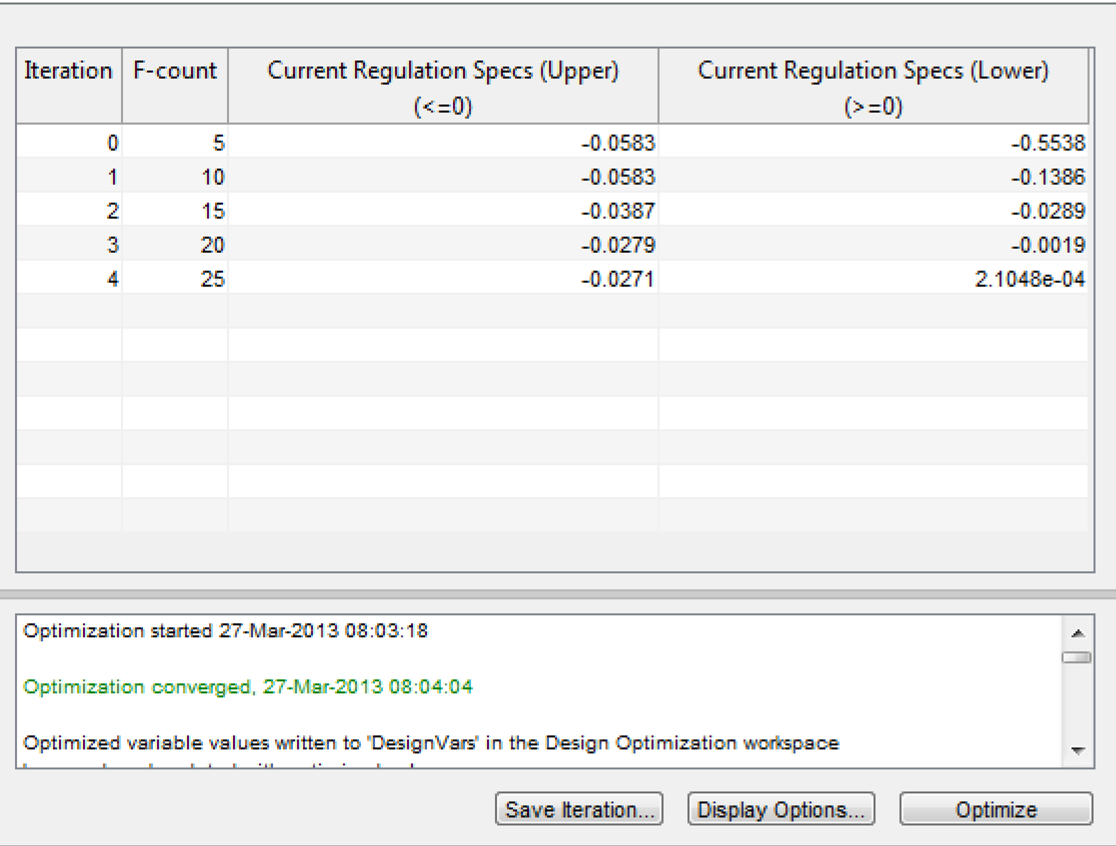
Double-click the `Current Regulation Specs` block to view constraints on the output current of the DC motor.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plot is updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
Ki
5.6015
Kp
3.1763
power_optim
1x1 SimPro...
r
0.0100
Model Workspace (power_demo)
power_optim
1x1 Sessio...
Data
DesignVars
2x1 Contin...
ReqValues
2x1 struct
Variable Preview
Time plot 1
power_demo/Current Regulation
Specs
Amplitude
Time (seconds)
Update block


Iteration	F-count	Current Regulation Specs (Upper) (<=0)	Current Regulation Specs (Lower) (>=0)
0	5	-0.0583	-0.5538
1	10	-0.0583	-0.1386
2	15	-0.0387	-0.0289
3	20	-0.0279	-0.0019
4	25	-0.0271	2.1048e-04

The plot now shows the final optimized current response.

```
% Close the model.
bdclose('power_demo')
```

Servomechanism Tuning

This example shows how to use Simulink® Design Optimization™ to optimize the position controller parameters for a servomotor piston. This model uses blocks from Stateflow®.

The controller sets the duty cycle of a pulse-width modulation circuit for the servomotor. The anti-windup controller Proportional and Integral gains are tuned to optimize the step response characteristics of the servomotor.

Open the `servo_demo` model using the command below and run the simulation. The simulation produces an unoptimized position of the piston and the initial data for optimization.

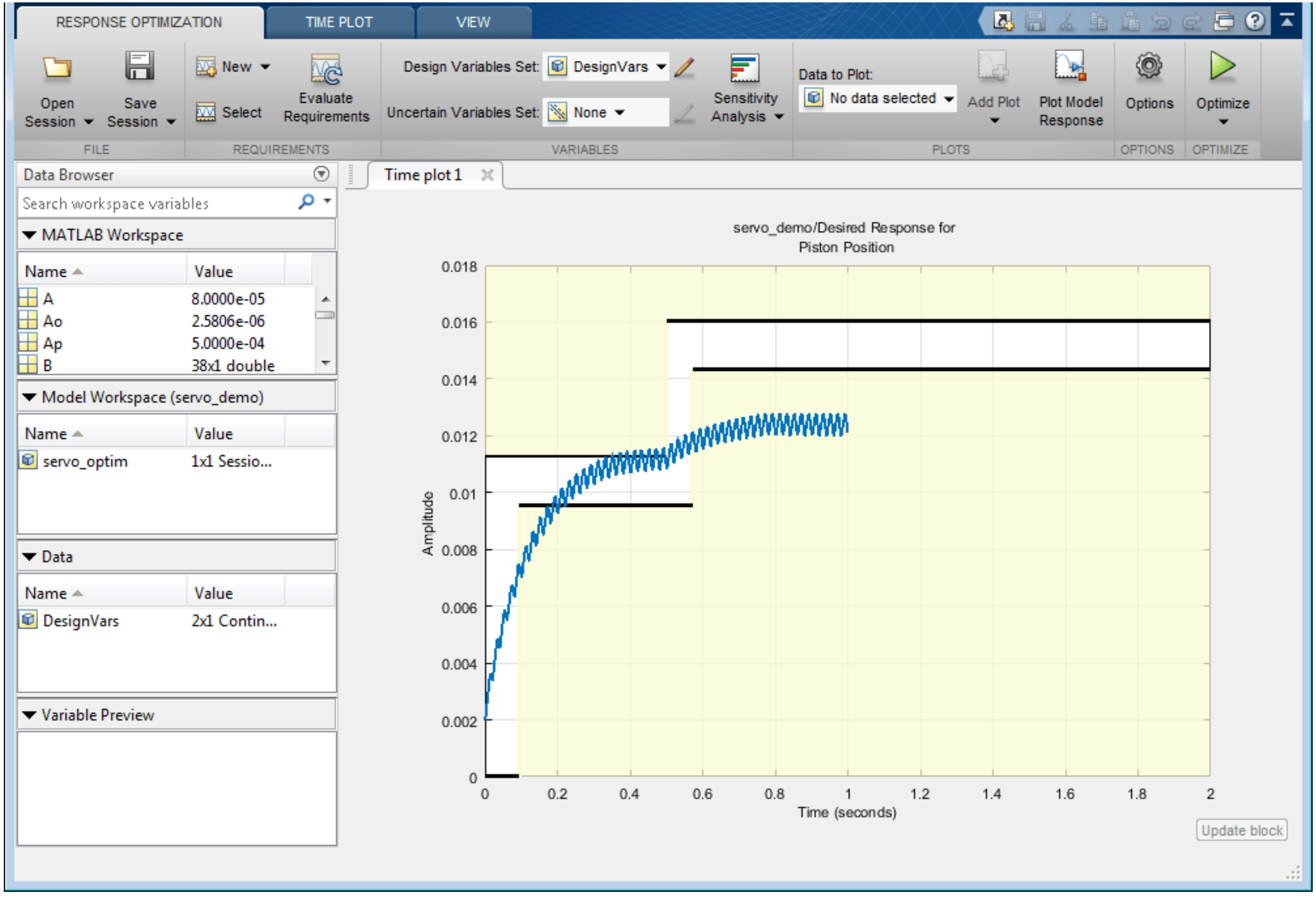
```
open_system('servo_demo')
```

There are two Scope blocks in the model. Double-click the `set point(yellow) and piston position` Scope block to view the set-point and the unoptimized position of the piston.

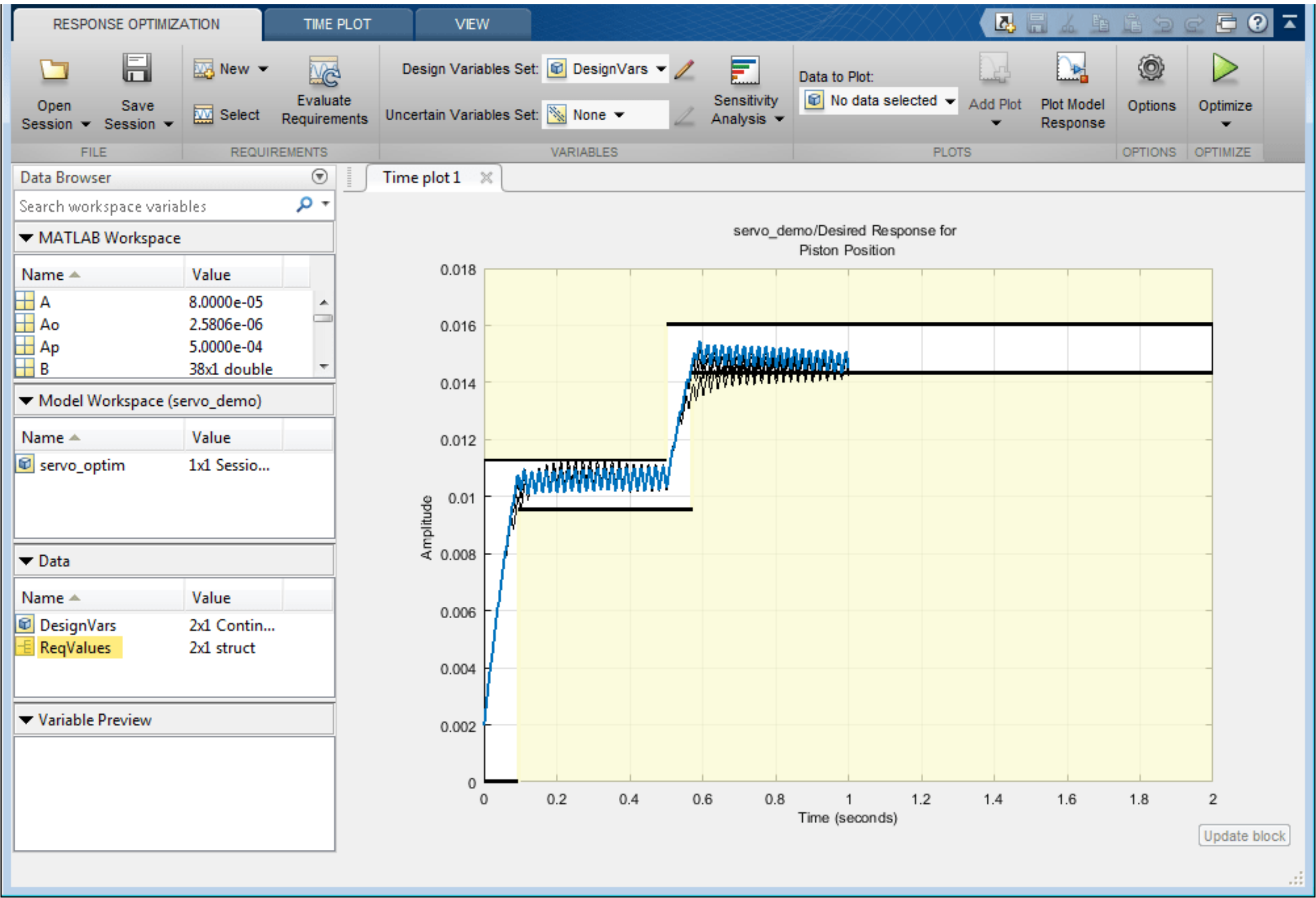
Double-click the `solenoid current(A)` Scope block to view the output solenoid current of Magnetic Circuit.

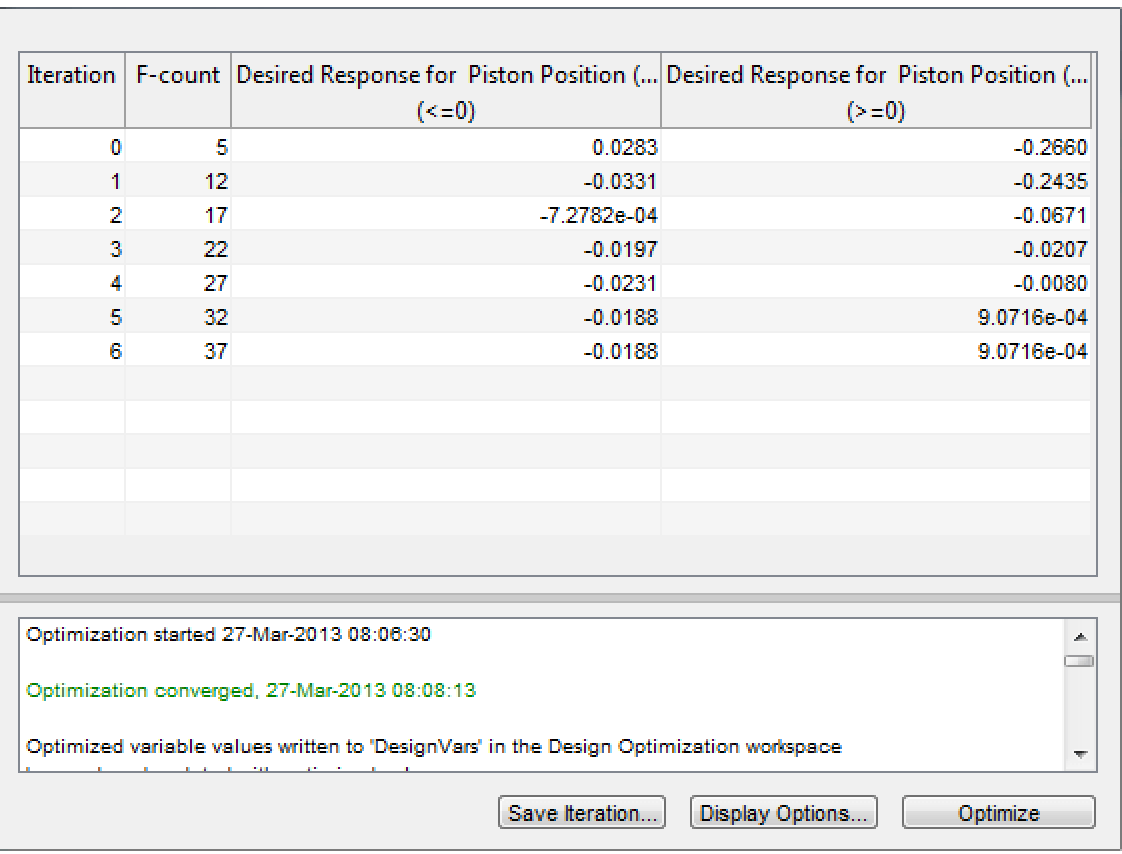
Double-click the `Desired Response for Piston Position` block to view constraints on the position of the piston.

You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
VARIABLES
Sensitivity Analysis
Data to Plot:
No data selected
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
A
8.0000e-05
Ao
2.5806e-06
Ap
5.0000e-04
B
38x1 double
Model Workspace (servo_demo)
servo_optim
1x1 Sessio...
Data
DesignVars
2x1 Contin...
ReqValues
2x1 struct
Variable Preview
Time plot 1
servo_demo/Desired Response for Piston Position
Amplitude
Time (seconds)
Update block



Iteration	F-count	Desired Response for Piston Position (... (<=0)	Desired Response for Piston Position (... (>=0)
0	5	0.0283	-0.2660
1	12	-0.0331	-0.2435
2	17	-7.2782e-04	-0.0671
3	22	-0.0197	-0.0207
4	27	-0.0231	-0.0080
5	32	-0.0188	9.0716e-04
6	37	-0.0188	9.0716e-04

The plot shows the final optimized piston position.

```
% Close the model.
bdclose('servo_demo')
```

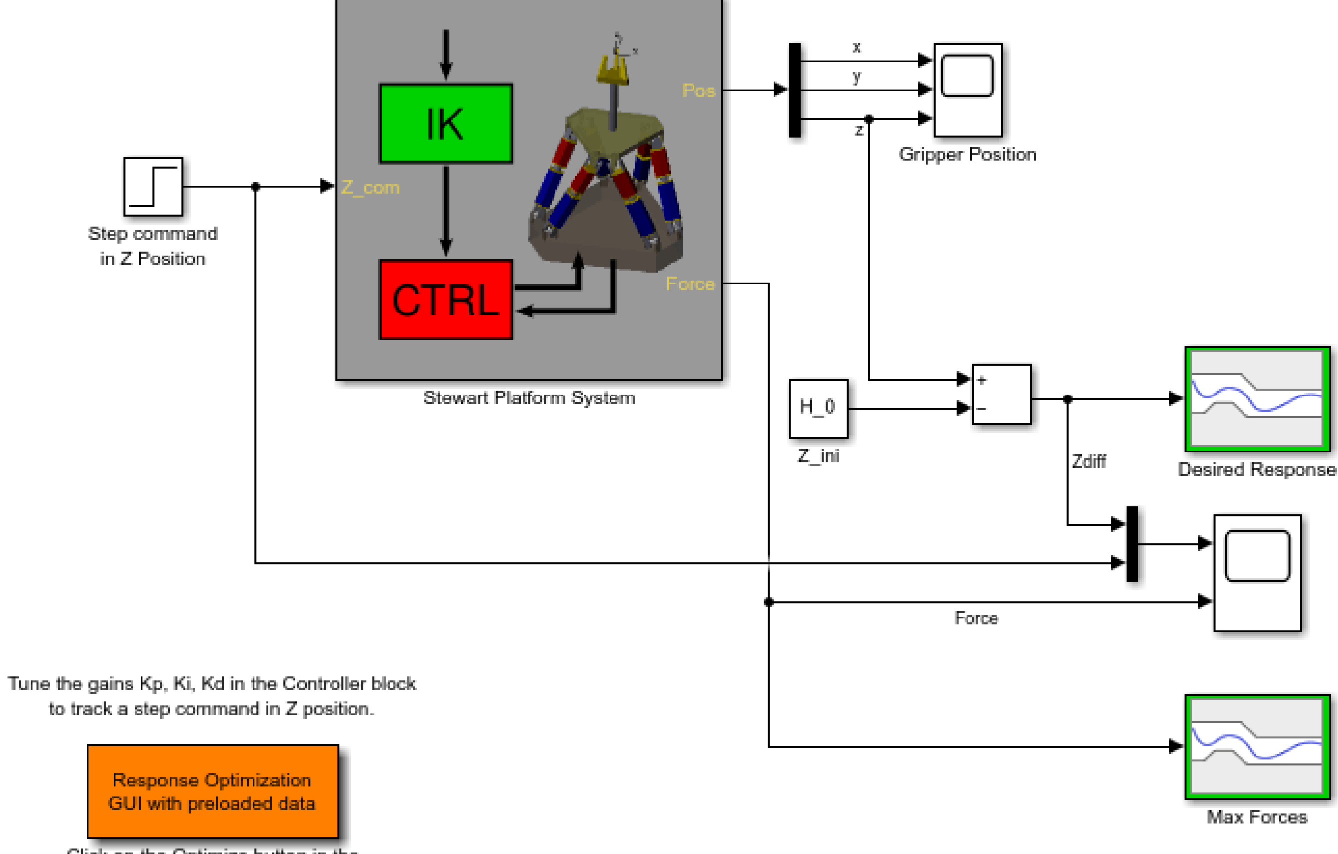
Stewart Platform Controller Tuning

This example shows how to use Simulink® Design Optimization™ to optimize the position controller parameters of a Stewart platform. The Stewart platform is modeled using Simscape™ Multibody™ blocks.

The model includes a vertical PID position controller and the gains are tuned to limit the maximum forces and track position with minimum overshoot and 0.05 second rise time.

Open the `stewart_demo` model using the command below and run the simulation. The simulation produces an unoptimized vertical position (Z direction) of the Stewart platform.

```
open_system('stewart_demo')
```

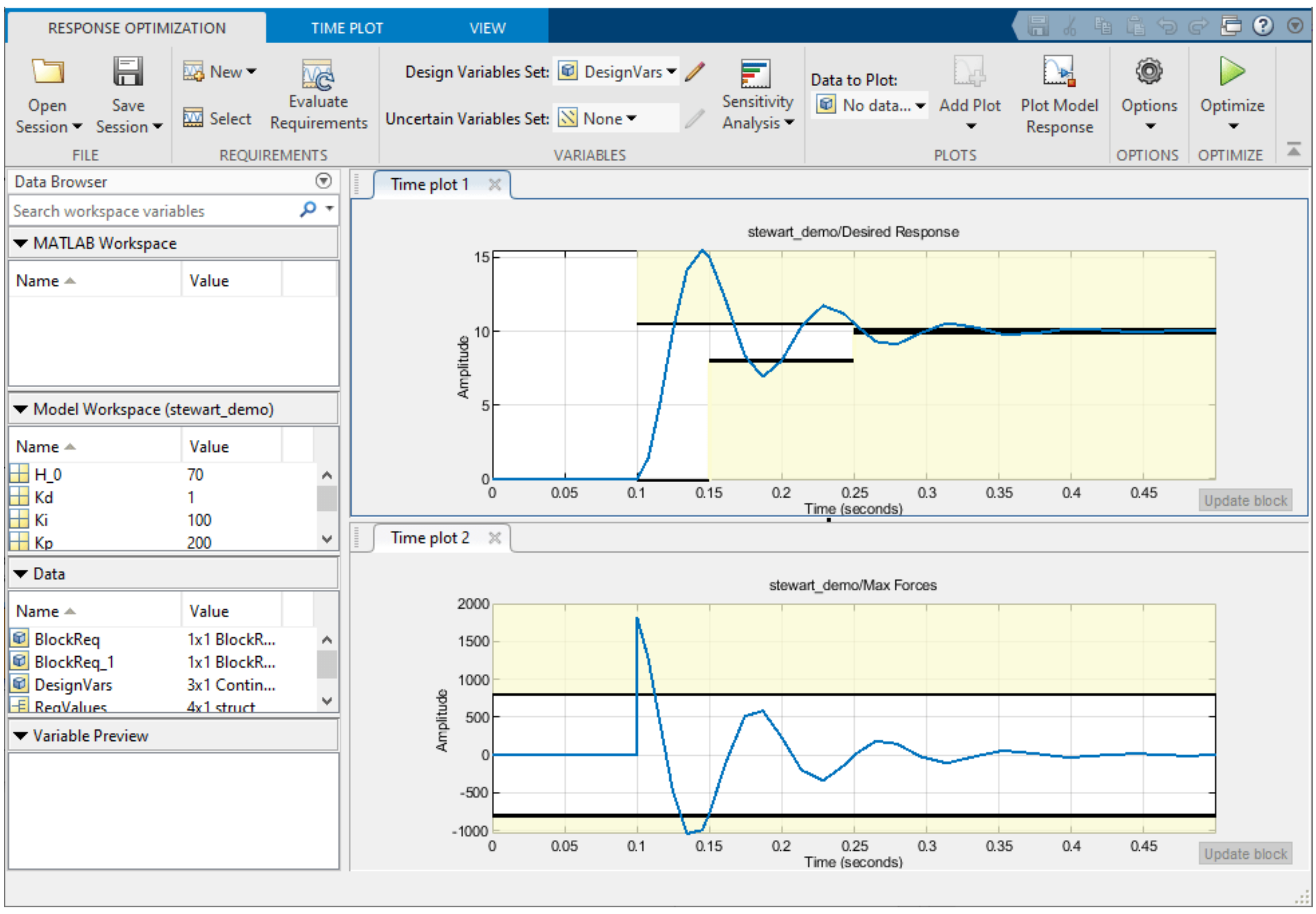


Double-click the Scope block to view the unoptimized position, the step input, and the controller's force actuation signal.

Double-click the down-arrow at the lower left corner of the `Stewart Platform System` block to view the details of the Stewart Platform. Note that this model uses the Simscape Multibody blockset.

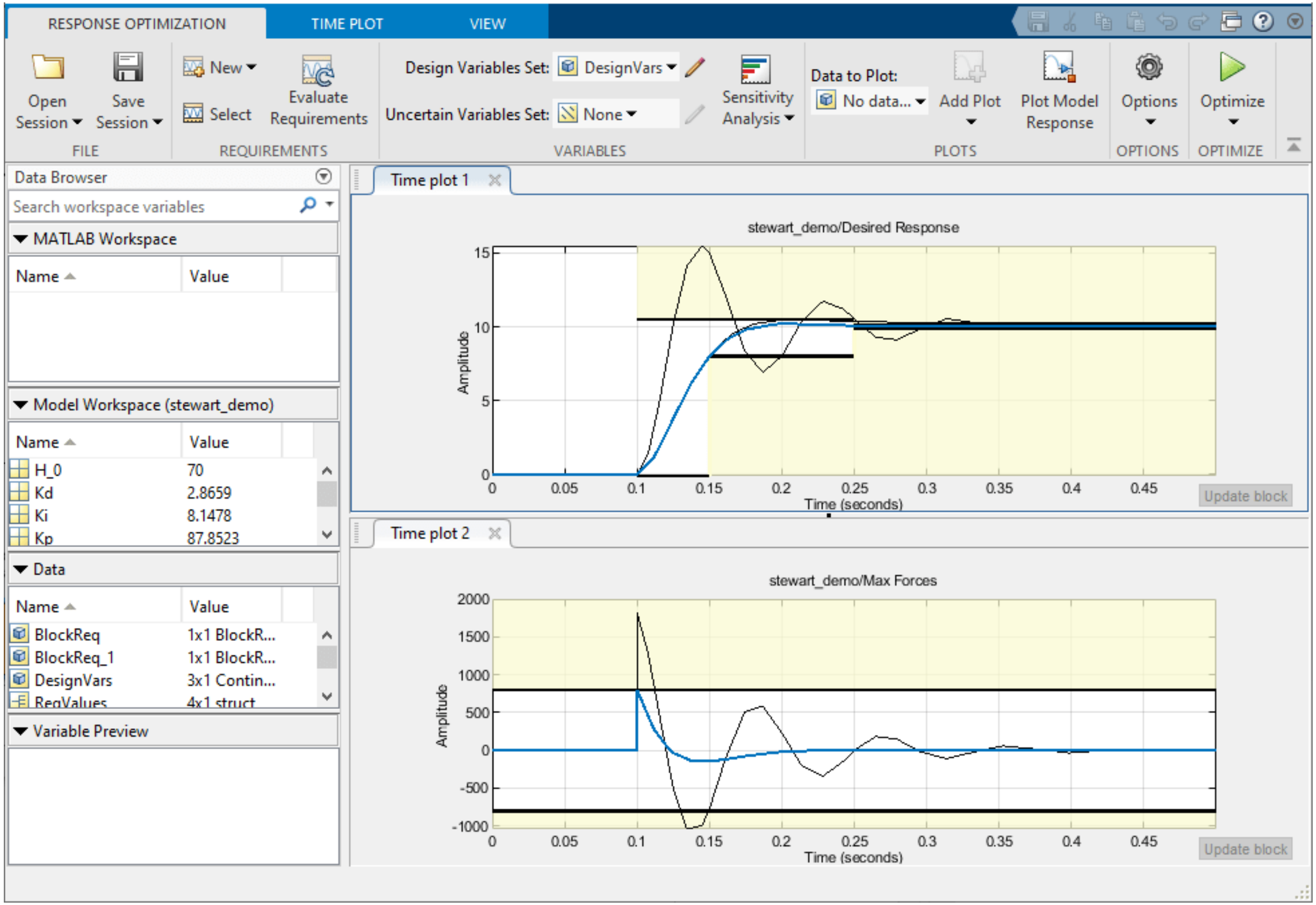
Double-click the `Desired Response` or the `Max Forces` blocks to view the constraints on the Stewart platform. The Max Forces block defines the constraints on the actuation signal of the controller.

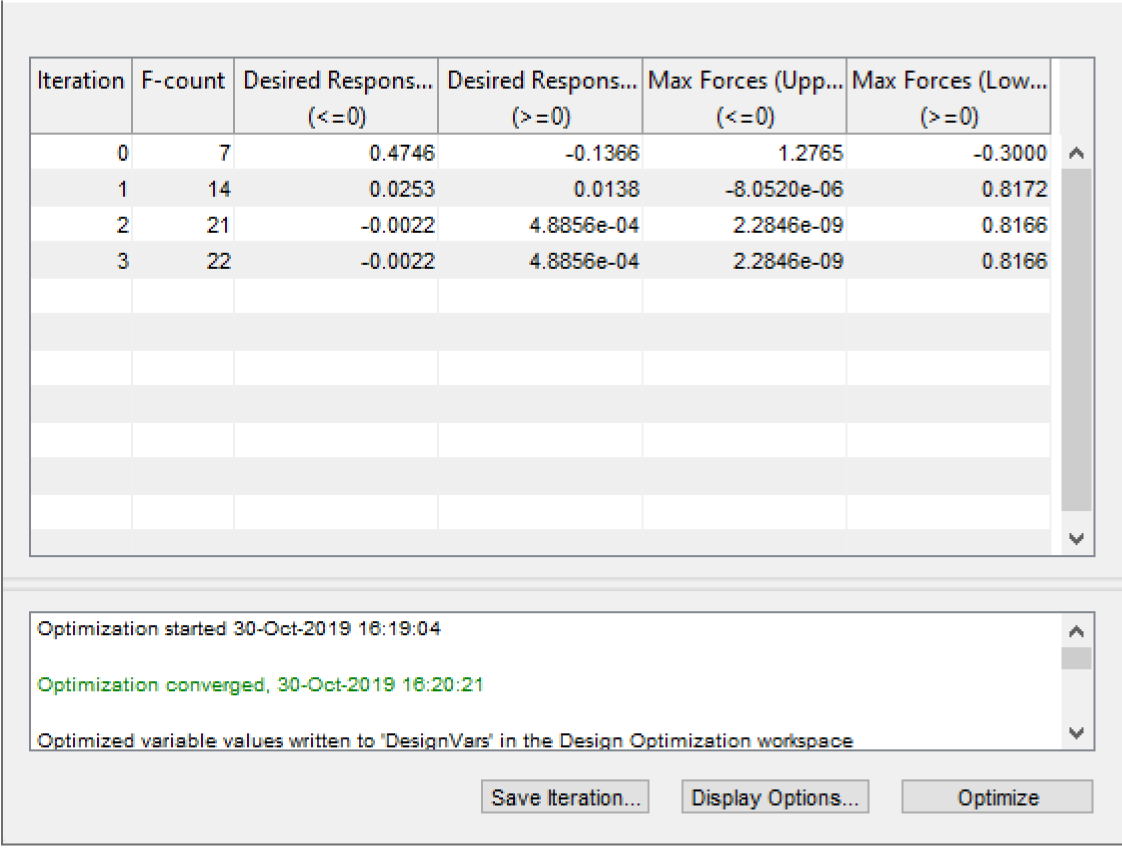
You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. You can launch a pre-configured optimization task in the **Response Optimizer** by first opening the model and by double-clicking on the orange block at the bottom of the model. From the **Response Optimizer**, press the **Plot Model Response** button to simulate the model and show how well the initial design satisfies the design requirements.



There are two plots representing the `Z Position` and `Leg Forces` of the platform.

We start the optimization by pressing the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
New
Select
Evaluate Requirements
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
Sensitivity Analysis
Data to Plot:
No data...
Add Plot
Plot Model Response
Options
Optimize
FILE
REQUIREMENTS
VARIABLES
PLOTS
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
Model Workspace (stewart_demo)
H_0
70
Kd
2.8659
Ki
8.1478
Kp
87.8523
Data
BlockReq
1x1 BlockR...
BlockReq_1
1x1 BlockR...
DesignVars
3x1 Contin...
ReqValues
4x1 struct
Variable Preview
Time plot 1
stewart_demo/Desired Response
Amplitude
Time (seconds)
Update block
Time plot 2
stewart_demo/Max Forces



Iteration	F-count	Desired Respons... (<=0)	Desired Respons... (>=0)	Max Forces (Upp... (<=0)	Max Forces (Low... (>=0)
0	7	0.4746	-0.1366	1.2765	-0.3000
1	14	0.0253	0.0138	-8.0520e-06	0.8172
2	21	-0.0022	4.8856e-04	2.2846e-09	0.8166
3	22	-0.0022	4.8856e-04	2.2846e-09	0.8166

Optimization started 30-Oct-2019 16:19:04

Optimization converged, 30-Oct-2019 16:20:21

Optimized variable values written to 'DesignVars' in the Design Optimization workspace

Save Iteration... Display Options... Optimize

The plots are now updated with the optimized position of the Stewart platform and the force actuation signal.

```
% Close the model.
bdclose('stewart_demo')
```

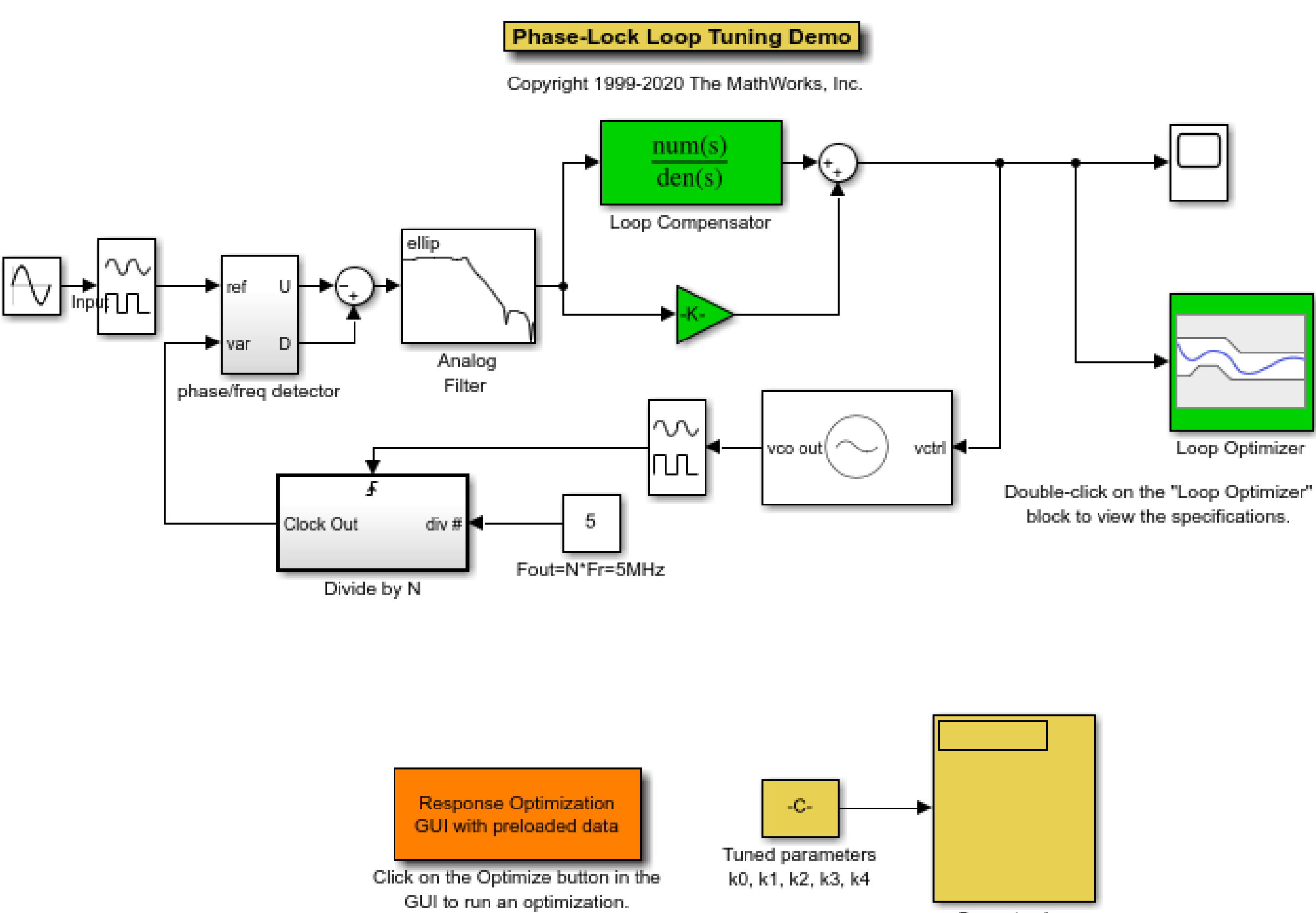
Phase Lock Loop Tuning

This example shows how to use Simulink® Design Optimization™ to tune an all-pass filter of a Phase Lock Loop. The filter includes a second-order low pass filter and a feedthrough gain. The feedthrough gain and the second order filter coefficients are tuned to apply a steady-state input to the Voltage Controlled Oscillator (VCO).

This example requires Mixed-Signal Blockset™ software.

Open the `phaselock_demo` model and run the simulation. The simulation produces an unoptimized input to the VCO and the initial data for optimization.

```
open_system('phaselock_demo')
```

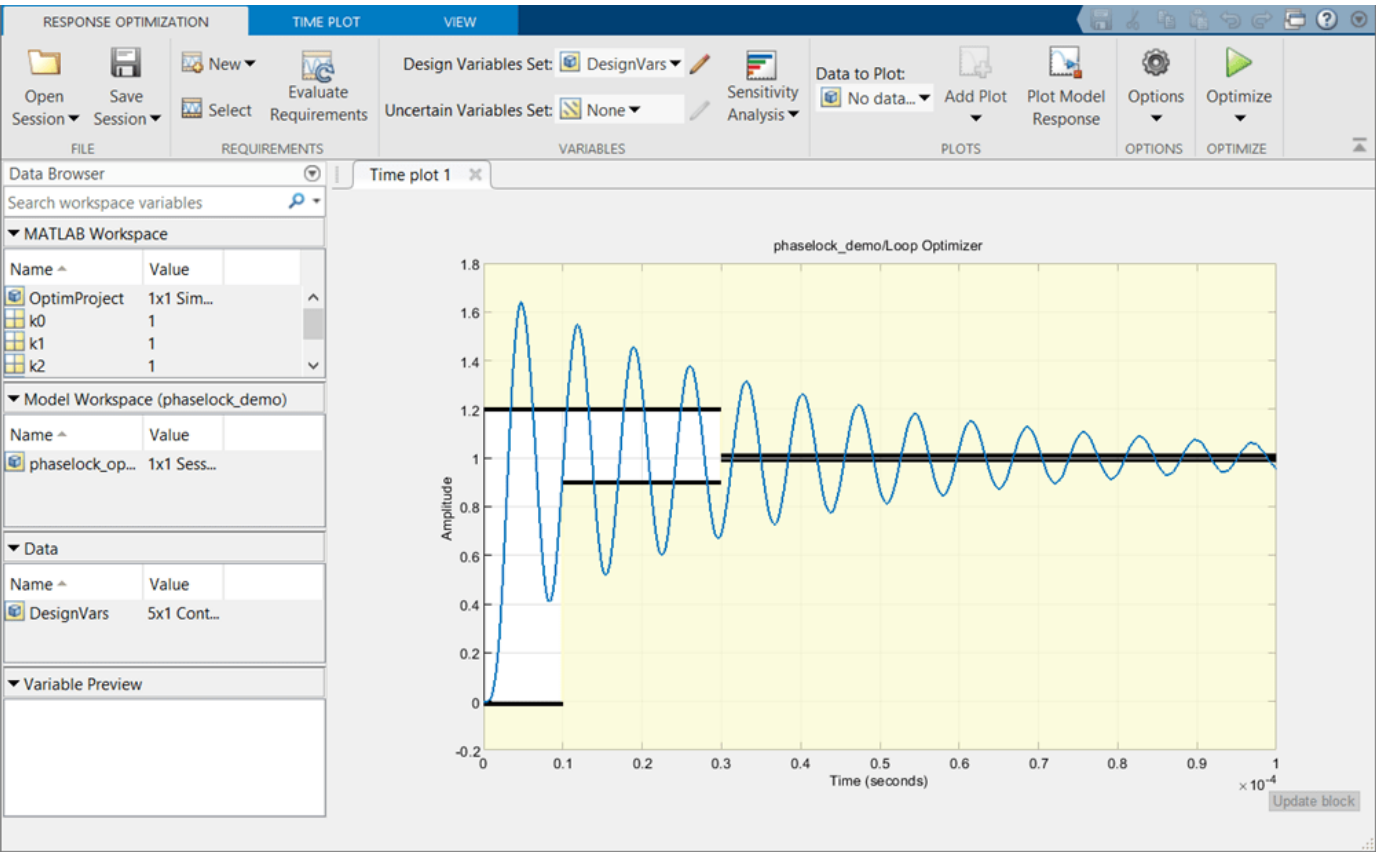


To view the unoptimized input to the VCO, double-click the Scope block.

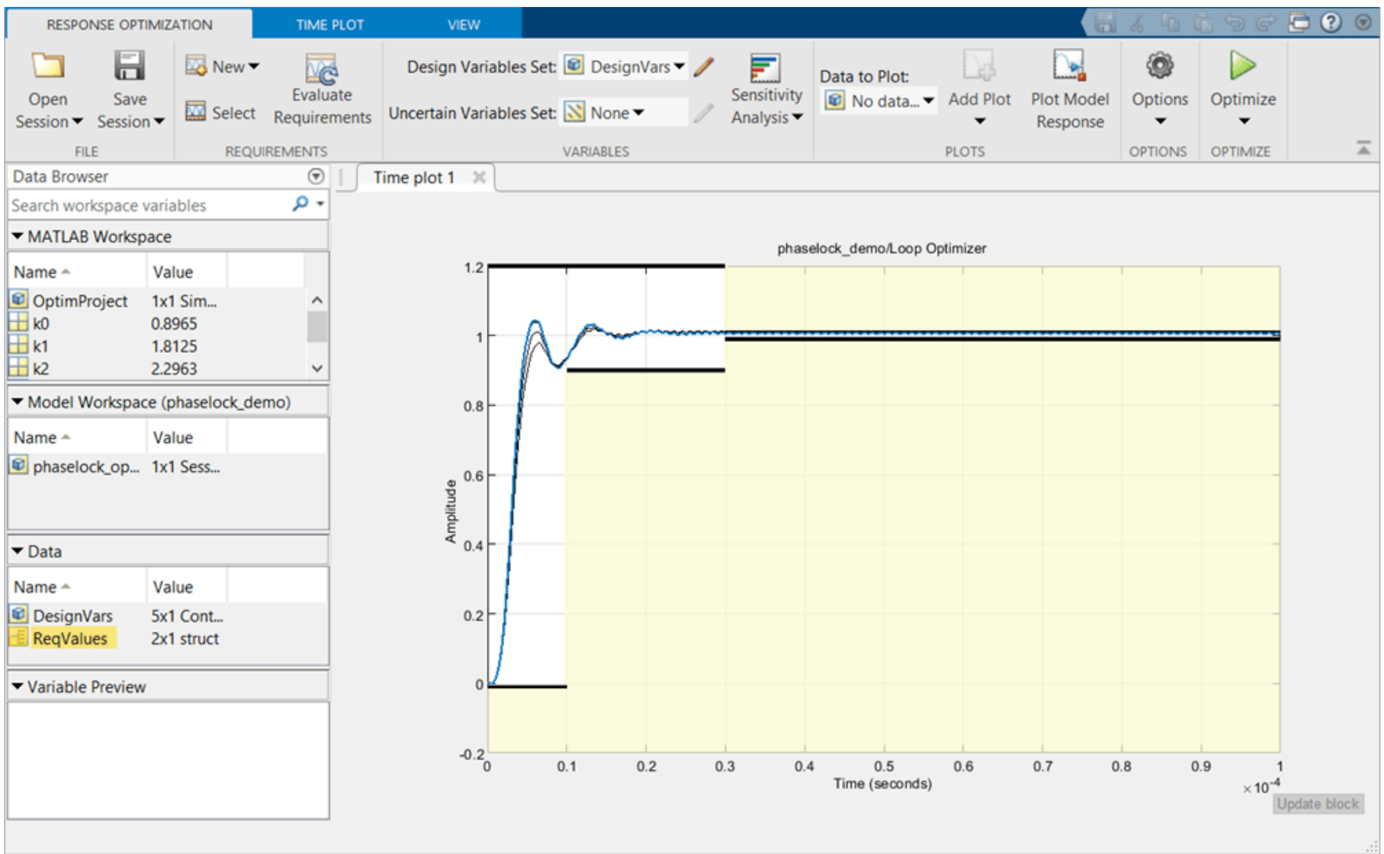
Double-click the `Loop Optimizer` block to view constraints on the input to the VCO. The constraints represent a step response with 0.1 second rise-time and 20 percent overshoot.

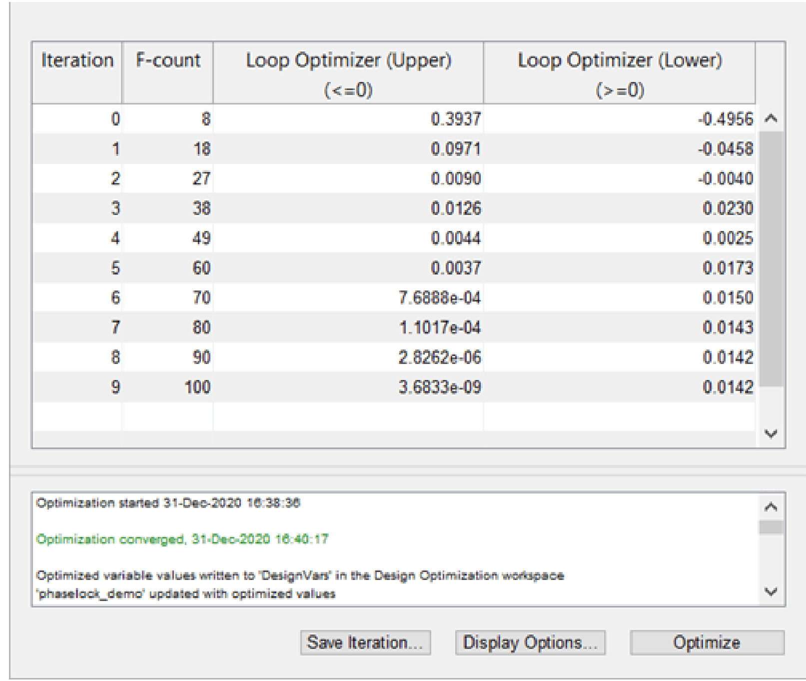
You can launch the **Response Optimizer** using the **Apps** menu in the Simulink toolstrip, or the `sdotool` command in MATLAB®. To launch a pre-configured optimization task in the **Response**

Optimizer, open the model, and double-click the orange block at the bottom of the model. To simulate the model and check if the initial design satisfies the design requirements, in the **Response Optimizer**, click the **Plot Model Response** button.



To start the optimization, click the **Optimize** button from the **Response Optimizer**. The plots are updated to indicate that the design requirements are now satisfied.





Iteration	F-count	Loop Optimizer (Upper) (<=0)	Loop Optimizer (Lower) (>=0)
0	8	0.3937	-0.4956
1	18	0.0971	-0.0458
2	27	0.0090	-0.0040
3	38	0.0126	0.0230
4	49	0.0044	0.0025
5	60	0.0037	0.0173
6	70	7.6888e-04	0.0150
7	80	1.1017e-04	0.0143
8	90	2.8262e-06	0.0142
9	100	3.6833e-09	0.0142

Optimization started 31-Dec-2020 16:38:36

Optimization converged, 31-Dec-2020 16:40:17

Optimized variable values written to 'DesignVars' in the Design Optimization workspace
'phaselock_demo' updated with optimized values

Save Iteration... Display Options... Optimize

The solid curve shows the final optimized input to the VCO.

Close the model.

```
bdclose('phaselock_demo')
```

Surrogate Optimization in Simulink Design Optimization

This example shows how to use surrogate optimization in Simulink Design Optimization™ to optimize the design of a hydraulic cylinder.

This example requires Parallel Computing Toolbox™ software.

Surrogate Optimization

Solving optimization problems involves using different values of the design variables and evaluating the objective function multiple times, especially if the objective function is sufficiently nonsmooth such that a derivative-based solver is not suitable. In such cases, you might need to use a derivative-free solver such as `patternsearch`, but these solvers tend to require running the objective function many more times. Using such a solver can be time consuming if the objective function is computationally expensive to evaluate. One way to overcome this problem is surrogate optimization. This approach creates a surrogate of the expensive objective function. The surrogate can be evaluated quickly and gives results very similar to the original objective function. Surrogate optimization also tries many starting points, which helps find a global optimum, rather than converging on a solution that, while locally optimal, might not be the global optimum.

Hydraulic Cylinder Model

This example shows how to use surrogate optimization to optimize the response of a hydraulic cylinder. Open the model.

```
open_system('sdoHydraulicCylinder')
```

The hydraulic cylinder model is based on the Simulink model `sldemo_hydcyl`. The model includes:

- `Pump` and `Cylinder Assembly` subsystems. For more information on the subsystems, see "Single Hydraulic Cylinder Simulation".
- A step change applied to the cylinder control valve orifice area that causes the cylinder piston position to change.

Specify Design Variables

Now, specify the design variables to tune: the cylinder cross-sectional area `Ac` and the piston spring constant `K`.

```
DesignVars = sdo.getParameterFromModel('sdoHydraulicCylinder',{'Ac','K'});
DesignVars(1).Value = 1e-3;
DesignVars(1).Minimum = 0.0003;
DesignVars(1).Maximum = 0.0013;
DesignVars(1).Scale = 0.001;

DesignVars(2).Value = 50000;
DesignVars(2).Minimum = 10000;
DesignVars(2).Maximum = 100000;
DesignVars(2).Scale = 1;
```

Specify Design Requirements

Next, specify design requirements to satisfy the following conditions during optimization:

- The pressure stays under 1,750,000 N/m.
- The piston position step response satisfies a rise time of 0.04 seconds and a settling time of 0.05 seconds.

```
Requirements = struct;
Requirements.MaxPressure = sdo.requirements.SignalBound(...
    'BoundMagnitudes', [1750000 1750000], ...
    'BoundTimes', [0 0.1]);
Requirements.PistonResponse = sdo.requirements.StepResponseEnvelope(...
    'FinalValue', 0.04, ...
    'PercentSettling', 1, ...
    'RiseTime', 0.04, ...
    'SettlingTime', 0.05);
```

Signal Logging

Next, specify model signals to log during model simulation. These signals are needed to evaluate the design requirements, that is, to determine whether they are satisfied.

```
Simulator = sdo.SimulationTest('sdoHydraulicCylinder');

PistonPosition_Info = Simulink.SimulationData.SignalLoggingInfo;
PistonPosition_Info.BlockPath = 'sdoHydraulicCylinder/Cylinder Assembly';
PistonPosition_Info.OutputPortIndex = 2;
PistonPosition_Info.LoggingInfo.LoggingName = 'PistonPosition';
PistonPosition_Info.LoggingInfo.NameMode = 1;

Pressures_Info = Simulink.SimulationData.SignalLoggingInfo;
Pressures_Info.BlockPath = 'sdoHydraulicCylinder/Cylinder Assembly';
Pressures_Info.LoggingInfo.LoggingName = 'Pressures';
Pressures_Info.LoggingInfo.NameMode = 1;

Simulator.LoggingInfo.Signals = [...
    PistonPosition_Info; ...
    Pressures_Info];
```

Create Optimization Objective Function

Create a function that is called at each optimization iteration to evaluate the design requirements. Use an anonymous function with one argument that calls `sdoHydraulicCylinder_optFcn`.

```
optimfcn = @(P) sdoHydraulicCylinder_optFcn(P,Simulator,Requirements);
```

The `sdoHydraulicCylinder_optFcn` function uses the simulator and requirements objects to evaluate the design. Type `edit sdoHydraulicCylinder_optFcn` to examine the function in more detail.

Optimization Using Derivative-Based Solver

Now, try solving this optimization problem using a derivative-based solver. Specify optimization options.

```
Options = sdo.OptimizeOptions;
Options.Method = 'fmincon';
Options.UseParallel = true;
Options.OptimizedModel = Simulator;
```

Run the optimization by calling `sdo.optimize` with the objective function handle, parameters to optimize, and options.

```
[Optimized_DesignVars,Info] = sdo.optimize(optimfcn,DesignVars,Options);
```

```
Starting parallel pool (parpool) using the 'local' profile ...
Connected to the parallel pool (number of workers: 6).
Configuring parallel workers for optimization...
Analyzing and transferring files to the workers ...done.
Parallel workers configured for optimization.

 Optimization started 05-Aug-2021 09:50:51

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      5        0.001      0.3033
    1     10   0.00123343      0.3726        0.233          100
    2     20   0.00117522      0.3545       0.0582          100
    3     28   0.00121802      0.3678       0.0428          100
    4     39   0.00117879      0.3556       0.0392          100
    5     48   0.00120789      0.3646       0.0291          100
    6     60   0.00119077      0.3593       0.0171          100
    7     72   0.00119977      0.3621      0.00901          100
    8     80   0.00119977      0.3621      0.00089          100
Converged to an infeasible point.

fmincon stopped because the size of the current step is less than
the value of the step size tolerance but constraints are not
satisfied to within the value of the constraint tolerance.
Removing data from parallel workers...
Data removed from parallel workers.
```

At the end of optimization iterations, the "`max constraint`" column is still positive, indicating that the derivative-based solver does not satisfy all of the requirements.

Optimization Options Using Surrogate Solver

Since the derivative-based solver does not satisfy all the requirements, try `surrogateopt` as a derivative-free solver. Specify optimization options.

```
Options = sdo.OptimizeOptions;
Options.Method = 'surrogateopt';
Options.MethodOptions.MaxFunctionEvaluations = 100;
Options.UseParallel = true;
Options.OptimizedModel = Simulator;
```

Run the optimization by calling `sdo.optimize` with the objective function handle, parameters to optimize, and options.

```
[Optimized_DesignVars,Info] = sdo.optimize(optimfcn,DesignVars,Options);
```

```
Configuring parallel workers for optimization...
Analyzing and transferring files to the workers ...done.
Parallel workers configured for optimization.

 Optimization started 05-Aug-2021 09:51:51

                                                         Current             Current
```

```
F-count          f(x)     max constraint             f(x)     max constraint     Trial ty
      1         0.001           0.303264            0.001           0.303264     initial
      2         0.001           0.303264           0.0003            0.41283     random
      3         0.001           0.303264           0.0008           0.982707     random
      4         0.001           0.303264          0.00055           0.573642     random
      5         0.001           0.303264          0.00105            1.25679     random
      6         0.001           0.303264              NaN                Inf     random
      7         0.001           0.303264         0.001175            2.14476     random
      8         0.001           0.303264              NaN                Inf     random
      9      0.000925           0.252177         0.000925           0.252177     random
     10      0.000925           0.252177              NaN                Inf     random
     11      0.000925           0.252177        0.0011125           0.333109     random
     12      0.000925           0.252177              NaN                Inf     random
     13      0.000925           0.252177        0.0008625           0.724191     random
     14      0.000925           0.252177              NaN                Inf     random
     15      0.000925           0.252177        0.0009875            1.46276     random
     16      0.000925           0.252177        0.0007375            4.26818     random
     17      0.000925           0.252177        0.0012375           0.399354     random
     18      0.000925           0.252177       0.00076875           0.985955     random
     19      0.000925           0.252177       0.00126875            1.39122     random
     20      0.000925           0.252177       0.00051875           0.477584     random
     21      0.000925           0.252177       0.00101875            1.23392     random
     22      0.000925           0.252177              NaN                Inf     random
     23    0.00089375           0.226608       0.00089375           0.226608     random
     24    0.00089375           0.226608              NaN                Inf     random
     25    0.00089375           0.226608       0.00114375            3.56038     random
     26    0.00089375           0.226608              NaN                Inf     random
     27    0.00089375           0.226608       0.00095625            8.44124     random
     28    0.00089375           0.226608              NaN                Inf     random
     29    0.00089375           0.226608       0.00120625           0.325598     random
     30    0.00058125          0.0293624       0.00058125          0.0293624     random
     31    0.00058125          0.0293624      0.000353121           0.114521     adaptive
     32    0.00058125          0.0293624              NaN                Inf     adaptive
     33    0.00058125          0.0293624              NaN                Inf     adaptive
     34    0.00058125          0.0293624              NaN                Inf     adaptive
     35    0.00058125          0.0293624      0.000387527           0.275913     adaptive
     36    0.00058125          0.0293624              NaN                Inf     adaptive
     37    0.00058125          0.0293624              NaN                Inf     adaptive
     38    0.00058125          0.0293624              NaN                Inf     adaptive
     39    0.00058125          0.0293624              NaN                Inf     adaptive
     40    0.00058125          0.0293624        0.0003626           0.130551     adaptive
     41    0.00058125          0.0293624              NaN                Inf     adaptive
     42    0.00058125          0.0293624      0.000373093            0.20491     adaptive
     43    0.00058125          0.0293624              NaN                Inf     adaptive
     44    0.00058125          0.0293624       0.00043983           0.376346     adaptive
     45    0.00058125          0.0293624      0.000510805           0.276542     adaptive
     46    0.00058125          0.0293624      0.000616738           0.353985     adaptive
     47    0.00058125          0.0293624      0.000652226            1.69733     adaptive
     48    0.00058125          0.0293624      0.000510274           0.602427     adaptive
     49    0.00058125          0.0293624      0.000651695           0.138744     adaptive
     50   0.000581641          0.0290052      0.000581641          0.0290052     adaptive

                                                  Current            Current
F-count          f(x)     max constraint             f(x)     max constraint     Trial ty
     51   0.000581641          0.0290052       0.00058125          0.0290879     adaptive
     52   0.000581641          0.0290052      0.000581445          0.0291836     adaptive
     53   0.000581641          0.0290052      0.000581152          0.0291773     adaptive
     54   0.000581641          0.0290052       0.00058125          0.0292252     adaptive
```

```
      55        0.000581641         0.0290052         0.00108125          0.821321     random
      56        0.000581641         0.0290052                NaN               Inf     random
      57        0.000581641         0.0290052         0.00083125           2.51611     random
      58        0.000581641         0.0290052                NaN               Inf     random
      59        0.000581641         0.0290052         0.00106562          0.768714     random
      60        0.000581641         0.0290052                NaN               Inf     random
      61        0.000581641         0.0290052        0.000815625          0.725618     random
      62        0.000581641         0.0290052        0.000440625          0.067243     random
      63        0.000581641         0.0290052        0.000940625          0.901158     random
      64        0.000581641         0.0290052        0.000690625          0.475563     random
      65        0.000581641         0.0290052         0.00119062           1.14814     random
      66        0.000581641         0.0290052                NaN               Inf     random
      67        0.000581641         0.0290052        0.000878125           1.83347     random
      68        0.000581641         0.0290052        0.000628125           7.48485     random
      69        0.000581641         0.0290052         0.00112812          0.359996     random
      70        0.000581641         0.0290052                NaN               Inf     random
      71        0.000581641         0.0290052         0.00125312          0.367383     random
      72        0.000581641         0.0290052                NaN               Inf     random
      73        0.000581641         0.0290052         0.00100312           2.73758     random
      74        0.000581641         0.0290052                NaN               Inf     random
      75        0.000581641         0.0290052                NaN               Inf     adaptive
      76        0.000581641         0.0290052                NaN               Inf     adaptive
      77        0.000581641         0.0290052                NaN               Inf     adaptive
      78        0.000581641         0.0290052        0.000365623         0.0538825     adaptive
      79        0.000581641         0.0290052                NaN               Inf     adaptive
      80        0.000581641         0.0290052                NaN               Inf     adaptive
      81        0.000581641         0.0290052        0.000392021         0.0600614     adaptive
      82        0.000581641         0.0290052                NaN               Inf     adaptive
      83        0.000581641         0.0290052                NaN               Inf     adaptive
      84        0.000581641         0.0290052                NaN               Inf     adaptive
      85        0.000581641         0.0290052                NaN               Inf     adaptive
      86        0.000581641         0.0290052                NaN               Inf     adaptive
      87        0.000581641         0.0290052                NaN               Inf     adaptive
      88         0.00046017        0.00145339         0.00046017        0.00145339     adaptive
      89         0.00046017        0.00145339        0.000373567         0.0128931     adaptive
      90         0.00046017        0.00145339        0.000367658         0.0168988     adaptive
      91         0.00046017        0.00145339        0.000369595         0.0335533     adaptive
      92         0.00046017        0.00145339         0.00036664          0.035673     adaptive
      93         0.00046017        0.00145339        0.000367609         0.0437603     adaptive
      94        0.000457045      -7.33841e-05        0.000457045      -7.33841e-05     adaptive
      95        0.000457045      -7.33841e-05        0.000458608      -0.000421362     adaptive
      96        0.000457045      -7.33841e-05        0.000459389      -0.000458651     adaptive
The current solution is feasible. surrogateopt stopped because it exceeded the function evaluatio
If the solution needs to be improved, you could try increasing the function evaluation limit.
Removing data from parallel workers...
Data removed from parallel workers.
```

Using surrogateopt, all the design requirements are satisfied, as indicated by a negative value in the "`max constraint`" column.

Update the model with the optimized parameter values.

```
sdo.setValueInModel('sdoHydraulicCylinder',Optimized_DesignVars);
```

In this example, a solver using surrogates successful on an optimization problem where a derivative-based solver is unsuccessful. The `surrogateopt` solver is a global solver that tries many starting

points. By using a surrogate of the model, `surrogateopt` needs to run the model only a moderate number of times.

See Also

`sdo.OptimizeOptions` | `sdo.optimize`

Related Examples

- “Single Hydraulic Cylinder Simulation”
- “Surrogate Optimization using the Response Optimizer App” on page 3-302

Surrogate Optimization using the Response Optimizer App

This example shows how to use surrogate optimization in Simulink Design Optimization™ to optimize the design of a hydraulic cylinder, using Response Optimizer app.

This example requires Parallel Computing Toolbox™ software.

Surrogate Optimization

Solving optimization problems involves using different values of the design variables and evaluating the objective function multiple times, especially if the objective function is sufficiently nonsmooth such that a derivative-based solver is not suitable. In such cases, you might need to use a derivative-free solver such as `patternsearch`, but these solvers tend to require running the objective function many more times. Using such a solver can be time consuming if the objective function is computationally expensive to evaluate. One way to overcome this problem is surrogate optimization. This approach creates a surrogate of the expensive objective function. The surrogate can be evaluated quickly and gives results very similar to the original objective function. Surrogate optimization also tries many starting points, which helps find a global optimum, rather than converging on a solution that, while locally optimal, might not be the global optimum.

Hydraulic Cylinder Model

This example shows how to use surrogate optimization to optimize the response of a hydraulic cylinder. Open the model.

```
open_system('sdoHydraulicCylinder')
```

The hydraulic cylinder model is based on the Simulink model `sldemo_hydcyl`. The model includes:

- `Pump` and `Cylinder Assembly` subsystems. For more information on the subsystems, see "Single Hydraulic Cylinder Simulation".
- A step change applied to the cylinder control valve orifice area that causes the cylinder piston position to change.

Set Up Optimization Problem

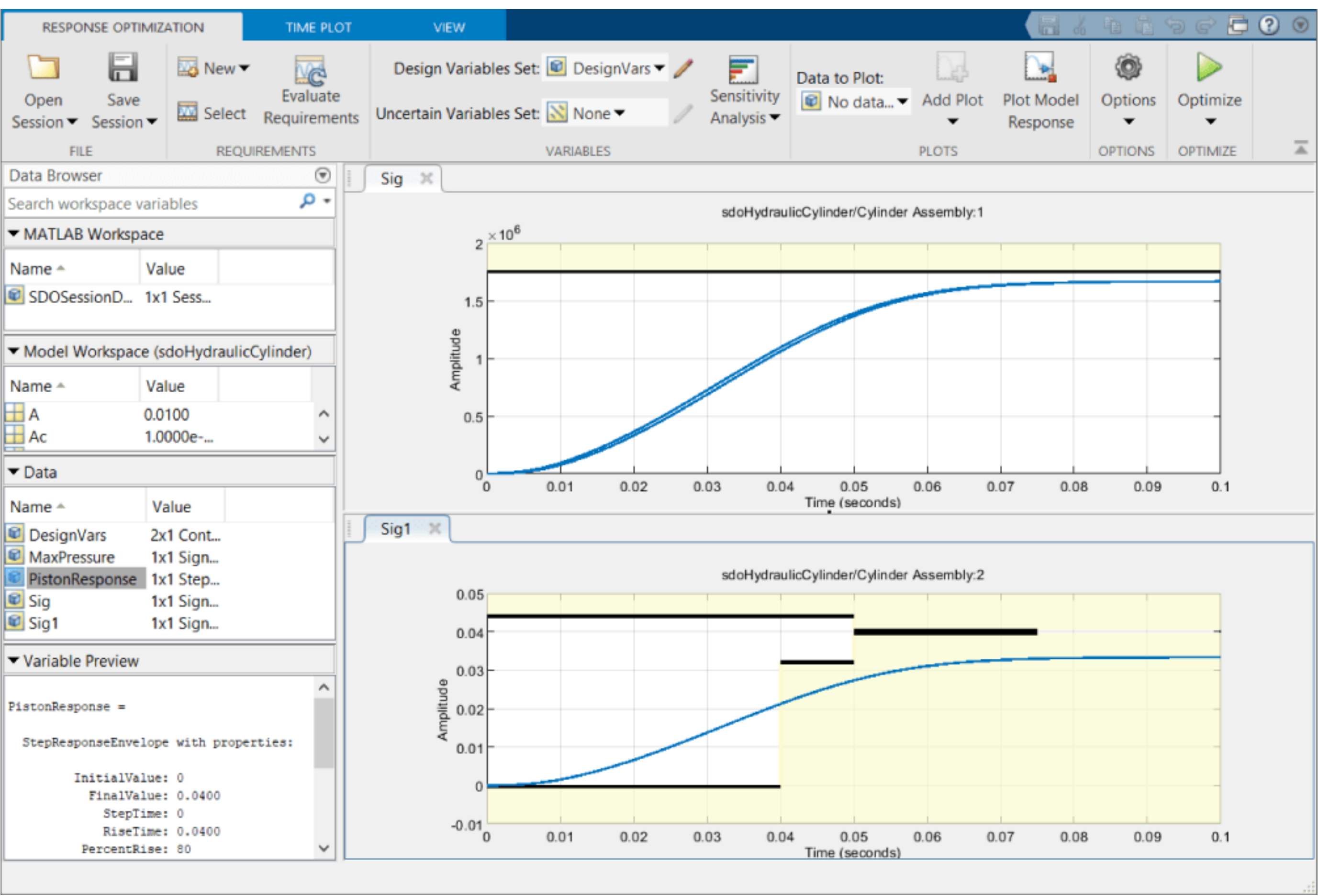
We will use Response Optimizer app to solve an optimization problem for this model. In the model, use the **Apps** tab to launch Response Optimizer app. In the app, navigate to **Open Session**, select **Open from file**, and open the file `sdoHydraulicCylinder_sdosession.mat`. This configures the app with the optimization problem already set up.

In the optimization problem, two design variables in the model are being optimized. These are the cylinder cross-sectional area `Ac` and the piston spring constant `K`. There are two design requirements to be satisfied:

- The pressure stays under 1,750,000 N/m. This requirement is named **MaxPressure** in the data browser of the app. It is a requirement on the **Pressures** signal in the model, which is an output of the Cylinder Assembly block.
- The piston position step response satisfies a rise time of 0.04 seconds and a settling time of 0.05 seconds. This requirement is named **PistonResponse** in the data browser. It is a requirement on the **PistonPosition** signal in the model, which is another output of the Cylinder Assembly block.

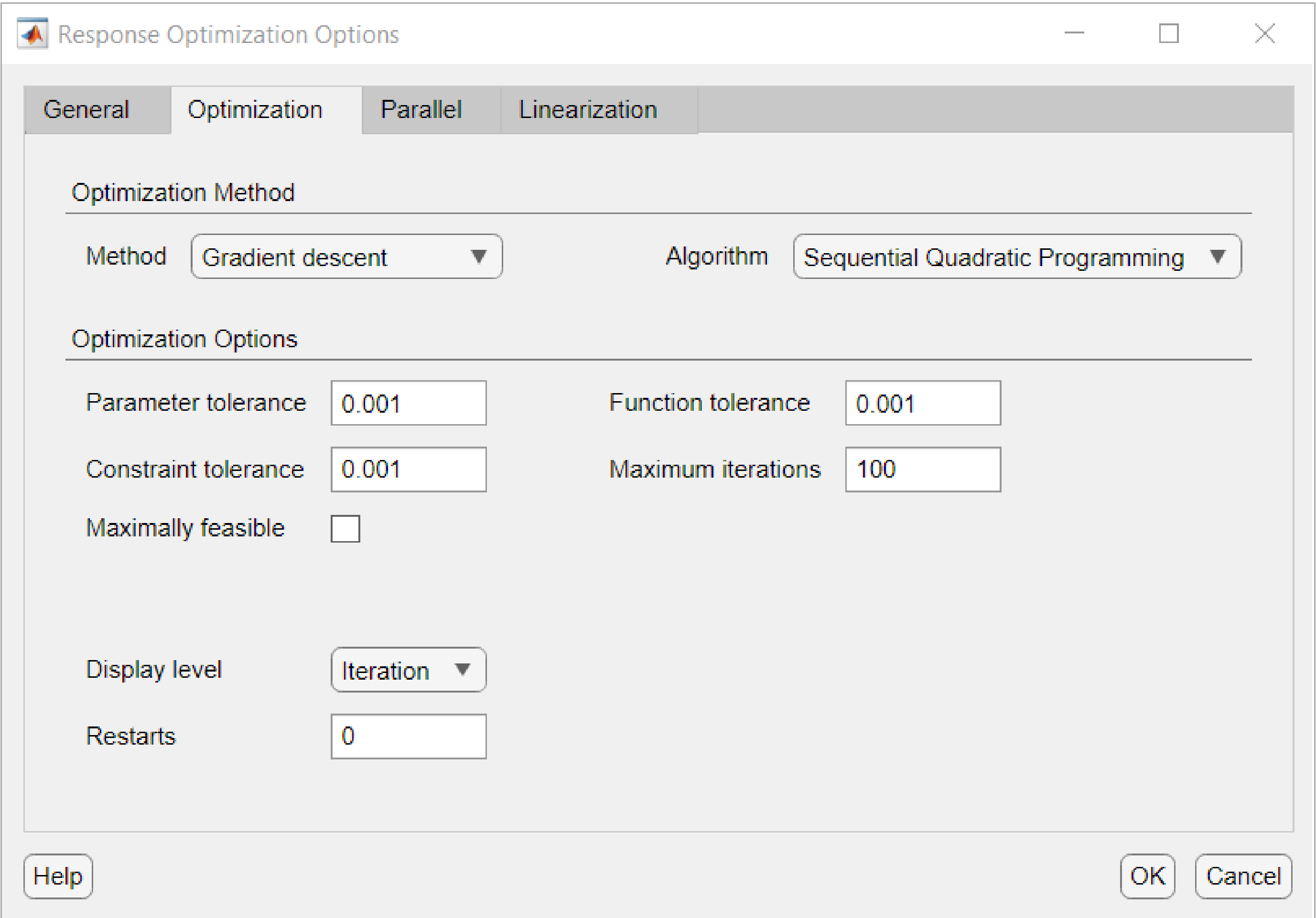
These requirements constitute the objective function which we want the optimization to satisfy. Click **Plot Model Response** in the toolstrip of the app. With the current values of the design variables, the

pressure does satisfy the bound requirement, but the piston position curve goes into the yellow area in the plot, violating the step response requirement. To satisfy both requirements, the optimization algorithm will run the model many times with different values for the design variables, check whether the requirements are satisfied, and try new values for the design variables in a search for values that satisfy all the requirements.

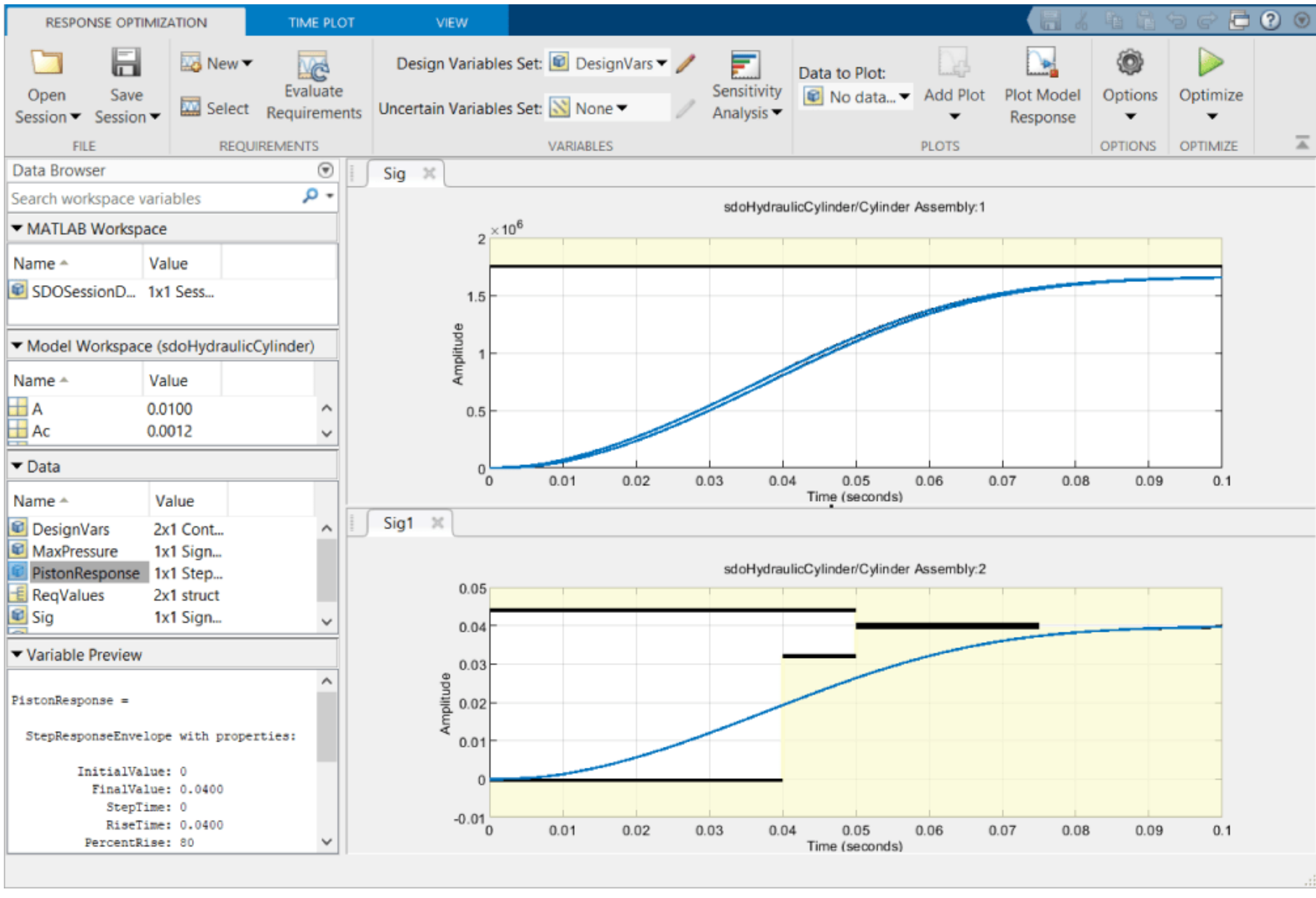


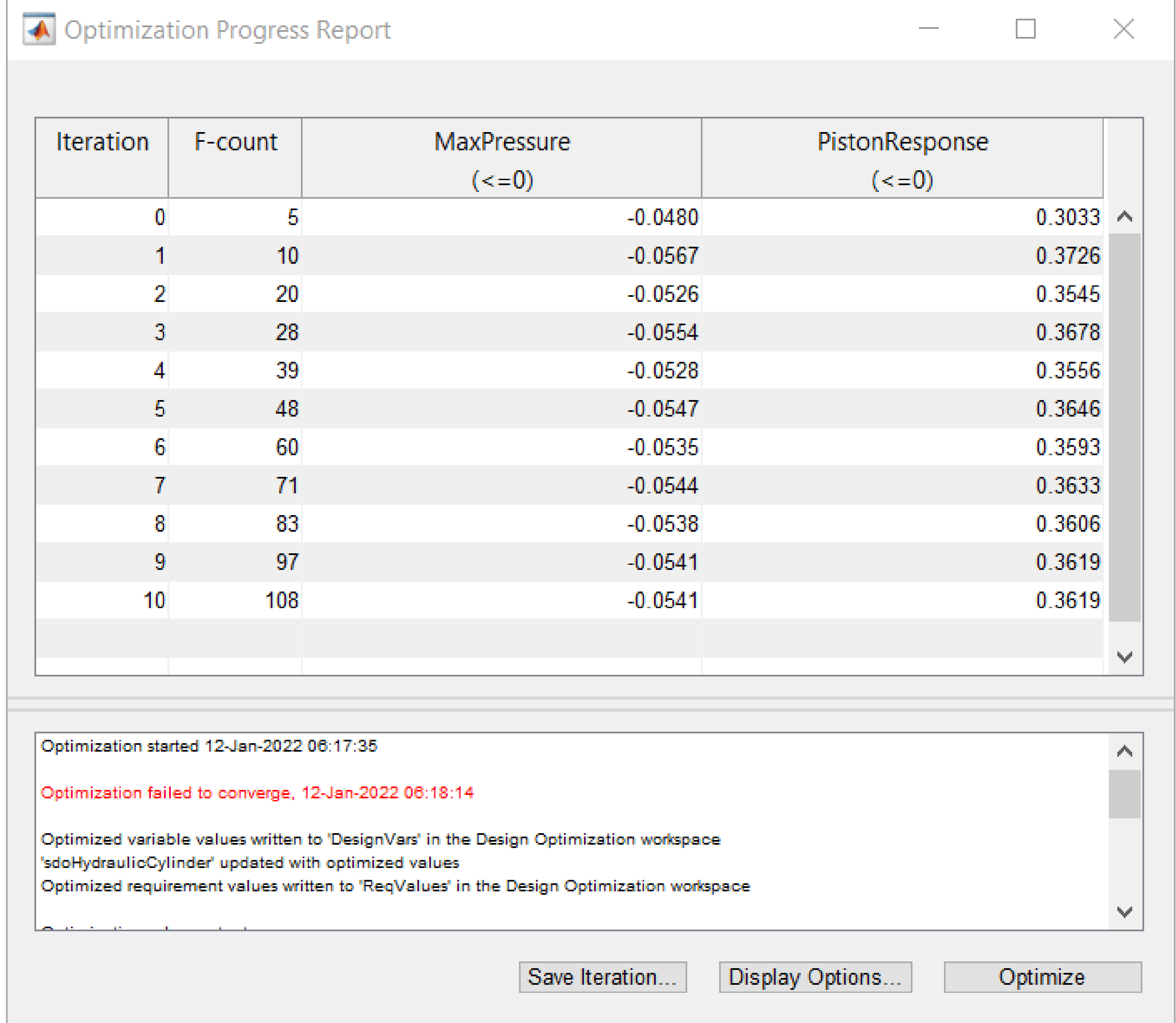
Optimization Using Derivative-Based Solver

Now, try solving this optimization problem using a derivative-based solver. The optimization options can be seen by clicking the **Options** button in the toolstrip of the app and navigating to the **Optimization** pane.



Run the optimization by clicking **Optimize** in the toolstrip of the app. At the end of optimization iterations, the piston response curve still goes into the yellow part of the plot, and in the numeric progress display, the bottom row of the piston response column is positive, indicating that the derivative-based solver does not satisfy all the requirements.

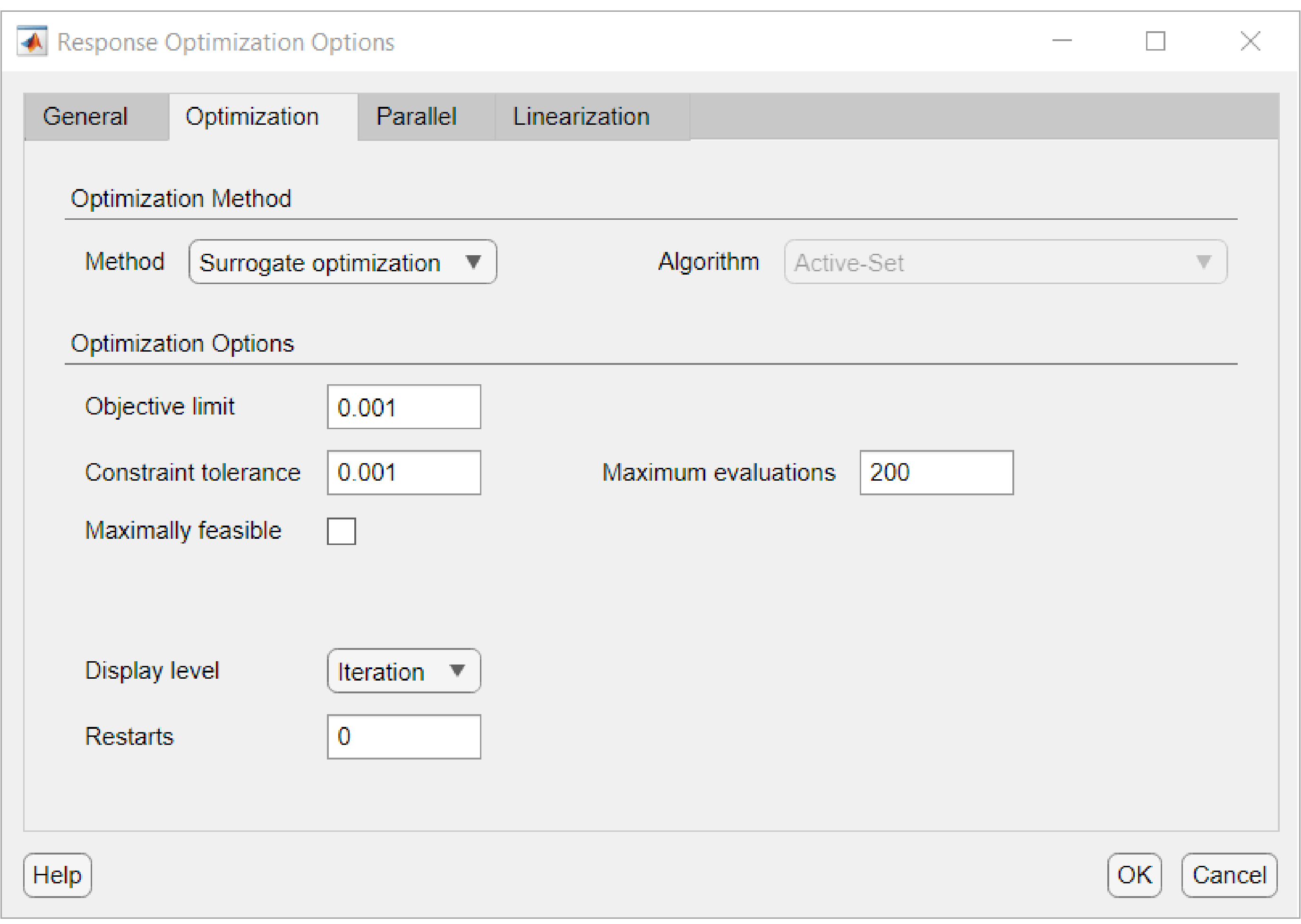

RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set: DesignVars
Uncertain Variables Set: None
VARIABLES
Sensitivity Analysis
Data to Plot: No data...
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name Value
SDOSessionD... 1x1 Sess...
Model Workspace (sdoHydraulicCylinder)
A 0.0100
Ac 0.0012
Data
DesignVars 2x1 Cont...
MaxPressure 1x1 Sign...
PistonResponse 1x1 Step...
ReqValues 2x1 struct
Sig 1x1 Sign...
Variable Preview
PistonResponse =
StepResponseEnvelope with properties:
InitialValue: 0
FinalValue: 0.0400
StepTime: 0
RiseTime: 0.0400
PercentRise: 80
Sig
sdoHydraulicCylinder/Cylinder Assembly:1
Amplitude
Time (seconds)
Sig1
sdoHydraulicCylinder/Cylinder Assembly:2



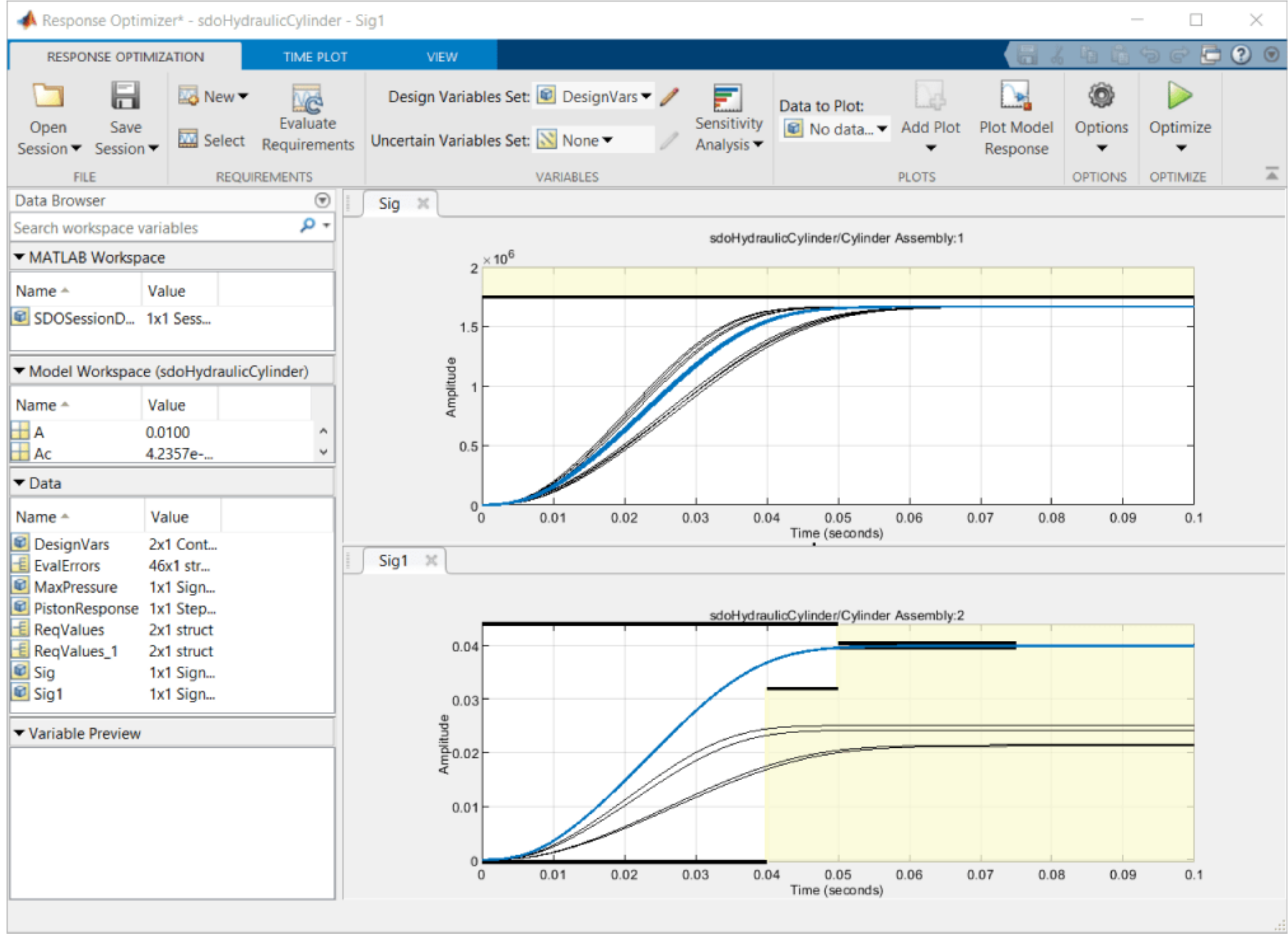
Iteration	F-count	MaxPressure (<=0)	PistonResponse (<=0)
0	5	-0.0480	0.3033
1	10	-0.0567	0.3726
2	20	-0.0526	0.3545
3	28	-0.0554	0.3678
4	39	-0.0528	0.3556
5	48	-0.0547	0.3646
6	60	-0.0535	0.3593
7	71	-0.0544	0.3633
8	83	-0.0538	0.3606
9	97	-0.0541	0.3619
10	108	-0.0541	0.3619

Optimization Options Using Surrogate Solver

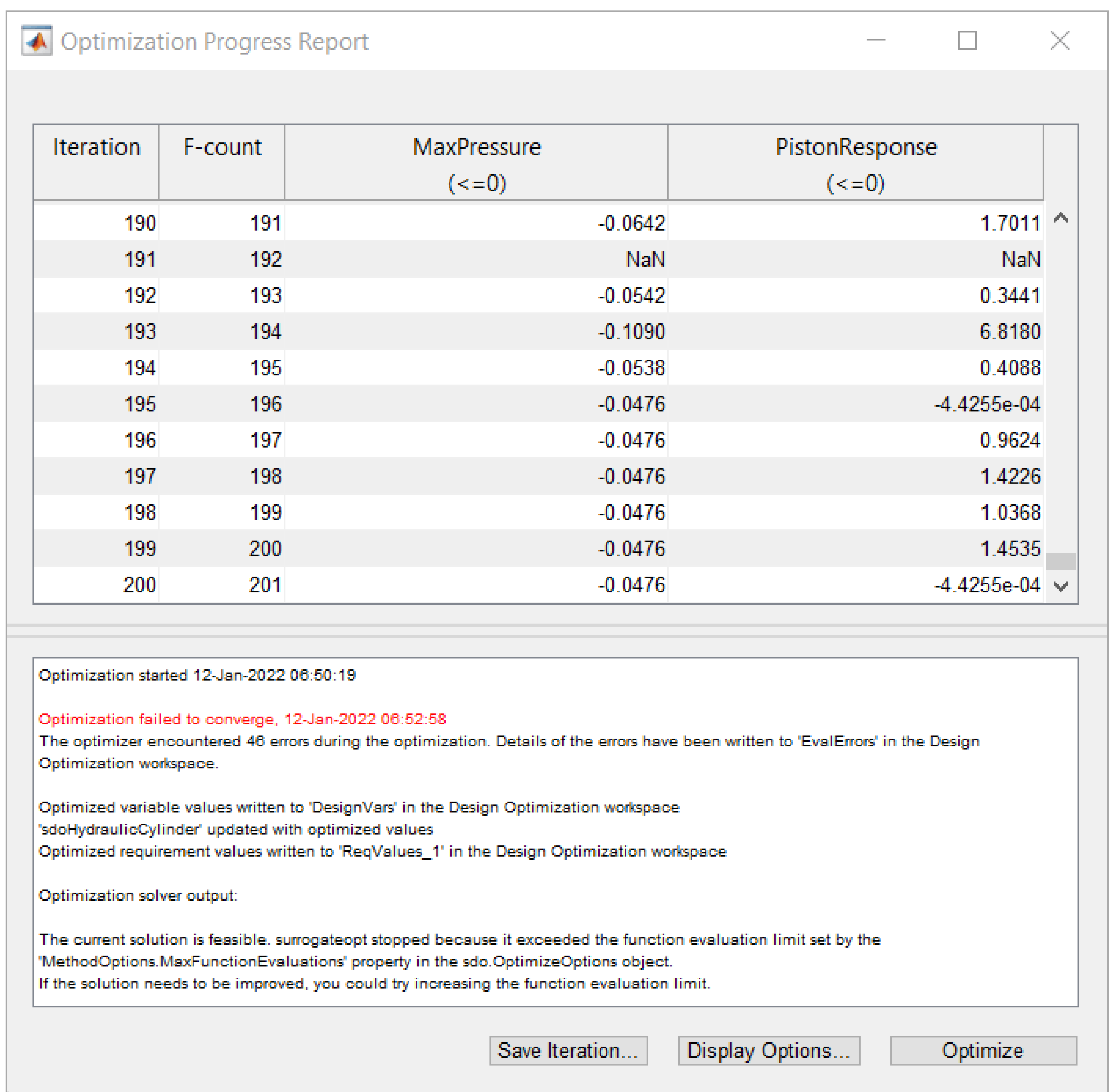
Since the derivative-based solver does not satisfy all the requirements, try surrogate optimization as a derivative-free solver. Click the **Options** button in the toolstrip of the app and navigate to the **Optimization** pane. Select the surrogate optimization solver and set the maximum evaluations to 200. Click **OK** to use these options.



Some stages of surrogate optimization use pseudo-random number generators to select points at which to evaluate the surrogate model. For reproducible results, type `rng('default')` in the MATLAB command window. Run the optimization by clicking **Optimize** in the toolstrip of the app. At the end of optimization, both requirements are satisfied, as seen in the curves in the plots in the app, and negative values in the bottom row of both requirement columns in the numeric progress display. The surrogate optimization solver does not have the same definitions of convergence as other solvers, and only declares that the optimization converged in cases where the objective function is designed to be minimized, and the final value of the objective function is below the objective limit in the options. The problem being solved here does not have an objective function being minimized; rather, it has requirements to be satisfied. For this problem, the optimization satisfied both of these constraint requirements.



Response Optimizer* - sdoHydraulicCylinder - Sig1
RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
Sensitivity Analysis
VARIABLES
Data to Plot:
No data...
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
Optimize
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
SDOSessionD...
1x1 Sess...
Model Workspace (sdoHydraulicCylinder)
A
0.0100
Ac
4.2357e-...
Data
DesignVars
2x1 Cont...
EvalErrors
46x1 str...
MaxPressure
1x1 Sign...
PistonResponse
1x1 Step...
ReqValues
2x1 struct
ReqValues_1
2x1 struct
Sig
1x1 Sign...
Sig1
1x1 Sign...
Variable Preview
Sig
sdoHydraulicCylinder/Cylinder Assembly:1
Amplitude
Time (seconds)
Sig1
sdoHydraulicCylinder/Cylinder Assembly:2



Iteration	F-count	MaxPressure (<=0)	PistonResponse (<=0)
190	191	-0.0642	1.7011
191	192	NaN	NaN
192	193	-0.0542	0.3441
193	194	-0.1090	6.8180
194	195	-0.0538	0.4088
195	196	-0.0476	-4.4255e-04
196	197	-0.0476	0.9624
197	198	-0.0476	1.4226
198	199	-0.0476	1.0368
199	200	-0.0476	1.4535
200	201	-0.0476	-4.4255e-04

In this example, a solver using surrogates is successful on an optimization problem while a derivative-based solver is unsuccessful. The `surrogateopt` solver is a global solver that tries many starting points. By using a surrogate of the model, `surrogateopt` needs to run the model only a moderate number of times.

See Also

`sdo.OptimizeOptions` | `sdo.optimize`

Related Examples

- “Single Hydraulic Cylinder Simulation”
- “Surrogate Optimization in Simulink Design Optimization” on page 3-296

Sensitivity Analysis

- “What is Sensitivity Analysis?” on page 4-2
- “Specify Parameters for Design Exploration” on page 4-4
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Specify Time-Domain Requirements” on page 4-21
- “Specify Parameters Requirements” on page 4-36
- “Specify Frequency-Domain Requirements” on page 4-48
- “Evaluate Design Requirements” on page 4-60
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67
- “Use Sensitivity Analysis to Configure Estimation and Optimization” on page 4-74
- “Interact with Plots in the Sensitivity Analyzer” on page 4-79
- “Validate Sensitivity Analysis” on page 4-96
- “Store Intermediate Data in the App” on page 4-100
- “Specify Steady-State Operating Point for Sensitivity Analysis” on page 4-102
- “Use Parallel Computing for Sensitivity Analysis” on page 4-104
- “Use Fast Restart Mode During Sensitivity Analysis” on page 4-109
- “Design Exploration Using Parameter Sampling (GUI)” on page 4-112
- “Identify Key Parameters for Estimation (GUI)” on page 4-131
- “Explore Design Reliability Using Parameter Sampling (GUI)” on page 4-145
- “Design Exploration Using Parameter Sampling (Code)” on page 4-157
- “Identify Key Parameters for Estimation (Code)” on page 4-169
- “Generate MATLAB Code for Sensitivity Analysis Statistics to Identify Key Parameters (GUI)” on page 4-179
- “Generate MATLAB Code for Sensitivity Analysis for Design Space Exploration and Evaluation (GUI)” on page 4-183

What is Sensitivity Analysis?

Sensitivity analysis is defined as the study of how uncertainty in the output of a model can be attributed to different sources of uncertainty in the model input[1]. In the context of using Simulink Design Optimization software, sensitivity analysis refers to understanding how the parameters and states (optimization design variables) of a Simulink model influence the optimization cost function. Examples of using sensitivity analysis include:

- Before optimization — Determine the influence of the parameters of a Simulink model on the output. Use sensitivity analysis to rank parameters in order of influence, and obtain initial guesses for parameters for estimation or optimization.
- After optimization — Test how robust the cost function is to small changes in the values of optimized parameters.

One approach to sensitivity analysis is local sensitivity analysis, which is derivative based (numerical or analytical). Mathematically, the sensitivity of the cost function with respect to certain parameters is equal to the partial derivative of the cost function with respect to those parameters. The term *local* refers to the fact that all derivatives are taken at a single point. For simple cost functions, this approach is efficient. However, this approach can be infeasible for complex models, where formulating the cost function (or the partial derivatives) is nontrivial. For example, models with discontinuities do not always have derivatives.

Local sensitivity analysis is a one-at-a-time (OAT) technique. OAT techniques analyze the effect of one parameter on the cost function at a time, keeping the other parameters fixed. They explore only a small fraction of the design space, especially when there are many parameters. Also, they do not provide insight about how the interactions between parameters influence the cost function.

Another approach to sensitivity analysis is global sensitivity analysis, often implemented using Monte Carlo techniques. This approach uses a representative (global) set of samples to explore the design space. Use Simulink Design Optimization software to perform global sensitivity analysis using the **Sensitivity Analyzer**, or at the command line. The workflow is as follows:

1. Sample the model parameters using experimental design principles. That is, for each parameter, generate multiple values that the parameter can assume. Define the parameter sample space by specifying probability distributions for each parameter. You can also specify parameter correlations.

   For information about sampling parameters, see “Generate Parameter Samples for Sensitivity Analysis” on page 4-8.
2. Define a cost function by creating a design requirement on the model signals.
3. Evaluate the requirement (cost function) at each combination of parameter values using Monte Carlo simulations. You can plot the cost function output for the samples to visually analyze trends.
4. (Optional) Formally analyze the relation between the evaluated requirement and the samples. Analysis methods include correlation, partial correlation (requires Statistics and Machine Learning Toolbox™ software), and standardized regression. You can configure each analysis method to use either raw or ranked data.

   For information about the analysis methods, see “Analyze Relation Between Parameters and Design Requirements” on page 4-67.

References

[1] Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., and Tarantola, S. *Global Sensitivity Analysis. The Primer*, John Wiley and Sons, 2008.

See Also

`sdo.sample` | `sdo.evaluate` | `sdo.analyze` | `sdo.scatterPlot`

Related Examples

- “Design Exploration Using Parameter Sampling (GUI)” on page 4-112
- “Design Exploration Using Parameter Sampling (Code)” on page 4-157
- “Identify Key Parameters for Estimation (GUI)” on page 4-131
- “Identify Key Parameters for Estimation (Code)” on page 4-169

More About

- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67
- “Validate Sensitivity Analysis” on page 4-96

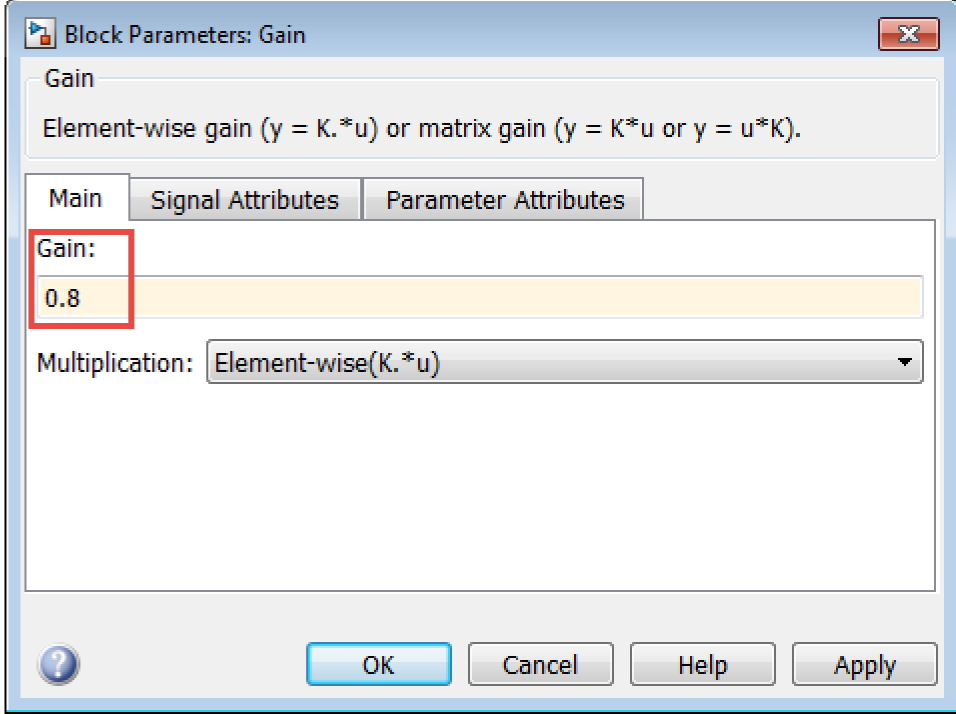
Specify Parameters for Design Exploration

This topic shows how to select parameters of a Simulink model for design exploration in the **Sensitivity Analyzer**. After you select the parameters, you generate parameter samples on page 4-8 by varying the parameter values in a specific range, and evaluate your design requirements for each combination of parameter values.

Add Model Parameters as Variables

The software can only evaluate variables that are in use by the model. Create variables in the MATLAB or model workspace, and specify your Simulink model or block parameters using these variables. If you have already specified model parameters as variables, Select Parameters for Design Exploration on page 4-6.

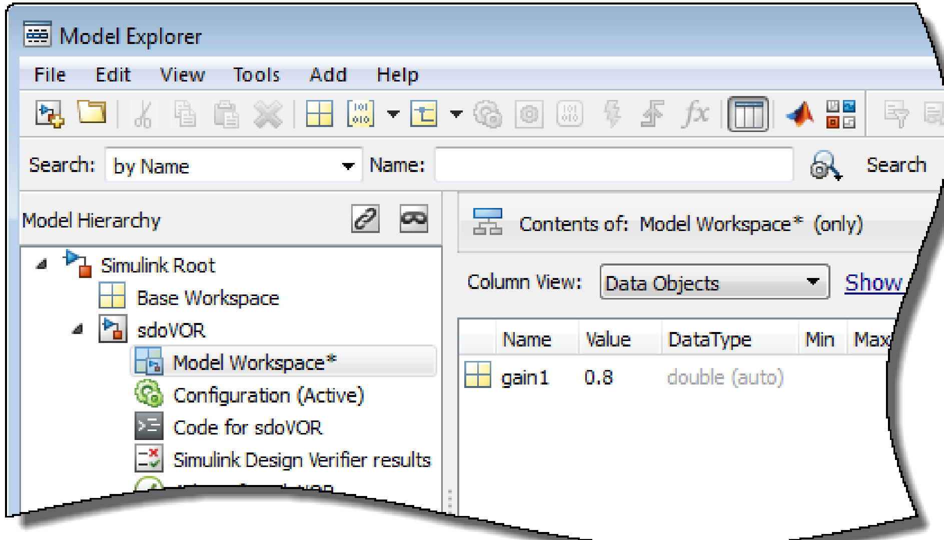
In this figure, the **Gain** parameter of a Gain block is specified as a numerical value.



To evaluate design requirements using the **Gain** parameter, specify it as variable `gain1`:

1 Create the variable `gain1` in one of the following ways:

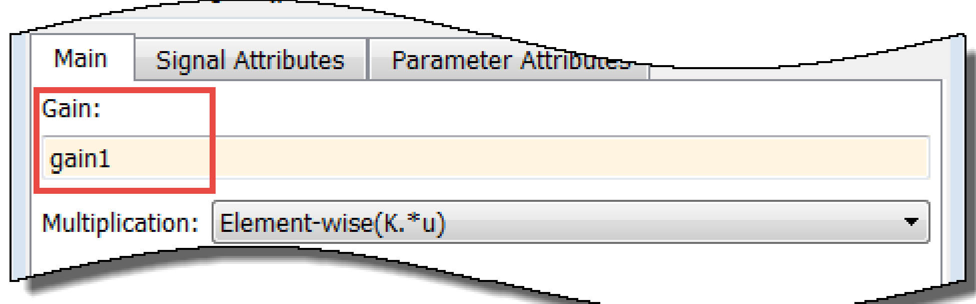
   - Add the variables to the model workspace, and specify initial values.



- Write initialization code in the **PreloadFcn** callback of the model. For more information, see “Model Callbacks”.

  ```
  gain1 = 0.8
  ```

2 Specify the block parameter as variable `gain1` in the Gain block dialog box.



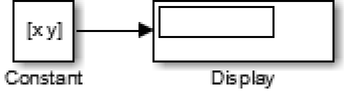
You can now select `gain1` for evaluation. See, “Select Parameters for Design Exploration” on page 4-6.

Specify Independent Parameters

You can also specify independent parameters that do not appear explicitly in the model as variables. However, you cannot use this workflow with Simulink fast restart.

Suppose that a model parameter `Kint` is related to independent parameters `x` and `y` such that `Kint = x+y`. To add `x` and `y` instead of `Kint`:

- Create the independent variables `x` and `y` by adding them to the model workspace and specifying initial values.
- The software only allows evaluation of variables that are used by model blocks. To ensure that the software detects `x` and `y` for evaluation, add a Constant block to your model, and specify the **Constant value** of the block as `[x y]`. Connect the block to a Display block.



- Write code in the **InitFcn** callback of the model that defines the relationship between `Kint`, `x`, and `y`. You must first use the `get_param` function to get the variables `x` and `y` from the model workspace before you can use them to define `Kint`.

```
wks = get_param(gcs,'ModelWorkspace')
x = evalin(wks,'x')
y = evalin(wks,'y')
Kint = x+y;
```

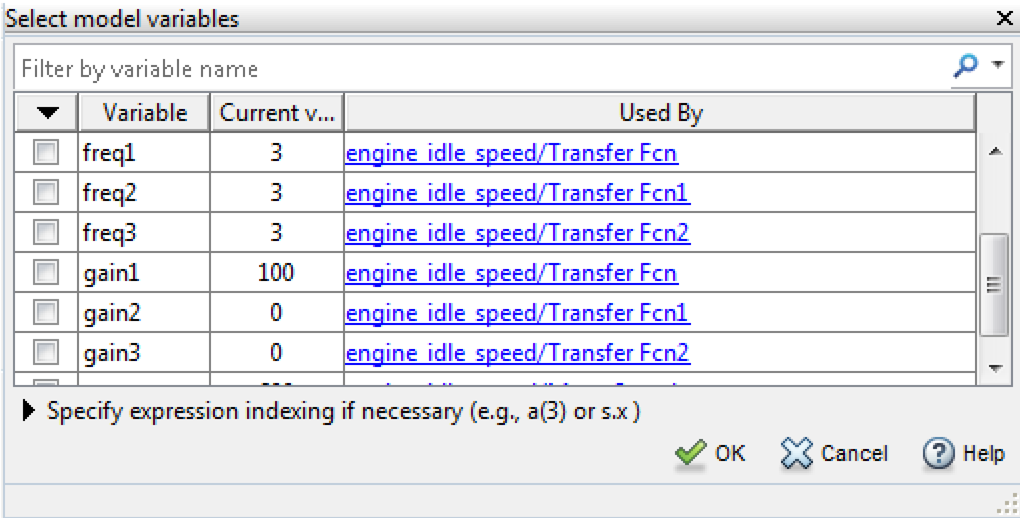
You can now select `x` and `y` for design exploration.

Select Parameters for Design Exploration

In the **Sensitivity Analyzer**, in the **Sensitivity Analysis** tab, click **Select Parameters** to open the Select model variables dialog box.

Use this dialog box to select parameters to vary. The table lists the variables that the model uses to set block parameter values. The variables can reside in the model workspace, the base workspace, or a data dictionary.

Select variables by clicking the check box next to each variable. If your model contains many variables, filter the list by typing in the **Filter by variable name** field. The **Used By** column lists all blocks in the model that use the variable. When a variable is used in more than one block, all blocks are listed. To highlight blocks in the model that use the variable, click the block name.



The variables that you select must have a numeric value that uses the data type `double`. If the value of a variable is not a `double` number, use these techniques:

- To select a single element or a subset of a matrix or array variable, click **Specify expression indexing if necessary**.

Specify expression indexing if necessary (e.g., a(3) or s.x)

Enter an expression such as `myArray(2)`, which selects the second element of an array variable `myArray`.

After you type the expression, press the **Enter** key to add the variable to the list of model variables.

- To use a variable of a numeric data type other than `double`, convert the variable to a `Simulink.Parameter` object, which separates a parameter value from its data type. Set the `Value` property to a default `double` number, and use the `DataType` property to control the data type.
- To use the value of a `Simulink.Parameter` object, specify the `Value` property. Enter the expression `myParamObj.Value`.
- To use a numeric field of a structure, enter `myStruct.PID.P1`. If you store the structure in a `Simulink.Parameter` object, enter `myStruct.Value.PID.P1`.
- To use one cell of a cell array, enter `myCells{3}`.

You cannot use mathematical expressions such as $a + b$. Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters, see “Add Model Parameters as Variables” on page 4-4.

See Also

Related Examples

- “What is Sensitivity Analysis?” on page 4-2
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8

Generate Parameter Samples for Sensitivity Analysis

This topic shows how to generate parameter samples for sensitivity analysis.

You can perform global sensitivity analysis using Simulink Design Optimization software. Using techniques such as design of experiments (DOE) (also referred to as experimental design), you can choose a parameter set for sensitivity analysis.

You generate parameter samples by varying the value of the Simulink model parameters and states of interest according to a specified probability distribution. These parameters and states are collectively referred to as parameters. Each combination of generated parameter values is referred to as a sample or sample point. A collection of samples is referred to as a design space, sample space, or parameter set.

After generating a parameter set, you define a cost function by creating design requirements on the model signals. You then evaluate the cost function for each sample in the parameter set. Then, you analyze the relation between the parameters and requirement to understand how the parameters influence the cost function.

You can generate two kinds of parameter values: random parameter values on page 4-8 or gridded parameter values on page 4-16.

Generate Random Parameter Values

When generating random parameter values, you specify the following characteristics of the parameter space:

- “Number of Samples” on page 4-8
- “Sampling Method” on page 4-8
- “Probability Distribution” on page 4-10
- “Parameter Correlations” on page 4-11

You can specify the characteristics of the parameter space either in the **Sensitivity Analyzer** or at the command line on page 4-14.

Number of Samples

Choose enough samples to yield useful results. However, each model evaluation has a computational expense and can be time intensive. As the number of parameters increases, the number of samples required to explore the design space generally increases. For correlation or regression analysis, consider using 10*Np* samples, where *Np* is the number of parameters.

Sampling Method

Specify the method used to generate the samples. You can choose from the following methods:

- **Random** — Random samples are drawn from the probability distributions specified for the parameters.

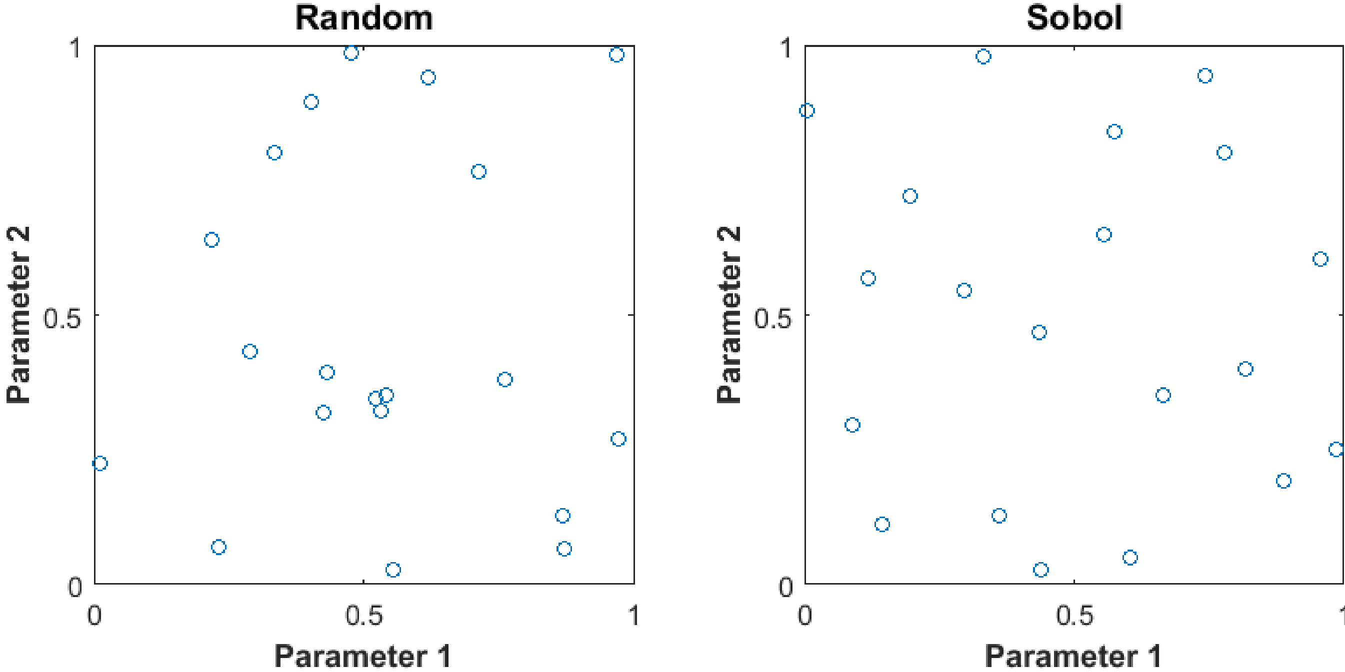
  If you specify correlation between parameters, the software uses the Iman-Conover algorithm to impose the parameter correlations.
- **Latin hypercube**— Latin hypercube samples are drawn from the probability distributions specified for the parameters. Use this option for a more systematic space-filling approach than

random sampling. The Sobol and Halton quasirandom sampling methods are more space-filling than the Latin hypercube method.

If you specify correlation between parameters, the software uses the Iman-Conover algorithm to impose the parameter correlations.

- **Sobol** — Requires Statistics and Machine Learning Toolbox software. Sobol quasirandom sequences are drawn from the probability distributions specified for the parameters. Use this method for highly systematic space-filling.

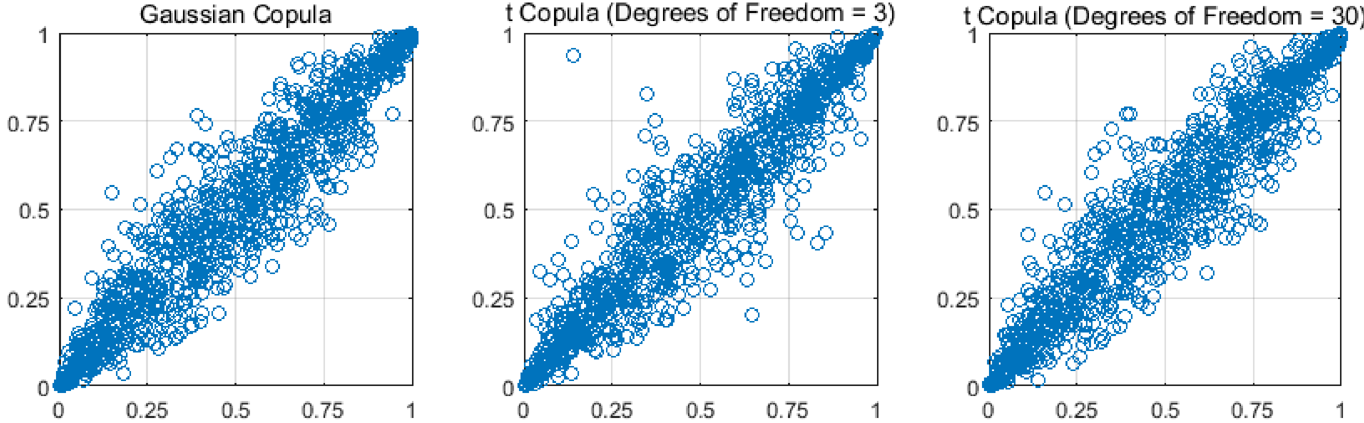
  The figure shows 20 samples for two parameters. The samples are generated from a uniform distribution, in the interval from 0 to 1. Random sampling can result in large gaps between some samples, and close clustering of other samples. Sobol and Halton quasirandom sampling methods avoid gaps and clustering of samples. If you have many parameters in your parameter set, Sobol sets gives more systematic space filling than Halton quasirandom sets. For more information, see “Generating Quasi-Random Numbers” (Statistics and Machine Learning Toolbox).



  If you specify correlation between parameters, the software uses the Iman-Conover algorithm to impose the parameter correlations.
- **Halton** — Requires Statistics and Machine Learning Toolbox software. Halton quasirandom sequences are drawn from the probability distributions specified for the parameters. Like the Sobol method, you can use Halton method for highly systematic space-filling. However, Sobol method gives more systematic space filling if you have many parameters in your parameter set. For more information, see “Generating Quasi-Random Numbers” (Statistics and Machine Learning Toolbox).

  If you specify correlation between parameters, the software uses the Iman-Conover algorithm to impose the parameter correlations.
- **Copula**— Requires Statistics and Machine Learning Toolbox software. Random samples are drawn from a copula. Use this option to impose correlations between the parameters using copulas.

You can use either a Gaussian copula (default) or a t copula. Use t copulas when the probability of extreme parameter values is not negligible (distribution is heavy-tailed), and specify the degrees of freedom. As you increase the degrees of freedom, the t copula converges to the Gaussian copula, and the probability of extreme parameter values becomes negligible. The following figure shows 1000 samples drawn for two parameters in the interval from 0 to 1 using the Gaussian and t copulas.



In comparison to the Gaussian copula, the t copula has more samples that represent the extreme values of the parameters. As the degrees of freedom are increased, the t copula converges to the Gaussian copula.

Specify the correlation type as either Spearman’s rank correlation or Kendall’s rank correlation.

Probability Distribution

Specify the probability distribution function and related distribution characteristics for each parameter. Use your knowledge of the system (empirical or theoretical) to choose the probability distributions.

Note Simulink Design Optimization software allows you to specify uniform (default), normal, multinomial, piecewise linear, and triangular distributions. For other distributions, you need Statistics and Machine Learning Toolbox software.

Consider the following characteristics of your parameters when choosing a distribution:

Parameter Characteristics	Applicable Distributions
Extends from -∞ to ∞	• Normal • Extreme value • Generalized extreme value — Single-ended or from -∞ to ∞, depending on distributional parameter values. • Logistic — heavy tailed compared to normal distribution. • t location-scale — heavy tailed compared to normal distribution.
Bounded at both ends	• Uniform • Beta • Binomial — discrete distribution • Multinomial— discrete distribution • Piecewise linear • Triangular
Extends from 0 to ∞	• Birnbaum-Saunders • Burr • Exponential • Gamma • Generalized extreme value — Single-ended or from -∞ to ∞, depending on parameter values. • Inverse Gaussian • Log-logistic • Log-normal • Nakagami • Negative binomial— discrete distribution • Poisson— discrete distribution • Rayleigh • Rician • Weibull
Custom distribution	Piecewise linear

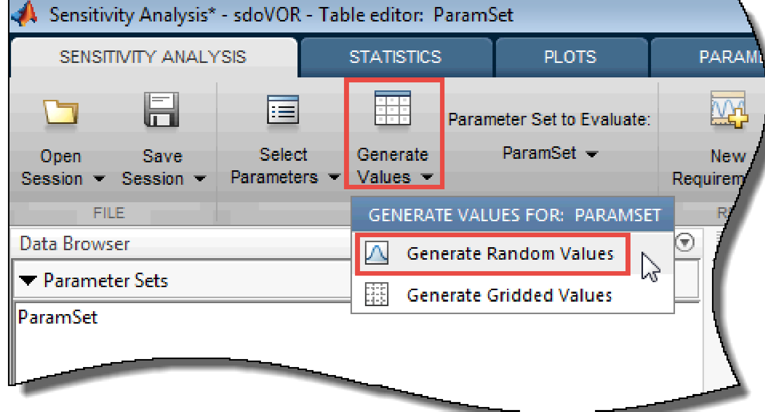
For more information about these distributions, see the “Probability Distributions” (Statistics and Machine Learning Toolbox) category.

Parameter Correlations

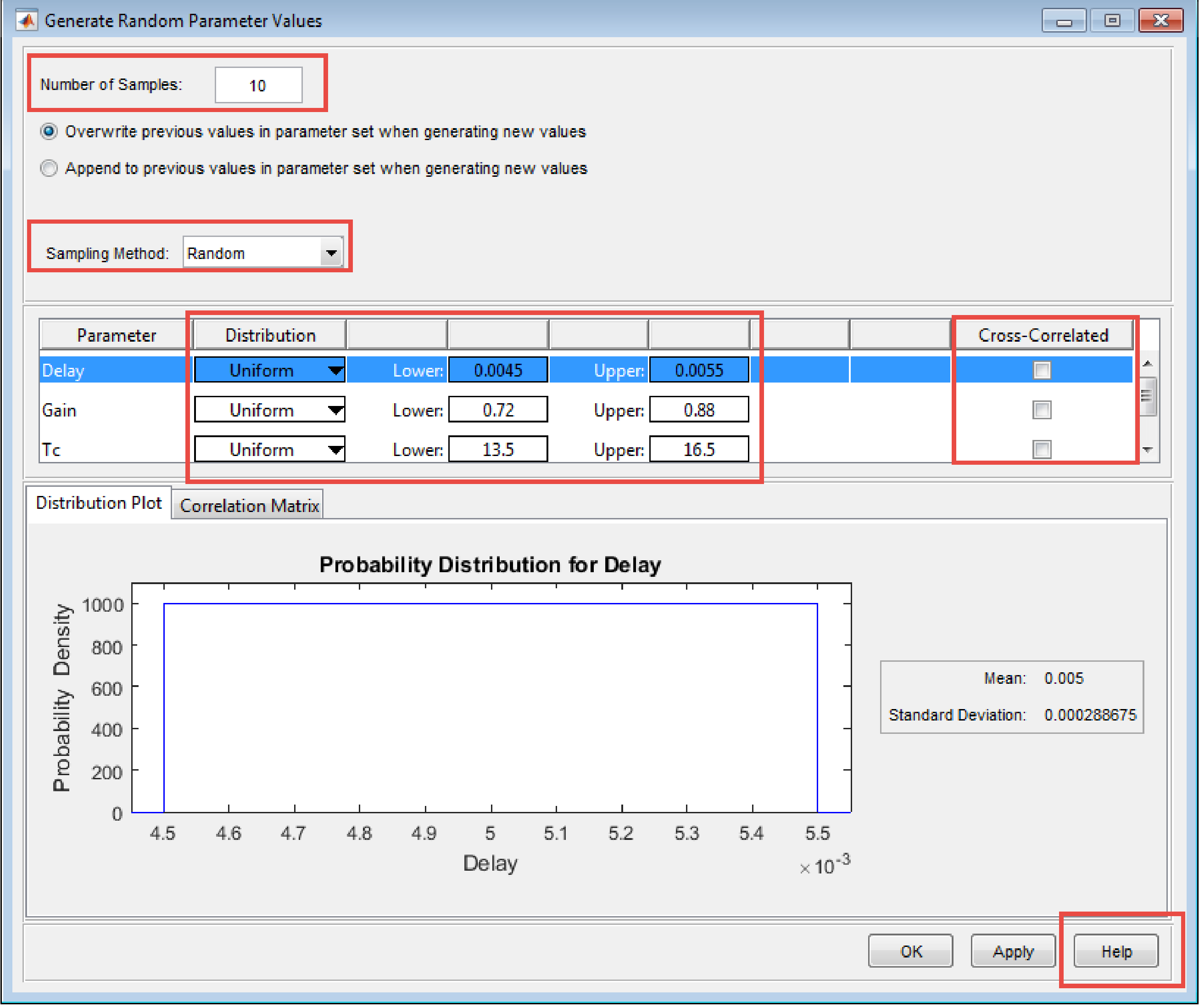
Specify the correlation between parameters. The algorithm used to impose the parameter correlations depends on the sampling method. For more information, see “Sampling Method” on page 4-8.

Generate Random Parameter Values in the App

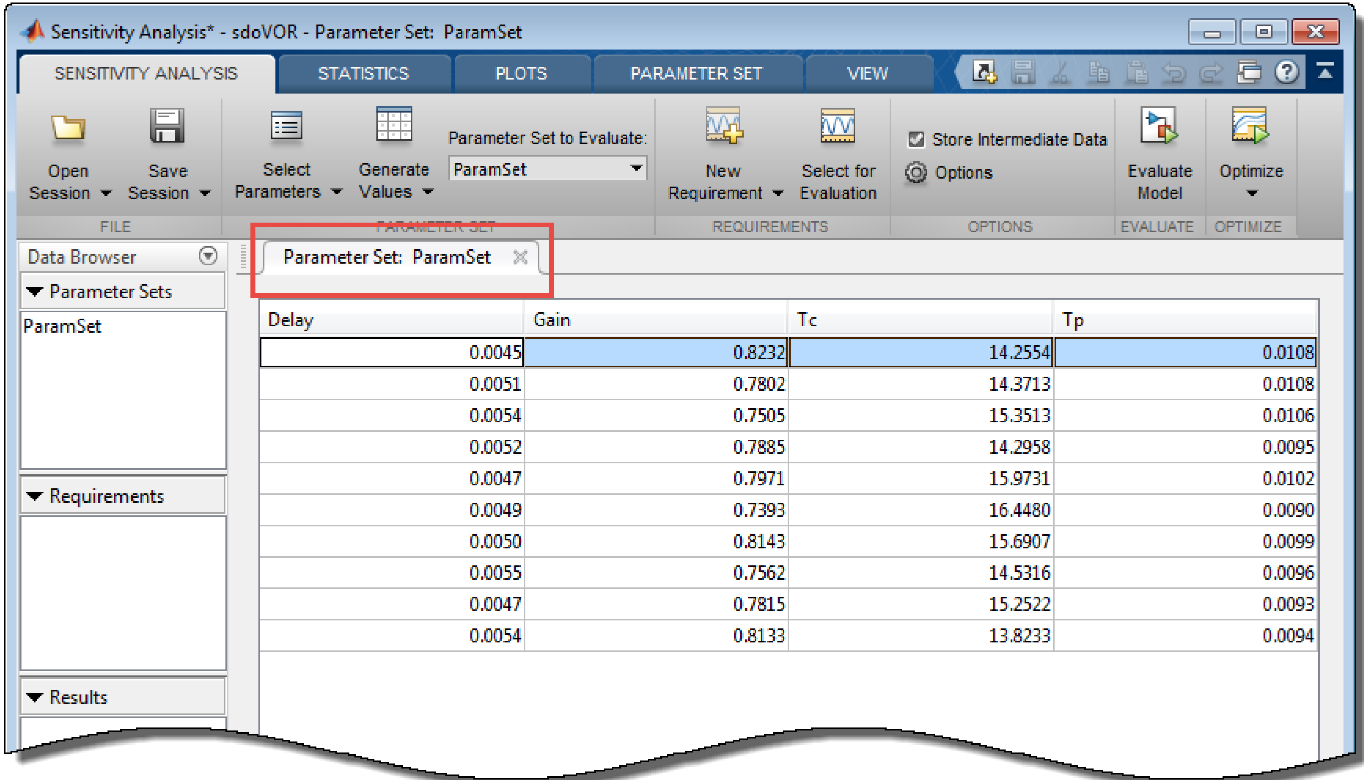
In the **Sensitivity Analyzer**, after you have selected the parameters in the parameter set on page 4-4, click **Generate Values** and, select **Generate Random Values**.



In the Generate Random Parameter Values dialog box, specify the number of samples, probability distributions, parameter bounds and correlations, and sampling method. For information about how to specify the fields in the dialog box, click **Help**.



The generated parameter set and the corresponding parameter set table are displayed in the app. The number of rows in the parameter set table correspond to the number of samples you specified.



After generating the parameter values, plot them to check if generated parameter values match the intended specifications. This is relevant if you generate a small number of random samples for each parameter set. For more information, see “Inspect the Generated Parameter Set” on page 4-96.

For an example, see “Identify Key Parameters for Estimation (GUI)” on page 4-131.

This functionality is not supported in Simulink Online.

Generate Random Parameter Values at the Command Line

At the command line, use `sdo.ParameterSpace` to define the parameter space. This object specifies the probability distributions and correlations for the parameters. Use this object as an input to `sdo.sample` for generating parameter values from the specified parameter space.

To generate the random parameter values:

- Specify the number of samples as the second input argument of `sdo.sample`.
- Specify the method used to generate these samples using the `Method` property of an `sdo.SampleOptions` object. Use this object as an input to `sdo.sample` to specify the sampling options.

  If the method chosen is `'sobol'` or `'halton'`, specify the `MethodOptions` property of `sdo.SampleOptions`.

  If the method chosen is `'copula'`, specify the choice of copula using the `MethodOptions` property of `sdo.SampleOptions`. Also specify the `RankCorrelation` property of the `sdo.ParameterSpace` object.

- Specify the probability distribution of a parameter using the `ParameterDistributions` property of an `sdo.ParameterSpace` object.
- Specify correlation between parameters, using the `RankCorrelation` property of the `sdo.ParameterSpace`.

After generating the parameter values, plot the generated values to check if they match the desired specifications. This is relevant if you generate a small number of random samples for each parameter set. For more information, see “Inspect the Generated Parameter Set” on page 4-96.

For an example, see “Identify Key Parameters for Estimation (Code)” on page 4-169.

Generate Custom Parameter Values at the Command Line

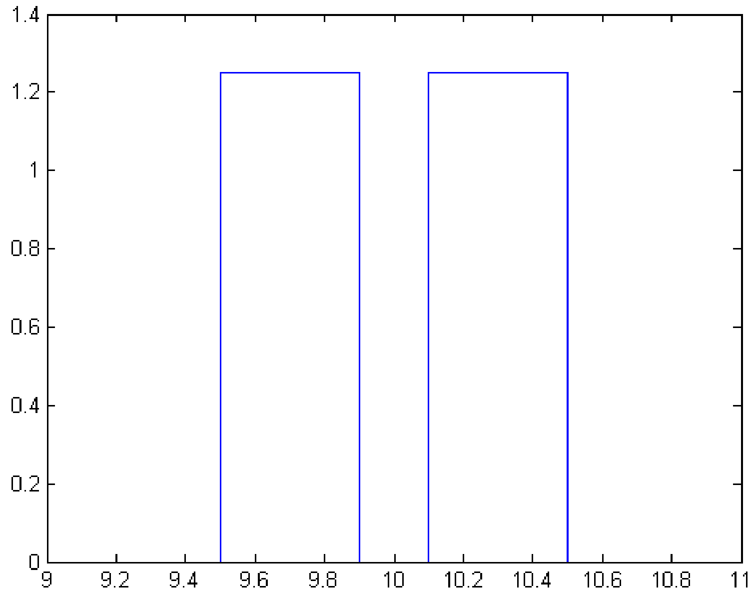
This example shows how to generate random parameter values with a custom distribution when performing sensitivity analysis at the command line. Generate a 1000 samples of a model parameter, R, in the 5% range of its nominal value, 10. R is a resistor. Resistors of 1% tolerance are removed by the manufacturer, so do not generate R values in the 1% range of its nominal value.

1. Construct a `param.Continuous` object.

```
R = param.Continuous('R',10);
```

2. Create a customized probability distribution, `pdR`, to configure the parameter space.

```
x = [0.95 0.99 1.01 1.05]*R.Value;
F = [0 0.5 0.5 1];
pdR = makedist('PiecewiseLinear','x',x,'Fx',F);
x = linspace(0.9*R.Value,1.1*R.Value,1e3);
plot(x,pdf(pdR,x));
```



`makedist` specifies a piecewise linear distribution for the resistor value, with a “hole” in the 1% range.

3 Specify pdR as the probability distribution for the R parameter in an `sdo.ParameterSpace` object.

```
ps = sdo.ParameterSpace(R,pdR);
```

4 Generate 1000 samples.

```
Ns = 1000;
x = sdo.sample(ps,Ns);
```

5 (Optional) Use `sdo.scatterPlot` to visualize the samples and validate the sample space.

Generate Gridded Parameter Values

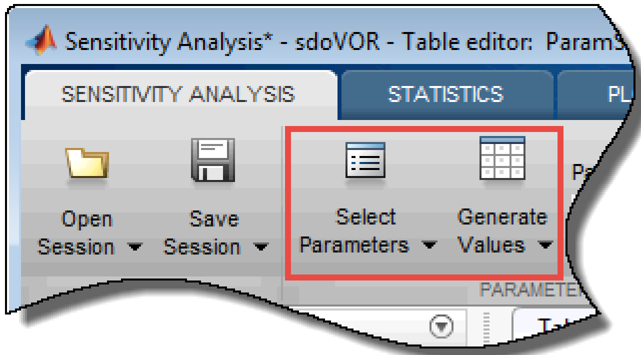
You can generate gridded parameter values in the **Sensitivity Analyzer** or at the command line.

Generate Gridded Parameter Values in the Sensitivity Analyzer

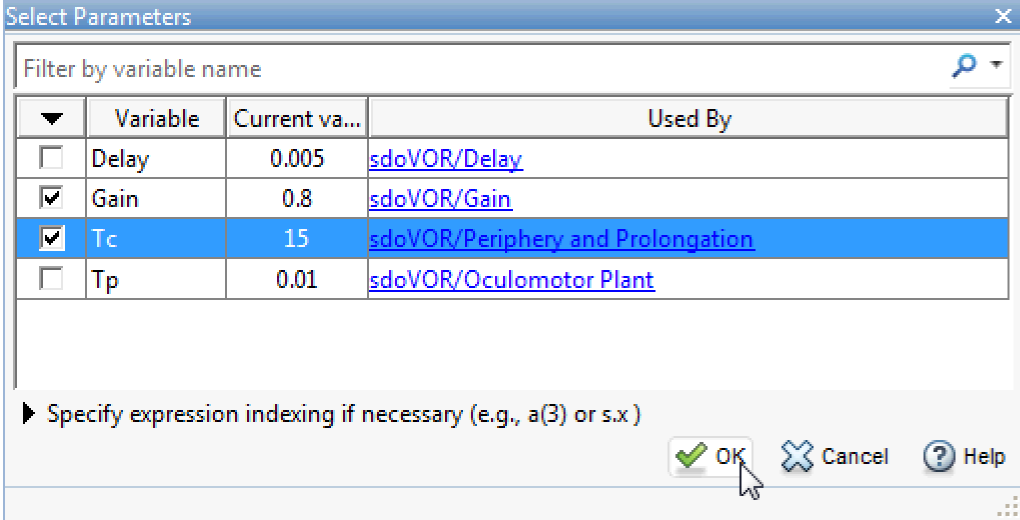
You can generate gridded parameters in the app after you have created a parameter set.

1 Create a parameter set.

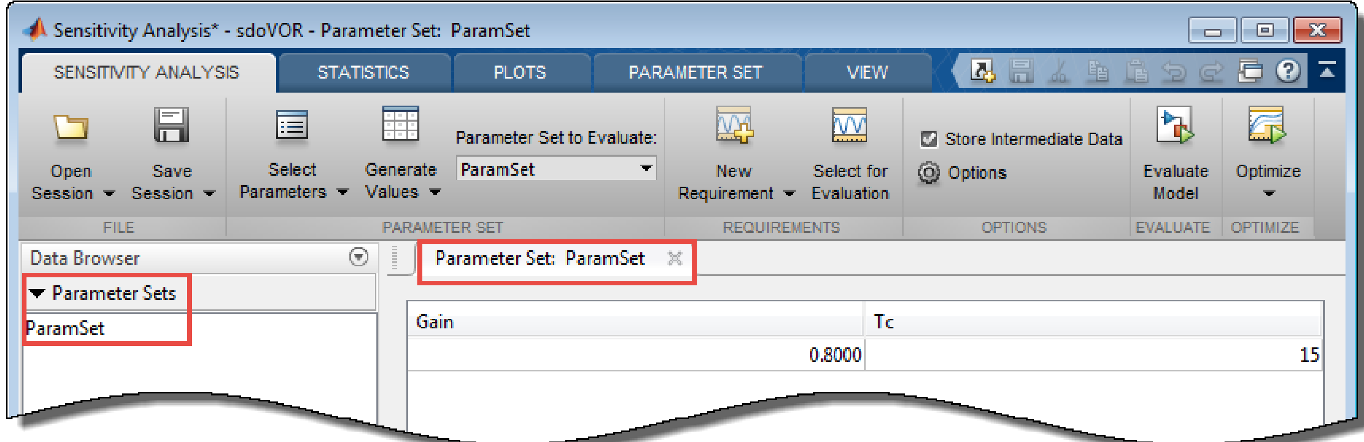
In the **Sensitivity Analyzer**, in the **Sensitivity Analysis** tab, click **Select Parameters**.



In the Select Parameters dialog box, select all the parameters you want to include in your parameter set, and click **OK**.

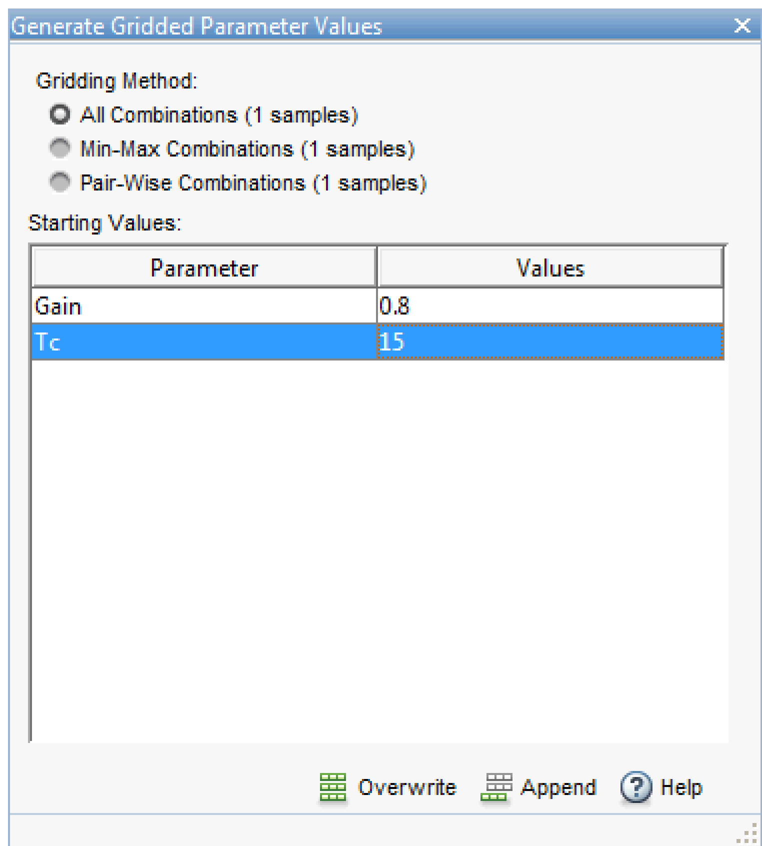


A `ParamSet` variable is created in the **Parameter Sets** area of the app. The current value for each parameter in the parameter set is displayed in a table.



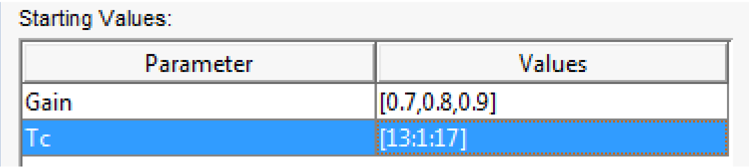
2 Specify the starting parameter values and gridding method for grid generation.

In the Sensitivity Analysis tab, click **Generate Values**, and select **Generate Gridded Values** from the drop-down menu.



In the Generate Gridded Parameter Values dialog box, specify the gridding method as **All Combinations**. The app generates all possible combinations of the values specified in **Values**.

Specify the starting parameter values in **Values**. The values you enter here determine the parameter space. To see the other ways to specify starting parameter values and gridding methods, click **Help**.



Starting Values:

Parameter	Values
Gain	[0.7,0.8,0.9]
Tc	[13:1:17]

3 Generate the parameters.

Click **Overwrite**. The parameter set table updates with the generated gridded parameter values.

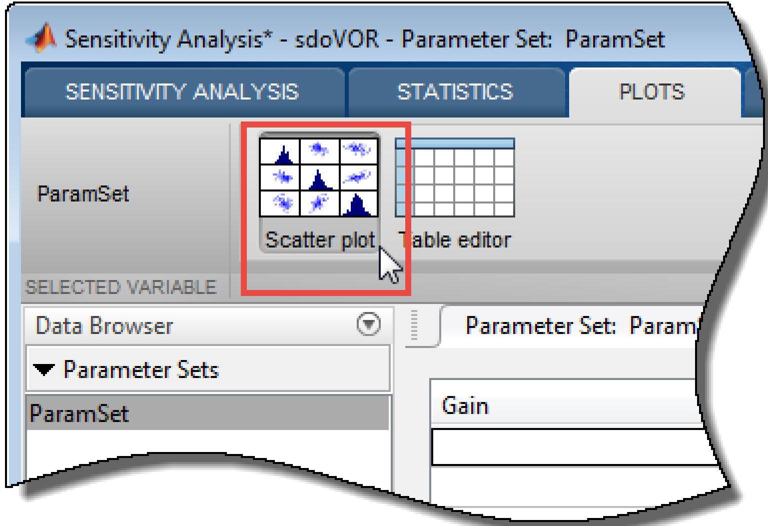
Parameter Set: ParamSet

Gain	Tc
0.7000	13
0.8000	13
0.9000	13
0.7000	14
0.8000	14
0.9000	14
0.7000	15
0.8000	15
0.9000	15
0.7000	16
0.8000	16
0.9000	16
0.7000	17
0.8000	17
0.9000	17

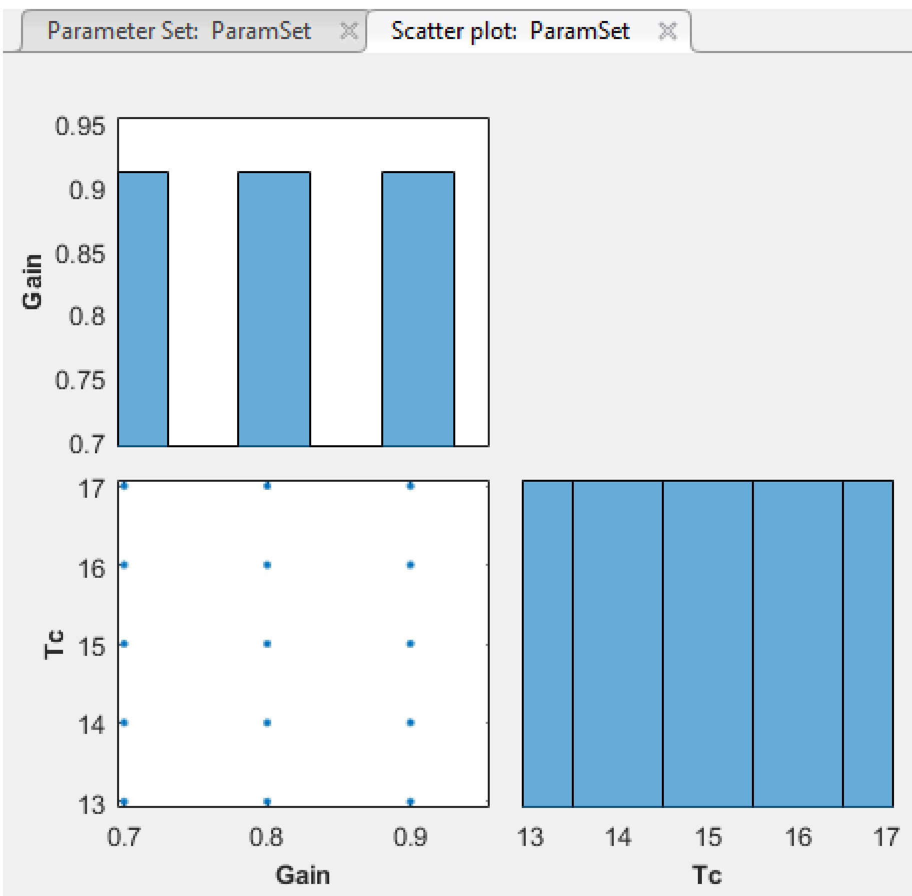
You can also append the generated values to previously generated random or gridded parameter values in the parameter set table. To do so, click **Append**.

4 (Optional) Plot the generated values.

In the **Parameter Sets** area of the app, select **ParamSet**. In the **Plots** tab of the app, select **Scatter Plot** from the plots gallery.



Plots are generated with histograms of the distribution of the parameter values shown on the diagonals. The off-diagonal plots display the scatter plots between pairs of parameters. To learn more about the plots, see "Interact with Plots in the Sensitivity Analyzer" on page 4-79.



This functionality is not supported in Simulink Online.

Generate Gridded Parameter Values at the Command Line

This example shows how to create a table of gridded parameter values at the command line.

Generate a grid of samples for two model parameters, A and B. Vary A between [2,3,4] and B between [20,30,40].

1. Construct a param.Continuous object.

```
A = param.Continuous('A',1);
B = param.Continuous('B',10);
```

2. Specify the parameter values for grid generation.

```
Avals = [2 3 4];
Bvals = [20 30 40];
```

3. Create a table of gridded parameter values. Specify one column for each parameter, and one row for each sample. The column names must be the same as the parameter names.

```
[Agrid,Bgrid] = meshgrid(Avals,Bvals);
x = table(Agrid(:),Bgrid(:),'VariableNames',{'A','B'});
```

```
x =

    A    B
    _    __

    2    20
    2    30
    2    40
    3    20
    3    30
    3    40
    4    20
    4    30
    4    40
```

See Also

sdo.sample | sdo.SampleOptions

Related Examples

- "Inspect the Generated Parameter Set" on page 4-96
- "Design Exploration Using Parameter Sampling (GUI)" on page 4-112
- "Design Exploration Using Parameter Sampling (Code)" on page 4-157
- "Explore Design Reliability Using Parameter Sampling (GUI)" on page 4-145

Specify Time-Domain Requirements

In the **Sensitivity Analyzer**, you can specify the following time-domain requirements:

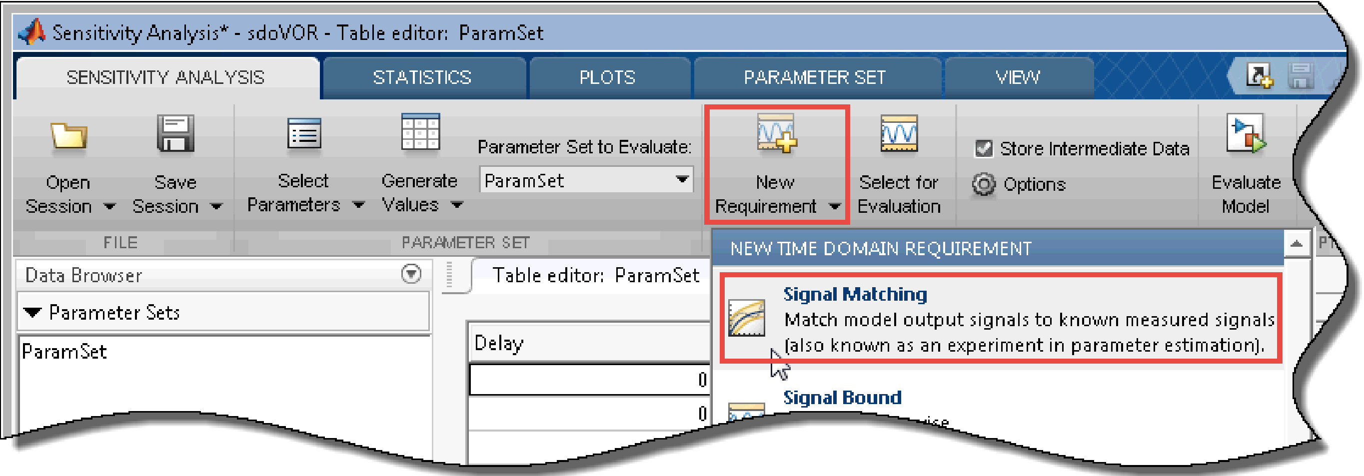
- **Signal Matching** — “Match Model Outputs to Measured Signals” on page 4-21
- **Signal Bound** — “Specify Piecewise-Linear Lower and Upper Bounds” on page 4-24
- **Signal Property** — “Specify Signal Property Requirements” on page 4-26
- **Step Response Envelope** — “Specify Step Response Characteristics” on page 4-27
- **Signal Tracking** — “Track Reference Signals” on page 4-29
- **Ellipse Region Constraint** — “Impose Elliptic Bound on Phase Plane Trajectory of Two Signals” on page 4-31
- **Custom Requirement** — “Specify Custom Requirements” on page 4-33

After you specify the constraints, you can see if the requirements are satisfied by evaluating the design requirements. For more information, see “Evaluate Design Requirements” on page 4-60.

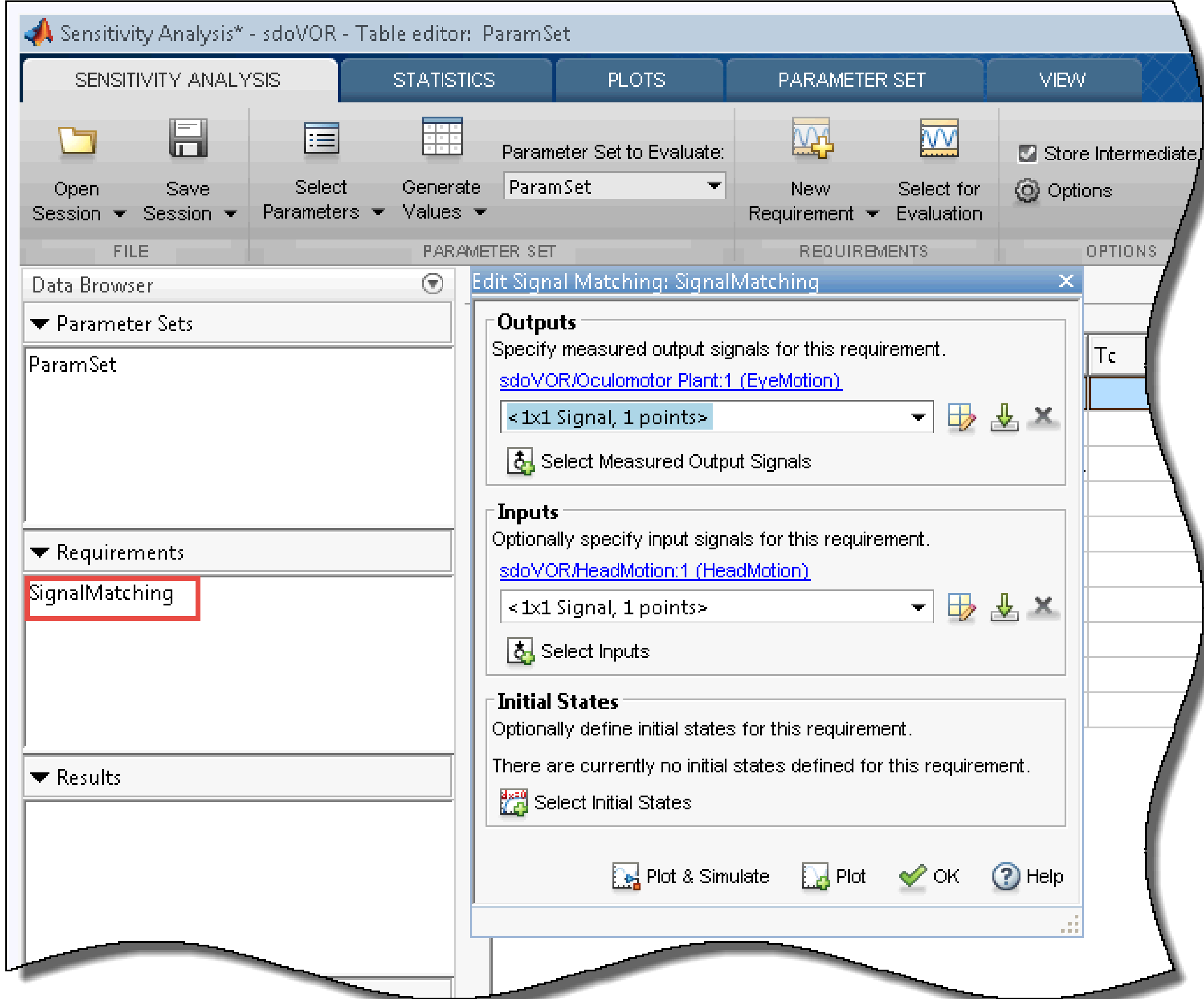
Match Model Outputs to Measured Signals

You can specify a signal matching requirement to match model outputs to measured signals. This requirement is also known as an experiment in the **Parameter Estimator**. To specify a signal matching requirement:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Signal Matching**.



A new signal matching requirement appears in the **Requirements** area of the app. An Edit Signal Matching dialog box opens where you specify this requirement. You specify model output and input signals, and assign measured data to them. You can also specify initial state values.

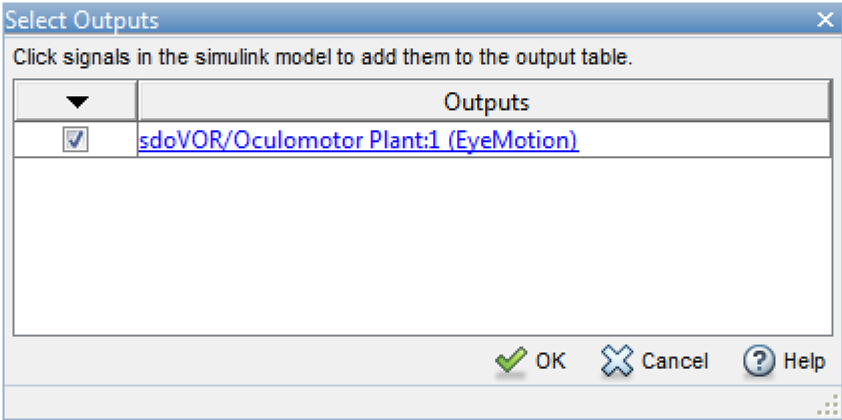


2 In the **Outputs** panel of the Edit Signal Matching dialog box, select output signals, and import output data. You can select more than one output signal, but you can have only one data set for a signal. If you have multiple data sets, create multiple requirements.

a Select the model output signals that you want to add the requirement to.

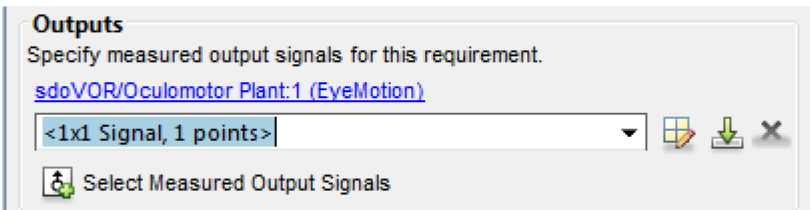
By default, the root-level model output ports and logged signals are already listed in the **Outputs** panel. To remove existing outputs from the signal matching requirement, click the corresponding . To add other output signals, click **Select Measured Output Signals**.

The Select Outputs dialog box opens to display the root-level model Outport blocks and logged signals.

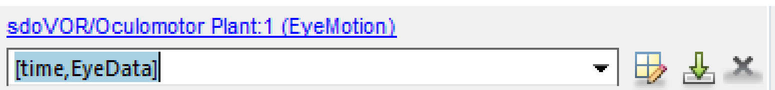


b In the Simulink model window, click the signal to add. The Select Outputs dialog box updates to show the new signals. To add these signals as outputs, select the corresponding check boxes. Click **OK**.

c In the Edit Signal Matching dialog box **Outputs** panel, for each output, import measured output data in one of the following ways:



- Import signal data from spreadsheets or text files — Click , and import the data from the file.
- Import data from the MATLAB workspace — Suppose that the signal data and time data are in the `EyeData` and `time` column vectors in the workspace, respectively. Specify the output data as `[time,EyeData]`.



If your data is stored in a time-series object, `t`, specify the output data as `[t.time,t.outputdata]`.

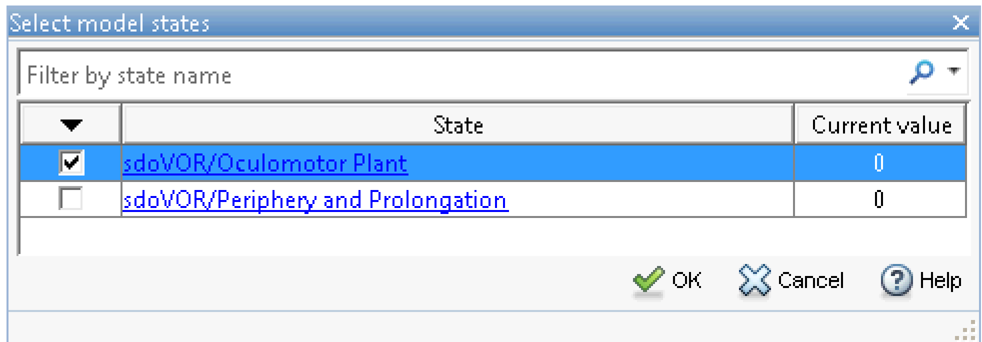
After importing data, to view or edit the data, click .

3 (Optional) Select input signals and import input data in the **Inputs** panel.

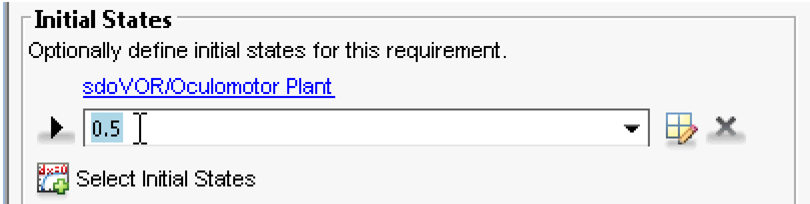
You can have more than one input signal, but you can have only one data set for a signal. If you have multiple data sets, create multiple requirements. By default, the root-level model input ports are already listed in the **Inputs** panel. Remove or add inputs, and import input data, in the same way as described for the output data.

4 (Optional) Specify initial states values in the **Initial States** panel.

By default, the initial conditions specified in the model are used for evaluating the requirement. To specify initial conditions other than the defaults, click **Select Initial States**. In the Select Model States dialog box, select the states to specify, and click **OK**.



The selected states appear in the Edit Signal Matching dialog box **Initial States** panel. Specify the initial states.



5 Close the Edit Signal Matching dialog box.

   The signal matching requirement in the **Requirements** area of the app is updated with the specified characteristics.

6 (Optional) Plot the requirement.

   a In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.

   b In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   Note You can preprocess the data using the preprocess tools in the **Experiment Plot** tab. For more information, see "Preprocess Data" on page 1-13.

Specify Piecewise-Linear Lower and Upper Bounds

To specify upper and lower bounds on a signal:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Signal Bound**.

   A Create Requirement dialog box opens where you specify upper or lower bounds on a signal. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.

2 Select the requirement type from **Type**.

3 Specify the edge start and end times and corresponding amplitude in the **Time (s)** and **Amplitude** columns.

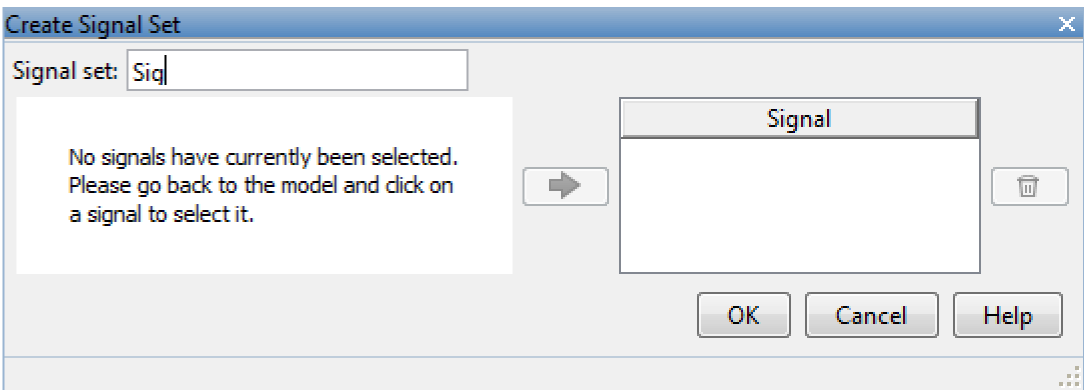
4. Click to specify additional bound edges.

   Select a row and click to delete a bound edge.
5. In the **Select Signals to Bound** area, select a logged signal to apply the requirement to.

   If you have already selected signals, as described in “Specify Signals to Log” on page 3-10, they appear in the list. Select the corresponding check-box.

   If you have not selected a signal to log:

   a. Click . A Create Signal Set dialog box opens where you specify the logged signal.
   b. In the Simulink model window, click the signal to which you want to add a requirement.

   The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.
   c. Select the signal and click to add it to the signal set.
   d. In **Signal set** field, enter a name for the selected signal set.

      Click **OK**. A new variable, with the specified name, appears in the Create Requirement dialog box.
6. Select the check-box corresponding to the signal, and close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
7. (Optional) Plot the requirement.

   a. In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.
   b. In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60.

Alternatively, you can add a Check Custom Bounds block to your model to specify piecewise-linear bounds.

Specify Signal Property Requirements

To specify signal property requirements:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Signal Property**. A Create Requirement dialog box opens where you specify signal property requirements. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2. In the **Specify Property** area, specify a signal property requirement using the **Property** and **Type** lists and the **Bound** box.

   Property List

Property	Description	Time weighting available
`Signal minimum`	Minimum of the signal	No
`Signal maximum`	Maximum of the signal	No
`Signal final value`	Last signal value	No
`Signal mean`	Average of signal value	Yes
`Signal median`	Middle value of signal	Yes
`Signal variance`	Variance of signal	Yes
`Signal interquartile range`	Difference between the 75th and 25th percentiles of signal values	No
`Signal sum`	$\sum_{i=t_0}^{t_N} S(i)$, where $S(t_0), \ldots, S(t_N)$ is the signal to constrain.	Yes
`Signal sum square`	$\sum_{i=t_0}^{t_N} S(i)^2$	Yes
`Signal sum absolute`	$\sum_{i=t_0}^{t_N} \lvert S(i) \rvert$	Yes

   For signal properties where the **Time-Weighted** option is available, you can select it to weight the property computation by the time intervals between samples.

   Custom Signal Property

   You can add a custom signal property to the **Property** list by editing the function `sdo.requirements.signalPropertyFcns`.

   a. At the MATLAB command prompt, enter `edit sdo.requirements.signalPropertyFcns`.
   b. Add your signal property function to the `FcnData` cell array.

      Your signal property function must be on the path.

3 In the **Select Signals to Bound** area, select the logged signal to which you want to apply the requirement.

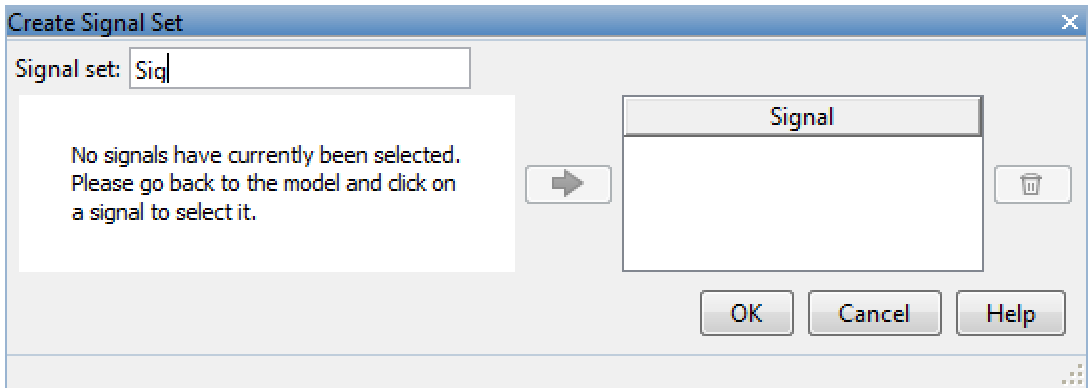
The signal selected must have numeric type data (either floating-point or integer). Also, if the property selected is `Signal median`, `Signal variance`, or `Signal interquartile range`, then the signal data must be floating-point (either double or single).

If you have already selected a signal, as described in “Specify Signals to Log” on page 3-10, the signal appears in the list. Select the corresponding check box for that signal.

If you have not selected a signal to log:

a Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.

b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [⇨] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

Click **OK**. A new variable, with the specified name, appears in the Create Requirement dialog box.

4 Select the check-box corresponding to the signal, and close the Create Requirement dialog box.

The requirement in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60. When you perform evaluation, a positive requirement value indicates that the requirement has been violated.

Specify Step Response Characteristics

To apply a step response requirement to a signal in your model, specify the step response characteristics as follows:

1 Select a step response requirement from the **Sensitivity Analyzer**.

In the **New Requirement** drop-down list of the app, in the **New Time Domain Requirement** section, select **Step Response Envelope**.

A Create Requirement dialog box opens where you specify the step response requirements on a signal. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.

2 Specify the step response characteristics:

- **Initial value** — Input level before the step occurs
- **Step time** — Time at which the step takes place
- **Final value** — Input level after the step occurs
- **Rise time** — The time taken for the response signal to reach a specified percentage of the step range. The step range is the difference between the final and initial values.
- **% Rise** — The percentage of the step range used with **Rise time** to define the overall rise time characteristics.
- **Settling time** — Time taken until the response signal settles within a specified region around the final value. This settling region is defined as the final step value plus or minus the settling range, defined in **% Settling**.
- **% Settling** — The percentage of the step range value that defines the settling range of settling time characteristic specified in **Settling time**.
- **% Overshoot** — The amount by which the response signal can exceed the final value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
- **% Undershoot** — The amount by which the response signal can undershoot the initial value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.

3 Specify the signal to be bound.

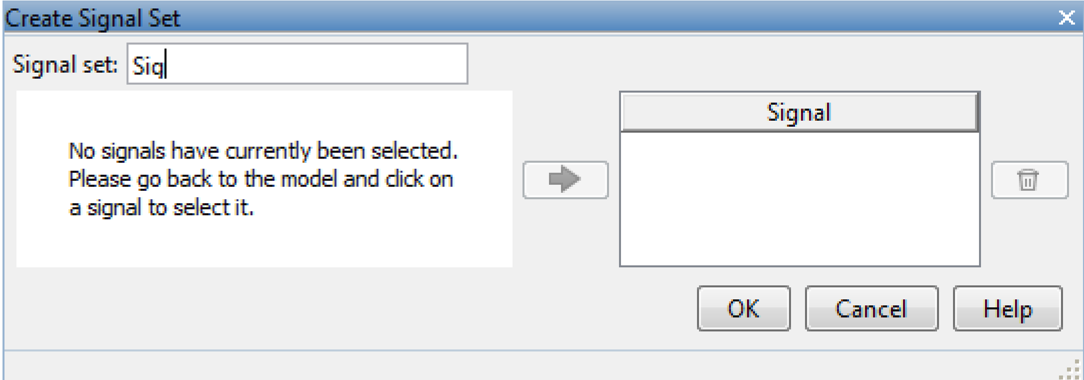
To apply this requirement to a model signal, in the **Select Signals to Bound** area, select a logged signal to which you will apply the requirement.

If you have already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, it appears in the list. Select the corresponding check-box.

If you have not selected a signal to log:

a Click [+]. The Create Signal Set dialog box opens where you specify the logged signal.

b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c. Select the signal and click [button] to add it to the signal set.
d. In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the Create Requirement dialog box.

4. Select the check-box corresponding to the signal, and close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
5. (Optional) Plot the requirement.

   a. In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.
   b. In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

You can now evaluate the requirement. For more information, see "Evaluate Design Requirements" on page 4-60.

Alternatively, you can use the Check Step Response Characteristics block to specify step response bounds for a signal.

Track Reference Signals

Use reference tracking to force a model signal to match a desired signal. To track a reference signal:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Signal Tracking**.

   A Create Requirement dialog box opens where you specify the reference signal to track. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2. Define the reference signal by entering vectors, or variables from the workspace, in the **Time vector** and **Amplitude** fields.

Click **Update reference signal data** to use the new amplitude and time vector as the reference signal.

3 Specify how the optimization solver minimizes the error between the reference and model signals using the **Tracking Method** list:

- SSE — Reduces the sum of squared errors
- SAE — Reduces the sum of absolute errors

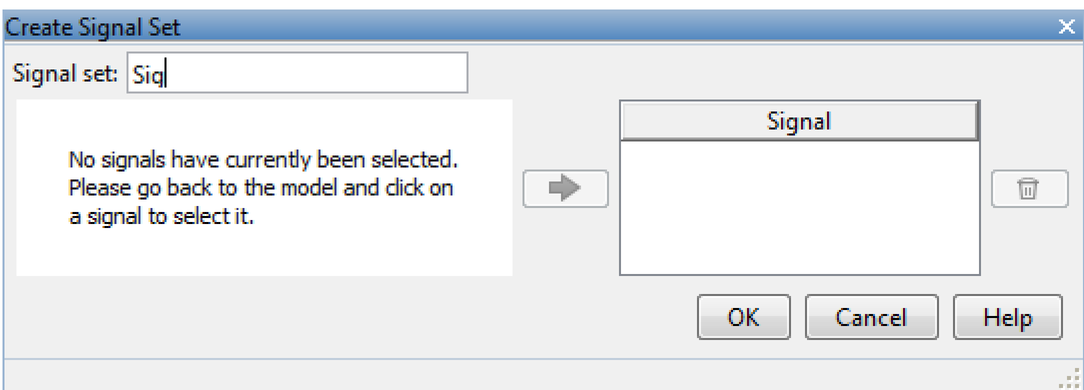
4 In the **Specify Signal to Track Reference Signal** area, select a logged signal to apply the requirement to.

If you already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, they appear in the list. Select the corresponding check-box.

If you have not selected a signal to log:

a Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.

b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [⇨] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

Click **OK**. A new variable, with the specified name, appears in the Create Requirement dialog box.

5 Select the check-box corresponding to the signal, and close the Create Requirement dialog box.

The requirement in the **Requirements** area of the app is updated with the specified characteristics.

6 (Optional) Plot the requirement.

a In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.

b In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

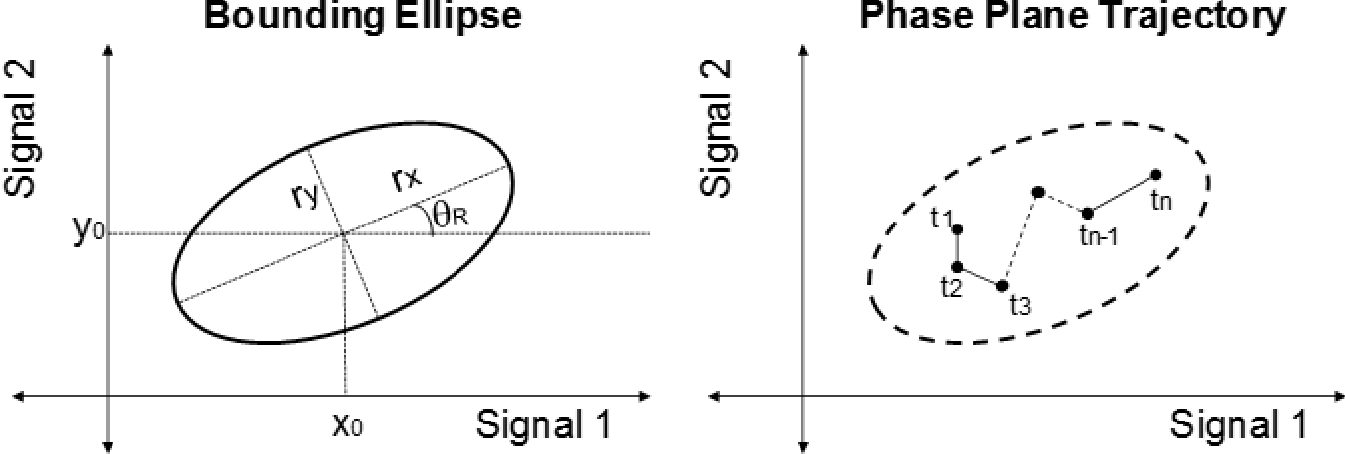
The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Against Reference block to specify a reference signal to track.

Impose Elliptic Bound on Phase Plane Trajectory of Two Signals

You can impose an elliptic bound on the phase plane trajectory of two signals in your Simulink model. The phase plane trajectory is a plot of the two signals against each other. You specify the radii, center, and rotation of the bounding ellipse. You also specify whether you require the trajectory of the two signals to lie inside or outside the ellipse.

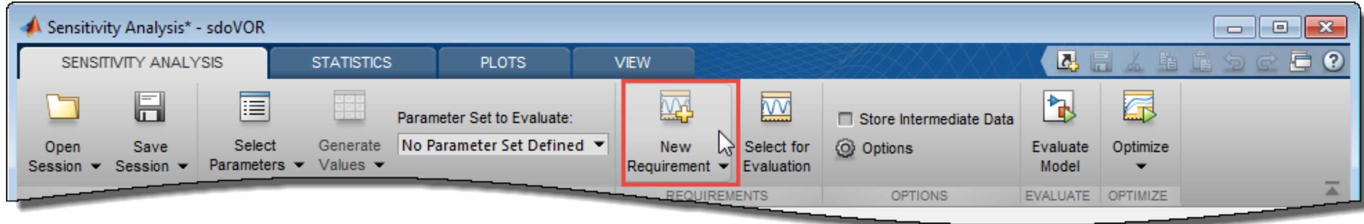
The following image shows the bounding ellipse and an example of the phase plane trajectory of two signals.



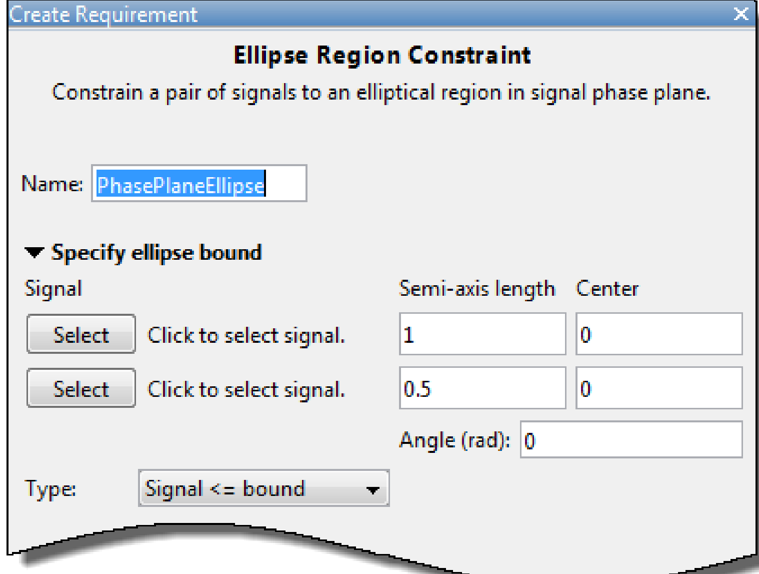
The X-Y plane is the phase plane defined by the two signals. r_x and r_y are the radii of the bounding ellipse along the x and y axes, and θ_R is the rotation of the ellipse about the center. The ellipse center is at (x_0,y_0). In the image, the phase plane trajectory of the signals lies within the bounding ellipse for all time points t_1 to t_n.

To specify the elliptical bound requirement:

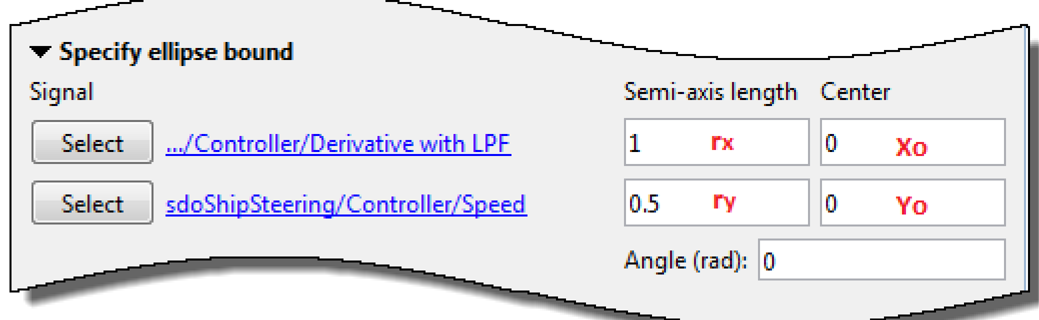
1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Ellipse Region Constraint**.



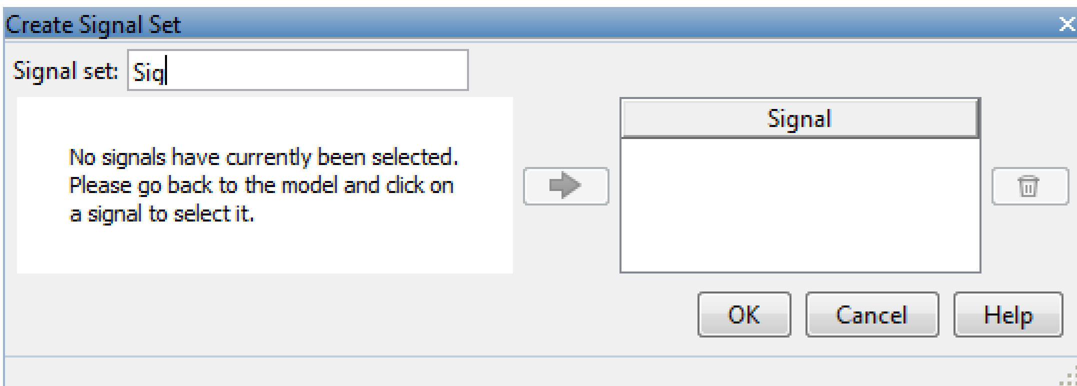
In the Create Requirement dialog box, specify the signals and elliptical bound. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



1 Specify the two signals that you want to impose the requirement on. The signals define the X-Y plane of the bounding ellipse. To specify the signals, click the corresponding **Select** buttons.



When you click **Select**, the Create Signal Set dialog box opens.



In the Simulink model window, click the signal to which you want to add the requirement. The Create Signal Set dialog box updates with the name of the block and the port number where the selected signal is located. Select the signal, and click to add it to the signal set.

Once you have specified the logged signal in the Create Signal Set dialog box, the signal appears in the Create Requirement dialog box.

2 Specify the radii of the bounding ellipse as real positive finite values in **Semi-axis length**. You specify r_x and r_y that are the x-axis and y-axis radii before any rotation about the ellipse center.
3 Specify the location of the center of the bounding ellipse in **Center**. You specify x_0 and y_0, the x and y coordinates of the center, as real finite values.
4 Specify the angle of rotation of the ellipse about its center as a real finite scalar in **Angle (rad)**.
5 Specify the bound **Type** as one of the following:

- `'<='` — Ellipse is an upper bound. The phase plane trajectory of the two signals should lie inside or on the ellipse.
- `'>='` — Ellipse is a lower bound. The phase plane trajectory of the two signals should lie outside or on the ellipse.

1 Close the Create Requirement dialog box.

The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

2 (Optional) Plot the requirement.

a In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.

b In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60.

Specify Custom Requirements

You can specify custom requirements, such as minimizing system energy. To specify custom requirements:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Custom Requirement**.

A Create Requirement dialog box opens where you specify the reference signal to track. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.

2 Specify the requirement type in the **Type** drop-down menu.
3 Specify the name of the function that contains the custom requirement in **Function**. The field must be specified as a function handle using `@`. The function must be on the MATLAB path. Click to review or edit the function.

If the function does not exist, clicking [folder button] opens a template MATLAB file. Use this file to implement the custom requirement. The default function name is `myCustomRequirement`.

4 (Optional) To prevent the solver from considering specific parameter combinations, select **Error if constraint is violated**. Use this option for parameter-only constraints.

   During an optimization iteration, the solver first evaluates requirements with this option selected.

   - If the constraint is violated, the solver skips evaluating any remaining requirements and proceeds to the next combination of parameters in the parameter set.
   - If the constraint is *not* violated, the solver evaluates the remaining requirements for the current combination of parameter values. If any of the remaining requirements bound signals or systems, then the solver simulates the model.

   Note If you select this check box, then do not specify signals or systems to bound. If you *do* specify signals or systems, then this check box is ignored.

5 (Optional) Specify the signal or system, or both, to be bound.

   You can apply this requirement to model signals, or a linearization of your Simulink model (requires Simulink Control Design), or both.

   Click **Select Signals and Systems to Bound (Optional)** to view the signal and linearization I/O selection area.

   - To apply this requirement to a model signal:

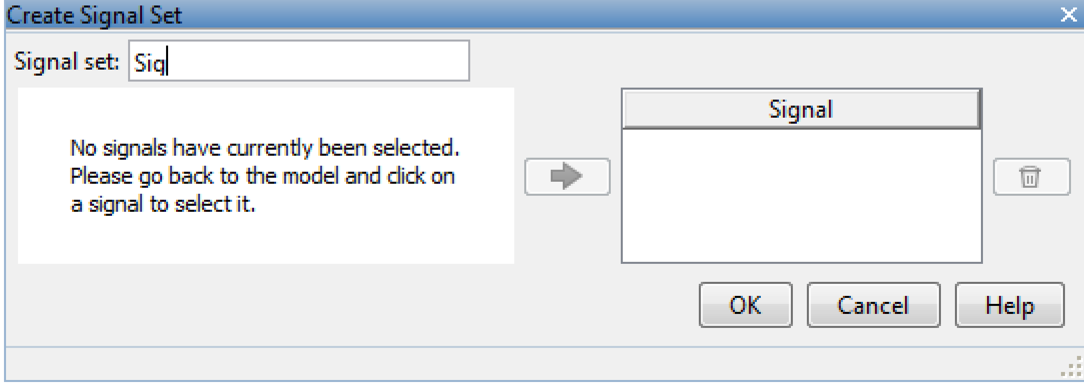
     In the **Signal** area, select a logged signal to which you will apply the requirement.

     If you have already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, it appears in the list. Select the corresponding check box.

     If you have not selected a signal to log:

     a Click [+ button]. A Create Signal Set dialog box opens where you specify the logged signal.

     b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [button] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

  Click **OK**. A new variable, with the specified name, appears in the Create Requirement dialog box.

- To apply this requirement to a linear system:

  a Specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.

  b Select the linearization input/output set from the **Linearization I/O** area.

    If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

    If you have not created a linearization input/output set, click [button] to open the Create linearization I/O set dialog box. For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

  For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

6 Select the check-box corresponding to the signal or system, and close the Create Requirement dialog box.

  The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60. When you perform evaluation, a positive requirement value indicates that the requirement has been violated.

See Also

Related Examples

- “Specify Parameters Requirements” on page 4-36
- “Specify Frequency-Domain Requirements” on page 4-48
- “Evaluate Design Requirements” on page 4-60
- “Identify Key Parameters for Estimation (GUI)” on page 4-131
- “Design Exploration Using Parameter Sampling (GUI)” on page 4-112

Specify Parameters Requirements

In the **Sensitivity Analyzer**, you can specify the following constraints on Simulink model parameters that are specified as variables:

- **Monotonic Variable** — "Impose Monotonic Constraint Requirement on Variable" on page 4-36
- **Smoothness Constraint** — "Impose Upper Bound on Gradient Magnitude of Variable" on page 4-38
- **Function Matching** — "Specify Linear or Quadratic Function Matching Constraint" on page 4-41
- **Vector Property** — "Specify Requirement on a Vector Property" on page 4-43
- **Relational Constraint** — "Impose Relational Constraint Between Two Variables" on page 4-45

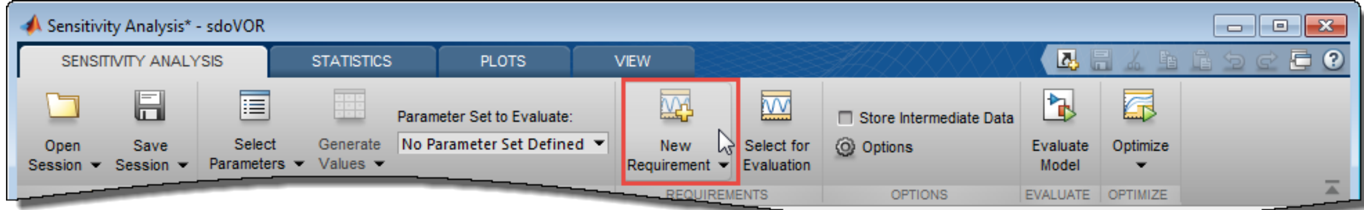
For information about how to specify a model parameter as a variable, see "Add Model Parameters as Variables" on page 4-4.

Impose Monotonic Constraint Requirement on Variable

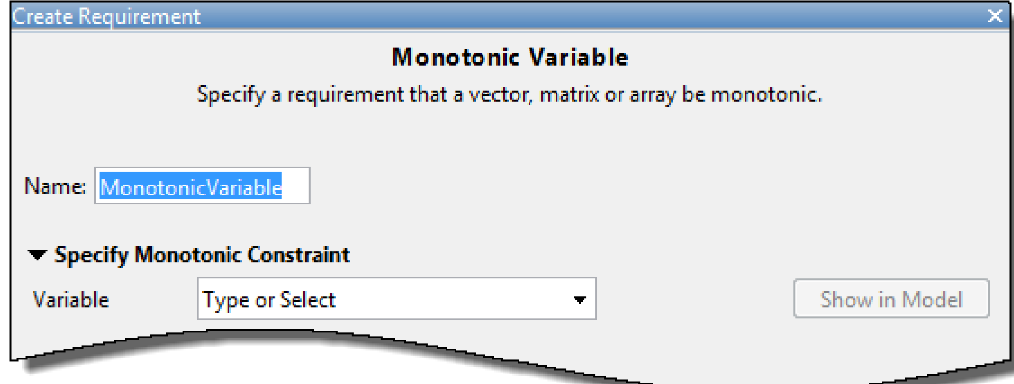
You can impose a monotonic constraint requirement on a variable in your Simulink model. For example, constrain a variable to be monotonically increasing. The variable can be a vector, matrix, or multidimensional array that is a parameter in your model, such as the breakpoints of a lookup table.

To specify the requirement:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Monotonic Variable**.



In the Create Requirement dialog box, specify the requirement. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



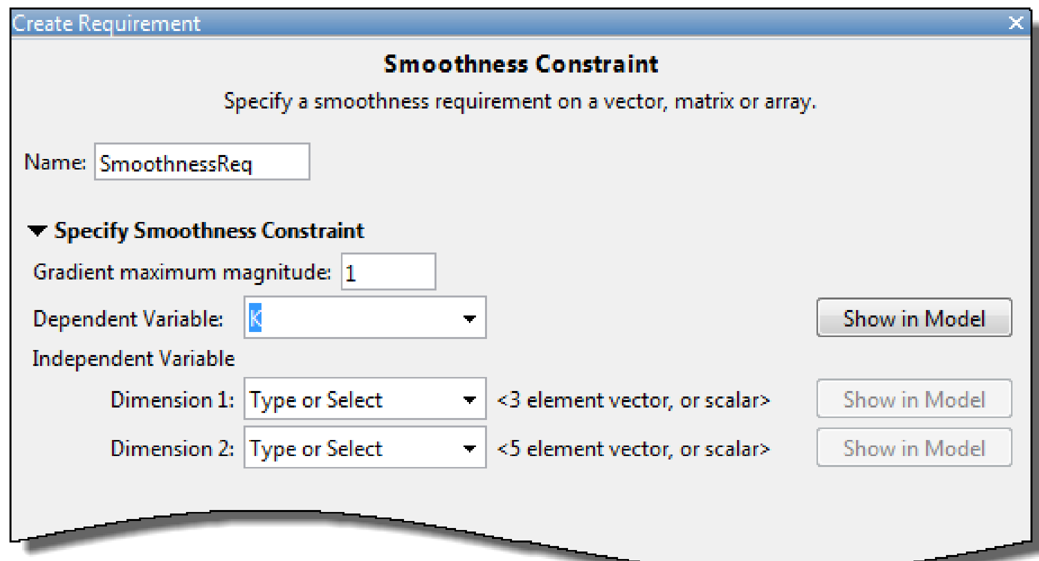
2. Specify the name of the variable in **Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single`.

   You can type the name of a nonscalar variable, or select the variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

   Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the app, see “Add Model Parameters as Variables” on page 4-4.

1. Specify the monotonicity for each dimension of the variable.

   After you select the variable, the dialog updates to show **Dimension 1** to **Dimension n**, corresponding to the *n* dimensions of the variable. For example, for a 2-dimensional variable `K` of size 3-by-5, the dialog updates as shown.



   Specify the monotonicity for the first dimension in **Dimension 1** and for the nth-dimension in **Dimension n** as one of the following options:

   - `Strictly increasing` — Each element of the variable is greater than the previous element in that dimension.
   - `Increasing` — Each element of the variable is greater than or equal to the previous element in that dimension.
   - `Decreasing` — Each element of the variable is less than or equal to the previous element in that dimension.
   - `Strictly decreasing` — Each element of the variable is less than the previous element in that dimension.
   - `Not constrained` — No constraint exists between the elements of the variable in that dimension.

1 Close the Create Requirement dialog box.

   The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60. When you perform evaluation, the app returns the evaluated requirement value corresponding to each dimension of the variable. A positive requirement value indicates that the requirement has been violated.

Impose Upper Bound on Gradient Magnitude of Variable

You can impose an upper bound on the gradient magnitude of a variable in your Simulink model. The variable can be a vector, matrix, or multidimensional array that is a parameter in your model, such as the data of a lookup table. For example, consider a car engine controller whose gain changes under different operating conditions determined by the car speed. You can use a gradient bound constraint to limit the rate at which the controller gain changes per unit change in vehicle speed.

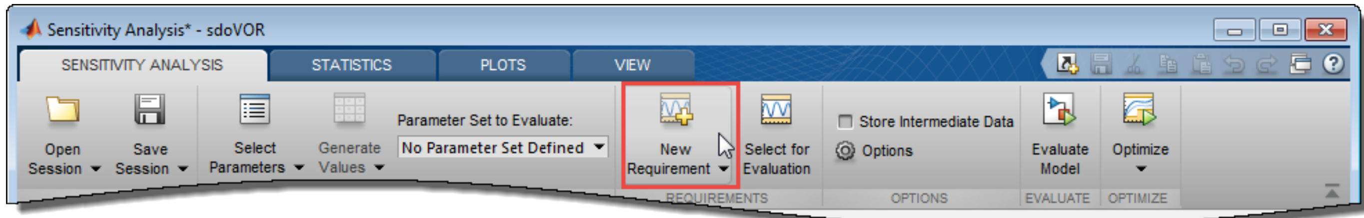
For an *N*-dimensional variable F that is a function of independent variables $x_1, \ldots, x_N$, the gradient magnitude is defined as:

$$|\nabla F| = \sqrt{\left(\frac{\partial F}{\partial x_1}\right)^2 + \left(\frac{\partial F}{\partial x_2}\right)^2 + \cdots + \left(\frac{\partial F}{\partial x_N}\right)^2}$$

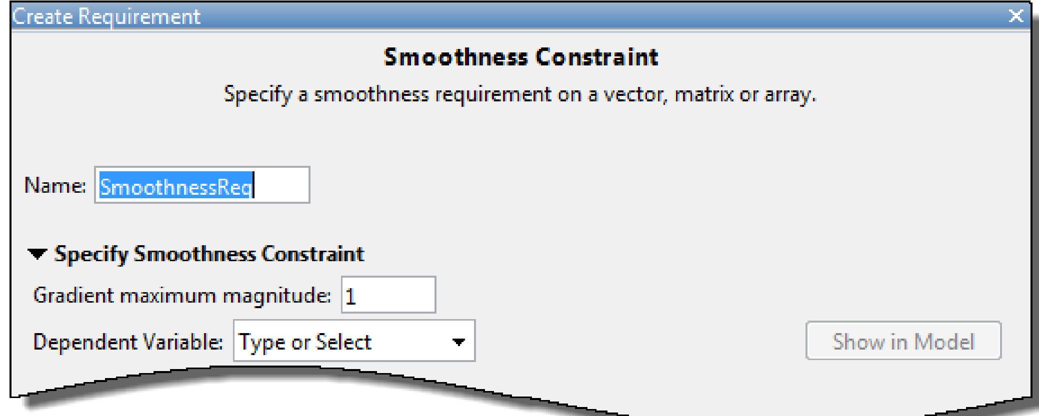
To compute the gradient magnitude, the software computes the partial derivative in each dimension by computing the difference between successive F data in that dimension and dividing by the spacing between the data in that dimension. You specify F and the spacing between the data. The software checks whether the gradient magnitude of the variable data is less than or equal to a specified bound. If the gradient magnitude of the data is greater than the required bound, the variable data is not smooth.

To specify the requirement:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Smoothness Constraint**.



   In the Create Requirement dialog box, specify the requirement. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



2 Specify the gradient magnitude bound as a nonnegative finite real scalar in **Gradient maximum magnitude**.

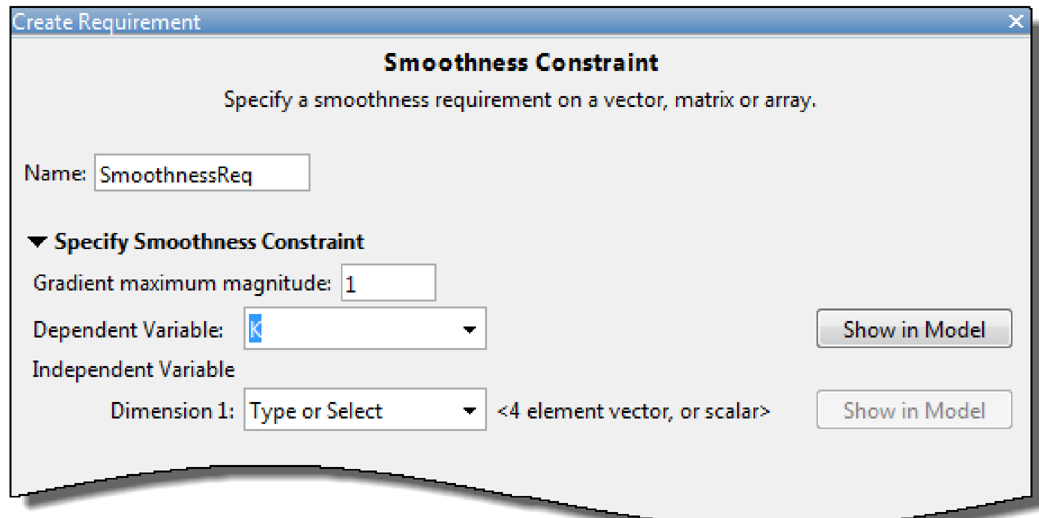
3 Specify the variable `F` that you want to impose the requirement on in **Dependent Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single`. The variable must be a parameter in your model or a constant that you enter.

   You can type the name of a nonscalar variable or a constant, or select the variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

   Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the app, see “Add Model Parameters as Variables” on page 4-4.

1 Specify the spacing between points of **Dependent Variable** data in each dimension in **Independent Variable**.

   After you select the **Dependent Variable**, the dialog updates to show **Dimension 1** to **Dimension n**, corresponding to the *n* dimensions of the dependent variable. For example, for a 1-dimensional variable `K`, the dialog updates as shown.



The first dimension specifies the spacing going down the dependent variable data rows, and the second specifies spacing across the columns. The *N*th dimension specifies the spacing along the *N*th dimension of dependent variable data. You can specify the independent variables in each dimension as scalars or vectors.

- Scalars — Specify the spacing between dependent variable data F in the corresponding dimension as a nonzero scalar. For example, suppose that **Dependent Variable** is two-dimensional, and the spacing between data in the first dimension is 5 and in the second dimension is 2. In the **Independent Variable** section, specify **Dimension 1** as 5 and **Dimension 2** as 2.
- Vectors — Specify the coordinates of F data in the corresponding dimension as real, numeric, monotonic vectors. The software uses the coordinates to compute the spacing between the dependent variable data points in the corresponding dimension. The length of the vector must match the length of F in the corresponding dimension. You do not have to specify coordinates with uniform spacing. For example, suppose that F is two-dimensional, and the length of the data in the first and second dimension is 3 and 5, respectively. The coordinates of the data in the first dimension are `[1 2 3]`. In the second dimension, the spacing is not uniform and the coordinates of the data are `[1 2 10 20 30]`. In the **Independent Variable** section, specify **Dimension 1** as `[1 2 3]` and **Dimension 2** as `[1 2 10 20 30]`.

You can also specify the independent variables by typing the name of a variable, or selecting a variable from the drop-down list. The list is prepopulated with all the variables in your model that have the appropriate size. To choose a subset of an array or matrix variable V, type an expression. For example, specify as `V(1,:)` to use the first row of the variable. To use a numeric field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

1 Close the Create Requirement dialog box.

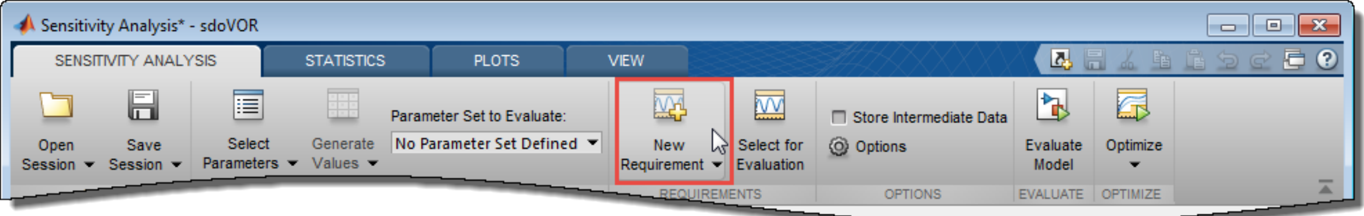
   The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60. When you perform evaluation, the app returns the evaluated requirement value. A positive requirement value indicates that the requirement has been violated.

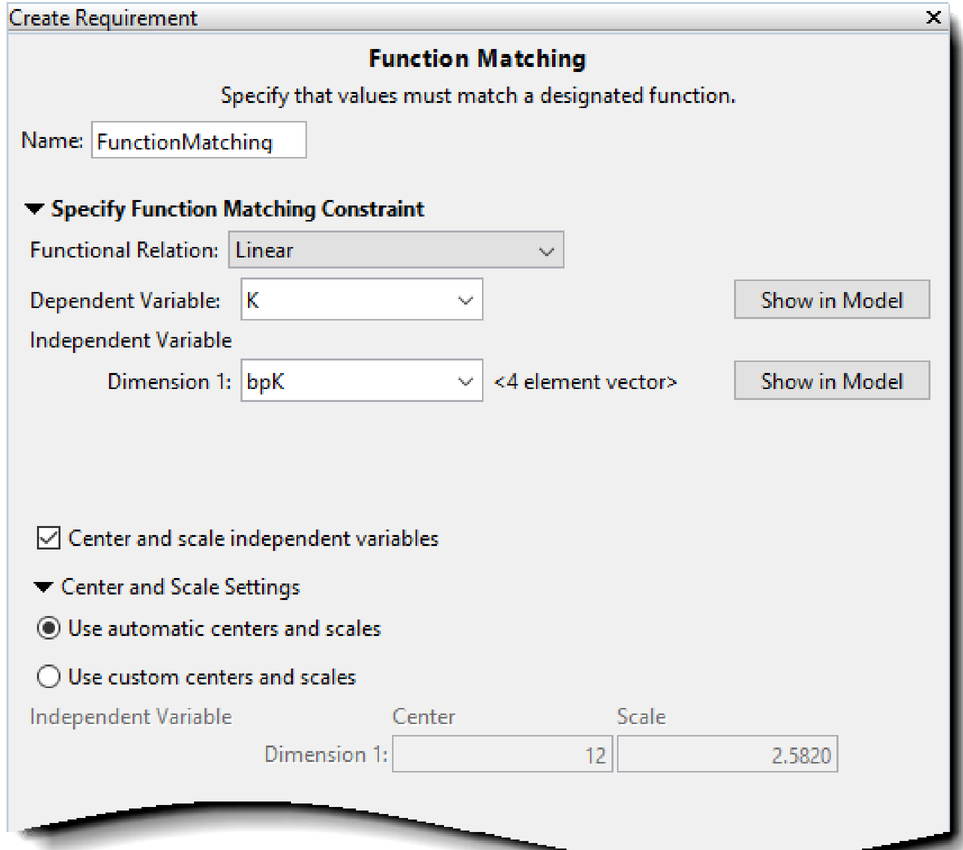
Specify Linear or Quadratic Function Matching Constraint

In the app, you can constrain a variable's values to match a linear or quadratic function. The variable can be a vector, matrix, or a multidimensional array that is a parameter in your model, such as the data of a lookup table in your model. To specify the requirement:

1. In **Sensitivity Analyzer**, from the **New Requirement** drop-down list, select **Function Matching**.



   In the Create Requirement dialog box, specify the requirement. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



2. Specify the function to be matched. To do so, set **Functional Relation** to one of the following values:

- `Linear` — Data from variable `V` are fit to a linear function. For example, for a two-dimensional variable with independent variables, X_1 and X_2, the linear function has the form:

$$V = a_0 + a_1X_1 + a_2X_2$$

  The software calculates the fit coefficients a_0, a_1, and a_2 and then calculates the sum of squares of the error between the data and the linear function.
- `Quadratic with no cross-terms` — Data are fit to a quadratic function with no cross-terms. For a two-dimensional variable, the pure quadratic function has the form:

$$V = a_0 + a_1X_1 + a_2X_1^2 + a_3X_2 + a_4X_2^2$$

- `Quadratic with all cross-terms` — Variable data are fit to a quadratic function that includes cross-terms. For a two-dimensional variable, the quadratic function has the form:

$$V = a_0 + a_1X_1 + a_2X_1^2 + a_3X_2 + a_4X_2^2 + a_5X_1X_2$$

  If the variable is one-dimensional, there are no cross-terms and so the computation is the same as when **Functional relation** is `Quadratic with no cross-terms`.

3 Specify the variable `V` to which you want to apply the requirement in **Dependent Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single` that is a parameter in your model.

   Type the name of a non scalar variable, or select a variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To see where the selected variable is used on your model, click **Show in Model**. To choose a subset of an array or matrix variable `A`, type an expression. For example, specify `A(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

   Sometimes models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as design variables in the app, see “Add Model Parameters as Variables” on page 4-4.

4 Specify the independent variable vectors used for computing the function in **Independent Variable**. The independent variables are specified as real, numeric, monotonic vectors.

   The number of independent variables must equal the number of dimensions of the dependent variable `V`. For example, you specify two independent variables when `V` is a matrix, and use three independent variables when `V` is three-dimensional. The first independent variable vector specifies coordinates going down the rows of `V`, and the second independent variable vector specifies coordinates going across the columns of `V`. The nth independent variable vector specifies coordinates along the nth dimension of `V`. The number of elements in each independent variable vector must match the size of `V` in the corresponding dimension. The independent variable vectors must be monotonically increasing or decreasing.

   You can also specify the independent variables by typing the name of a variable, or selecting a variable from the drop-down list. The list is prepopulated with all the variables in your model that have the appropriate size. To choose a subset of an array or matrix variable `A`, type an expression. For example, specify `A(1,:)` to use the first row of the variable. To use a numeric field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`. To use an equally spaced vector, select `[1 2 ...N]` from the drop-down menu.

5 Specify whether you want to center and scale the independent variables. When you select the **Center and scale independent variables** option, the independent variable vectors you specify are divided by a scale value after subtracting a center value. Centering can improve numerical conditioning when one or more independent variable vectors have a mean that differs from 0 by several orders of magnitude. Scaling can improve numerical conditioning when independent variable vectors differ from each other by several orders of magnitude.

   To specify the center and scale values for each independent variable, expand the **Center and Scale Settings** section, and select one of the following:

   - **Use automatic centers and scales -** The center and scale values are the mean and standard deviation for each independent variable. Using the mean and standard deviation values to center and scale the independent variables is the default option.
   - **Use custom centers and scales -** Specify the **Center** and **Scale** values for each independent variable. The independent variable vectors are divided by the corresponding **Scale** value after subtracting the value you specify in **Center**.

6 Close the Create Requirement dialog box.

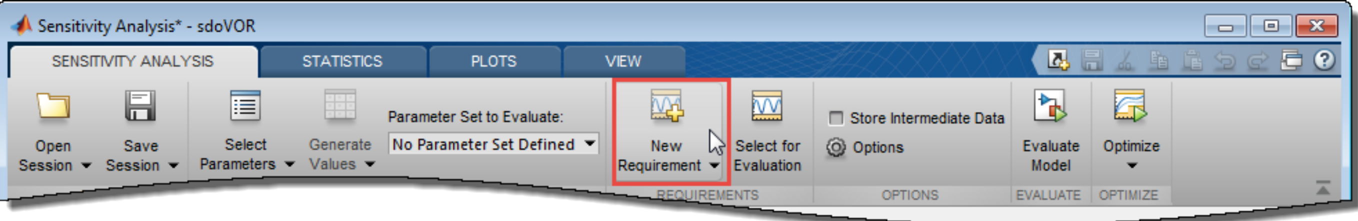
   The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60. When you perform evaluation, the app returns the evaluated requirement value. The app computes an error signal that is the difference between the dependent variable data and the specified function of the independent variables. The app returns the sum of squares of this error as the evaluated requirement value. A positive value indicates that the requirement has been violated, and `0` value indicates that the requirement is satisfied. The closer the value is to `0`, the better is the match between the function and dependent variable data.

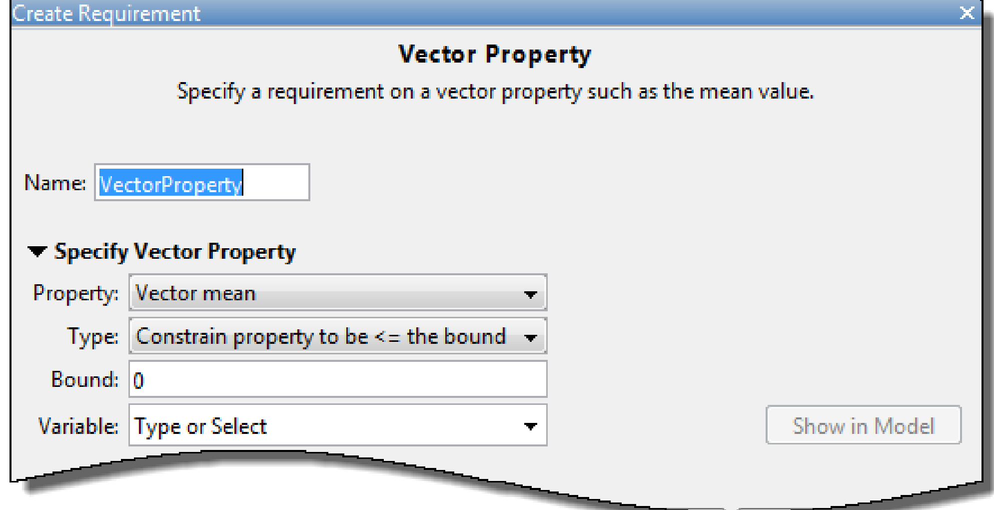
Specify Requirement on a Vector Property

In the app, you can specify a requirement on a vector property, such as the mean value of the vector. The vector must be a parameter in your model. To specify the requirement:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Vector Property**.



   In the Create Requirement dialog box, specify the requirement. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



1 Specify the vector property in **Property**. For a vector V with N elements, you can specify one of the following properties:

- `Vector mean` — $mean(V)$
- `Vector median` — $median(V)$
- `Vector variance` — $variance(V)$
- `Vector inter-quartile range` — Difference between the 75th and 25th percentiles of the vector values.
- `Vector sum` — $\sum_{i=1}^{N} V(i)$
- `Vector sum of squares` — $\sum_{i=1}^{N} V(i)^2$
- `Vector sum of absolute values` — $\sum_{i=1}^{N} |V(i)|$
- `Vector minimum` — $min(V)$
- `Vector maximum` — $max(V)$

2 Specify the type of requirement you want to impose on the vector property in **Type**. You can set an upper or lower bound on the vector property, or require the property to equal a particular value. You can also choose to maximize or minimize the vector property. For example, to maximize the mean value of your vector, specify **Property** as `Vector mean` and **Type** as `Maximize the property`.

3 Specify the value of the bound imposed on the vector property in **Bound**. Specify the bound as a finite real scalar value. For example, if for a vector variable V you require `mean(V) = 5`, specify **Property** as `Vector mean`, **Type** as `Constrain property to be == the bound`, and **Bound** as 5.

1 Specify the name of the variable in **Variable**. The variable must be a vector, matrix, or multidimensional array of data type `double` or `single`.

You can type the name of a nonscalar variable, or select the variable from the drop-down list. The list is prepopulated with all the nonscalar variables in your model. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric nonscalar field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the app, see "Add Model Parameters as Variables" on page 4-4.

2 Close the Create Requirement dialog box.

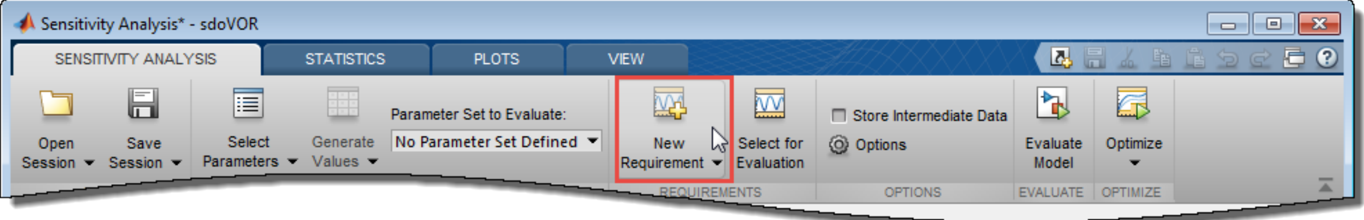
   The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see "Evaluate Design Requirements" on page 4-60. When you perform evaluation, the app returns the evaluated requirement value. A positive requirement value indicates that the requirement has been violated.

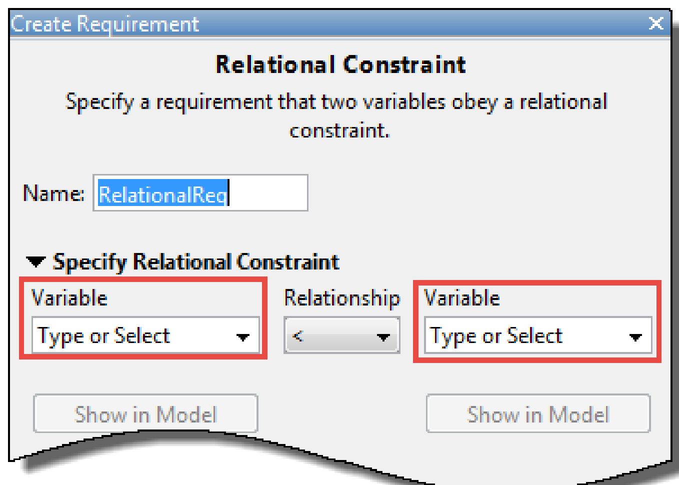
Impose Relational Constraint Between Two Variables

You can impose a relational constraint requirement on a pair of variables in your Simulink model. For example, require that variable *a* is always greater than variable *b*. To specify the requirement:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Relational Constraint**.



   In the Create Requirement dialog box, specify the requirement. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



2 Specify the name of the two variables in **Variable**. The variables can be vectors or arrays but must be the same size.

Type the name of two variables, or select the variables from the drop-down lists. The lists are prepopulated with all the variables in your model. To see where a selected variable is used on your model, click **Show in Model**. To choose a subset of an array or matrix variable `V`, type an expression. For example, specify **Variable** as `V(1,:)` to use the first row of the variable. To use a numeric field `x` of a structure `S`, type `S.x`. You cannot use mathematical expressions such as `a + b`.

Sometimes, models have parameters that are not explicitly defined in the model itself. For example, a gain `k` could be defined in the MATLAB workspace as `k = a + b`, where `a` and `b` are not defined in the model but `k` is used. To add these independent parameters as variables in the app, see "Add Model Parameters as Variables" on page 4-4.

1 Specify the relation between the elements of the two variables as one of the following in **Relationship**:

- `'<'` — Each data element in the first variable is less than the corresponding element in the second variable.
- `'<='` — Each data element in the first variable is less than or equal to the corresponding element in the second variable.
- `'>'` — Each data element in the first variable is greater than the corresponding element in the second variable.
- `'>='` — Each data element in the first variable is greater than or equal to the corresponding element in the second variable.
- `'=='` — Each data element in the first variable is equal to the corresponding element in the second variable.
- `'~='` — Each data element in the first variable is not equal to the corresponding element in the second variable.

1 Close the Create Requirement dialog box.

The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see "Evaluate Design Requirements" on page 4-60. When you perform evaluation, the app returns the evaluated requirement value. The interpretation of the evaluated requirement value depends on the requirement **Type**.

Type	Evaluated Requirement Value	
	Requirement is Satisfied	Requirement is Violated
`'>'` or `'<'`	Negative number	Positive number, or `0` if the elements are equal
`'>='` or `'<='`	Negative number, or `0` if the elements are equal	Positive number
`'=='`	`0`	Non-zero number
`'~='`	`0`	`1`

See Also

Related Examples

- "Specify Parameters for Design Exploration" on page 4-4
- "Specify Time-Domain Requirements" on page 4-21
- "Specify Frequency-Domain Requirements" on page 4-48

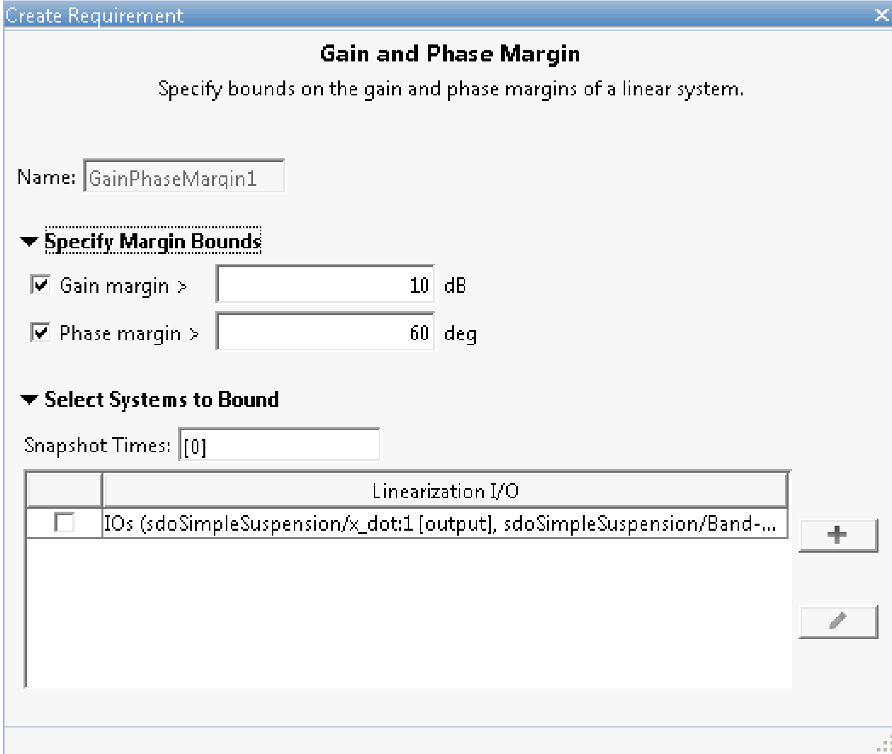
Specify Frequency-Domain Requirements

This topic shows how to specify frequency-domain requirements in the **Sensitivity Analyzer**. To specify frequency-domain requirements, you require the Simulink Control Design toolbox.

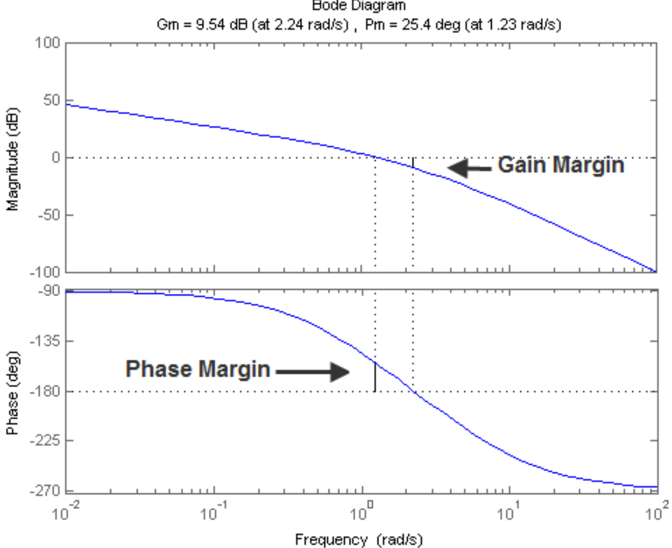
Specify Lower Bounds on Gain and Phase Margin

To specify lower bounds on the gain and phase margin of a linear system:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Gain and Phase Margin**. A Create Requirement dialog box opens where you specify upper or lower bounds on the gain and phase margin. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.



2. Specify bounds on the gain margin or phase margin, or both.



- **Gain margin** — Amount of gain increase or decrease required to make the loop gain unity at the frequency where the phase angle is –180°.
- **Phase margin** — Amount of phase increase or decrease required to make the phase angle –180° when the loop gain is 1.0

To specify a lower bound on the gain margin or phase margin, or both, select the corresponding check box and enter the lower bound value.

3. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
4. Close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.

5 (Optional) Plot the requirement.

   a In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.

   b In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Specify Piecewise-Linear Lower and Upper Bounds on Frequency Response

To specify upper or lower bounds on the magnitude of a system response:

1 In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Bode Magnitude**. A Create Requirement dialog box opens where you specify the lower or upper bounds on the magnitude of the system response. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.

2 Specify the requirement type in the **Type** drop-down list.

3 Specify the edge start and end frequencies and corresponding magnitude in the **Frequency** and **Magnitude** columns.

4 Insert or delete bound edges.

   Click to specify additional bound edges.

   To delete a bound edge, select a row, and click .

5 In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.

   b Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

6 Close the Create Requirement dialog box.

The requirement in the **Requirements** area of the app is updated with the specified characteristics.

7 (Optional) Plot the requirement.

   a In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.

   b In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Bode Characteristics block to specify bounds on the magnitude of the system response. (Requires Simulink Control Design.)

Specify Bound on Closed-Loop Peak Gain

To specify an upper bound on the closed-loop peak response of a system:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Closed-Loop Peak Gain**. A Create Requirement dialog box opens where you specify an upper bound on the closed-loop peak gain of the system. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2. Specify the upper bound in **Closed-Loop peak gain**.
3. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.

   b Select the linearization input/output set from the **Linearization I/O** area.

   If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

   If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

   For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
4. Close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
5. (Optional) Plot the requirement.

   a In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.

b In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Nichols Characteristics block to specify bounds on the magnitude of the system response. (Requires Simulink Control Design.)

Specify Lower Bound on Damping Ratio

To specify a lower bound on the damping ratio of the poles of a system:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Damping Ratio**. A Create Requirement dialog box opens where you specify a lower bound on the damping ratio of the system. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2. Specify the lower bound on the damping ratio in **Damping ratio**.
3. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click + to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
4. Close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
5. (Optional) Plot the requirement.

   a. In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.
   b. In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Pole-Zero Characteristics block to specify a bound on the damping ratio. (Requires Simulink Control Design.)

Specify Upper and Lower Bounds on Natural Frequency

To specify a bound on the natural frequency of the poles of a system:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Natural Frequency**. A Create Requirement dialog box opens where you specify a bound on the natural frequency of the system. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2. Specify a lower or upper bound on the natural frequency in **Natural frequency**.
3. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
4. Close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
5. (Optional) Plot the requirement.

   a. In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.
   b. In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Pole-Zero Characteristics block to specify a bound on the natural frequency. (Requires Simulink Control Design.)

Specify Upper Bound on Approximate Settling Time

To specify an upper bound on the approximate settling time of a system:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Settling Time**. A Create Requirement dialog box opens where you specify an upper bound on the approximate settling time of the system. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2. Specify the upper bound on the approximate settling time in **Settling time**.
3. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
4. Close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
5. (Optional) Plot the requirement.

   a. In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.
   b. In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Pole-Zero Characteristics block to specify the approximate settling time. (Requires Simulink Control Design.)

Specify Piecewise-Linear Upper and Lower Bounds on Singular Values

To specify piecewise-linear upper and lower bounds on the singular values of a system:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Singular Values**. A Create Requirement dialog box opens where you specify the lower or upper bounds on the

singular values of the system. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.

2. Specify the requirement type using the **Type** drop-down list.
3. Specify the edge start and end frequencies and corresponding magnitude in the **Frequency** and **Magnitude** columns, respectively.
4. Insert or delete bound edges.

   Click to specify additional bound edges.

   Select a row and click to delete a bound edge.
5. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
6. Close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
7. (Optional) Plot the requirement.

   a. In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.
   b. In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Singular Value Characteristics block to specify bounds on the singular value. (Requires Simulink Control Design).

Specify Step Response Characteristics

To apply a step response requirement to a linearization of your model (requires Simulink Control Design), specify the step response characteristics as follows:

1 Select a step response requirement from the **Sensitivity Analyzer**.

   In the **New Requirement** drop-down list of the app, in the **New Frequency Domain Requirement** section, select **Step Response Envelope**.

   A Create Requirement dialog box opens where you specify the step response requirements on a signal. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2 Specify the step response characteristics:

   - **Initial value** — Input level before the step occurs
   - **Step time** — Time at which the step takes place
   - **Final value** — Input level after the step occurs
   - **Rise time** — The time taken for the response signal to reach a specified percentage of the step range. The step range is the difference between the final and initial values.
   - **% Rise** — The percentage of the step range used with **Rise time** to define the overall rise time characteristics.
   - **Settling time** — Time taken until the response signal settles within a specified region around the final value. This settling region is defined as the final step value plus or minus the settling range, defined in **% Settling**.
   - **% Settling** — The percentage of the step range value that defines the settling range of settling time characteristic specified in **Settling time**.
   - **% Overshoot** — The amount by which the response signal can exceed the final value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
   - **% Undershoot** — The amount by which the response signal can undershoot the initial value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
3 Specify the systems to be bound.

   To apply this requirement to a linearization of your Simulink model:

   a In the **Select Systems to Bound** area, specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.
   b Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

4. Close the Create Requirement dialog box.

   The requirement in the **Requirements** area of the app is updated with the specified characteristics.
5. (Optional) Plot the requirement.

   a. In the **Sensitivity Analysis** tab of the app, in the **Requirements** area, select the requirement.
   b. In the **Plots** tab of the app, select the plot type to generate a graphical display of the requirement.

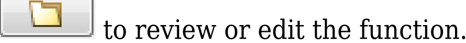
   The plot is populated when you perform evaluation. A positive value indicates that the requirement has been violated.

Alternatively, you can use the Check Step Response Characteristics block to specify step response bounds for a signal.

Specify Custom Requirements

You can specify custom requirements, such as minimizing system energy. To specify custom requirements:

1. In the **Sensitivity Analyzer**, in the **New Requirement** drop-down list, select **Custom Requirement**.

   A Create Requirement dialog box opens where you specify the reference signal to track. A new requirement with the name specified in **Name** appears in the **Requirements** area of the app.
2. Specify the requirement type in the **Type** drop-down menu.
3. Specify the name of the function that contains the custom requirement in **Function**. The field must be specified as a function handle using `@`. The function must be on the MATLAB path. Click  to review or edit the function.

   If the function does not exist, clicking opens a template MATLAB file. Use this file to implement the custom requirement. The default function name is `myCustomRequirement`.
4. (Optional) To prevent the solver from considering specific parameter combinations, select **Error if constraint is violated**. Use this option for parameter-only constraints.

   During an optimization iteration, the solver first evaluates requirements with this option selected.

   - If the constraint is violated, the solver skips evaluating any remaining requirements and proceeds to the next combination of parameters in the parameter set.
   - If the constraint is *not* violated, the solver evaluates the remaining requirements for the current combination of parameter values. If any of the remaining requirements bound signals or systems, then the solver simulates the model.

Note If you select this check box, then do not specify signals or systems to bound. If you *do* specify signals or systems, then this check box is ignored.

---

5 (Optional) Specify the signal or system, or both, to be bound.

   You can apply this requirement to model signals, or a linearization of your Simulink model (requires Simulink Control Design), or both.

   Click **Select Signals and Systems to Bound (Optional)** to view the signal and linearization I/O selection area.

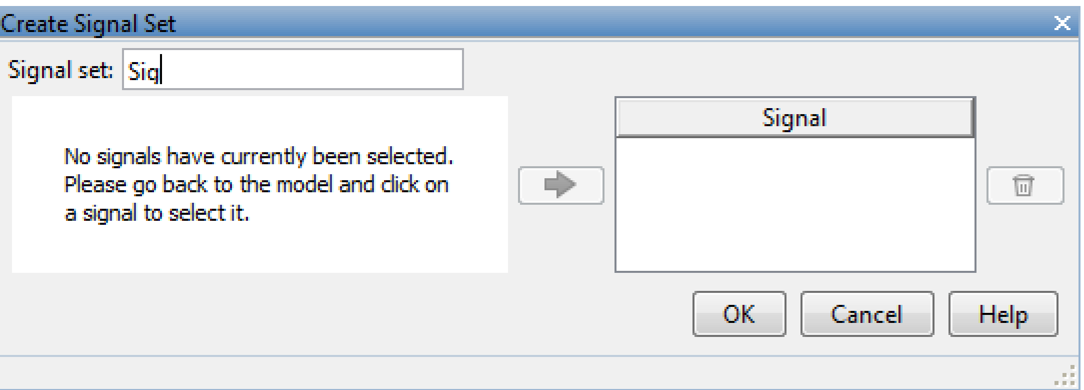
   - To apply this requirement to a model signal:

     In the **Signal** area, select a logged signal to which you will apply the requirement.

     If you have already selected a signal to log, as described in "Specify Signals to Log" on page 3-10, it appears in the list. Select the corresponding check box.

     If you have not selected a signal to log:

     a Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.
     b In the Simulink model window, click the signal to which you want to add a requirement.



       The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

     c Select the signal and click [→] to add it to the signal set.
     d In **Signal set** field, enter a name for the selected signal set.

       Click **OK**. A new variable, with the specified name, appears in the Create Requirement dialog box.

   - To apply this requirement to a linear system:

     a Specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.
     b Select the linearization input/output set from the **Linearization I/O** area.

       If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box. For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

6 Select the check-box corresponding to the signal or system, and close the Create Requirement dialog box.

   The requirement created in the **Requirements** area of the app is updated with the specified characteristics.

You can now evaluate the requirement. For more information, see “Evaluate Design Requirements” on page 4-60. When you perform evaluation, a positive requirement value indicates that the requirement has been violated.

See Also

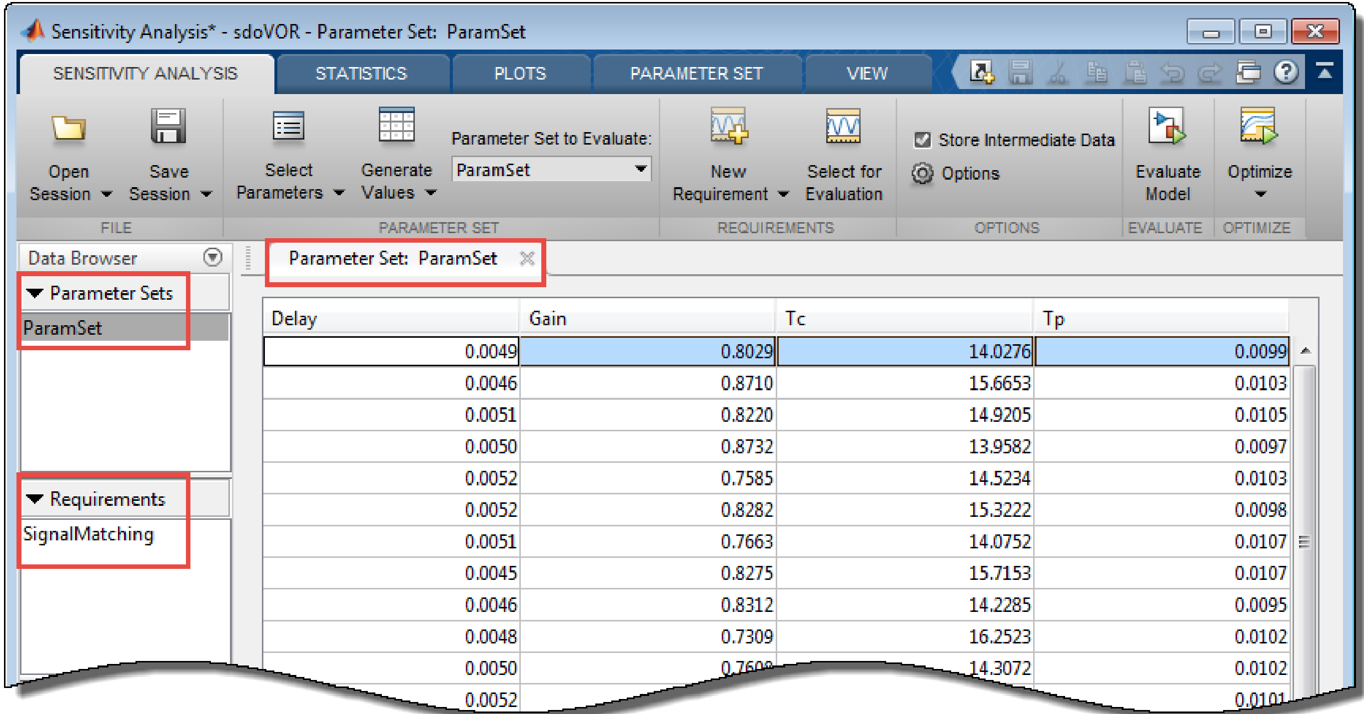
Related Examples

- “Specify Time-Domain Requirements” on page 4-21
- “Evaluate Design Requirements” on page 4-60
- “Design Exploration Using Parameter Sampling (GUI)” on page 4-112
- “Identify Key Parameters for Estimation (GUI)” on page 4-131

Evaluate Design Requirements

This topic shows how to evaluate your design requirements in the **Sensitivity Analyzer**. After you generate values for your parameter set and specify design requirements, you can evaluate your design requirements (cost function) at each sample of parameter values in your parameter set.

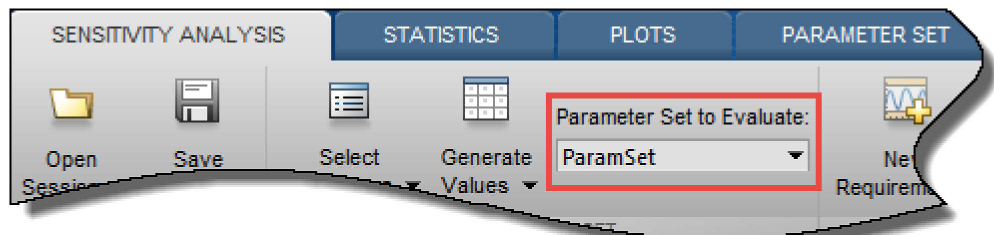
The generated parameter set, the corresponding parameter set table, and specified requirements are displayed in the app.



To evaluate the design requirements:

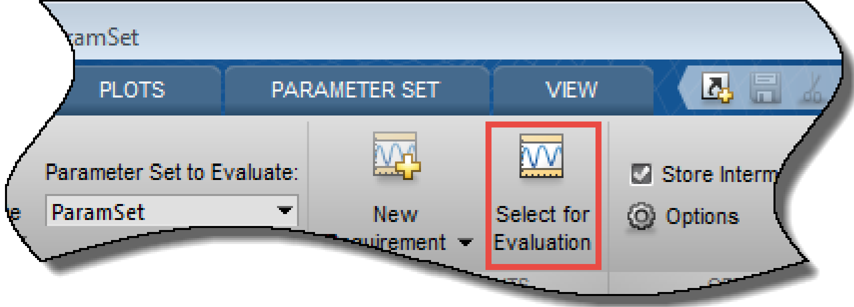
1 Select the parameter set to use for evaluation.

If you have multiple parameter sets defined, select the parameter set to use from the **Parameter Set to Evaluate** drop-down list.



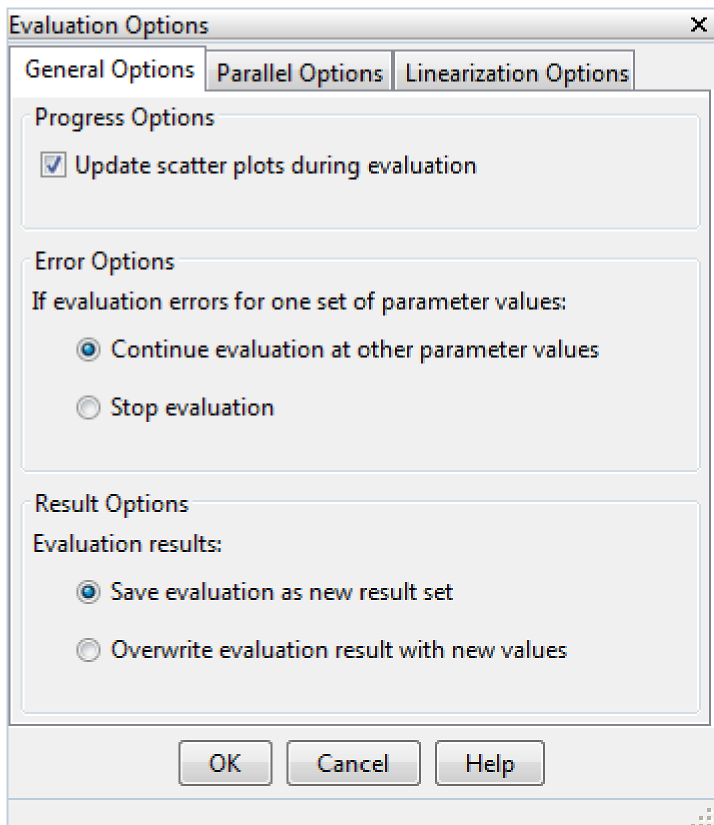
2 Select the requirements you want to evaluate.

If you have multiple requirements defined, they are all selected by default for evaluation. To exclude a requirement from evaluation, click **Select for Evaluation**.



3 Specify evaluation options.

Click **Options**. In the Evaluation Options dialog box, in the **General Options** tab, specify options related to evaluation progress and results. If you have Parallel Computing Toolbox, you can specify options for parallel computing in the **Parallel Options** tab. If you have Simulink Control Design software, you can specify options for linearizing your model in the **Linearization Options** tab. For details about these options, click **Help**.



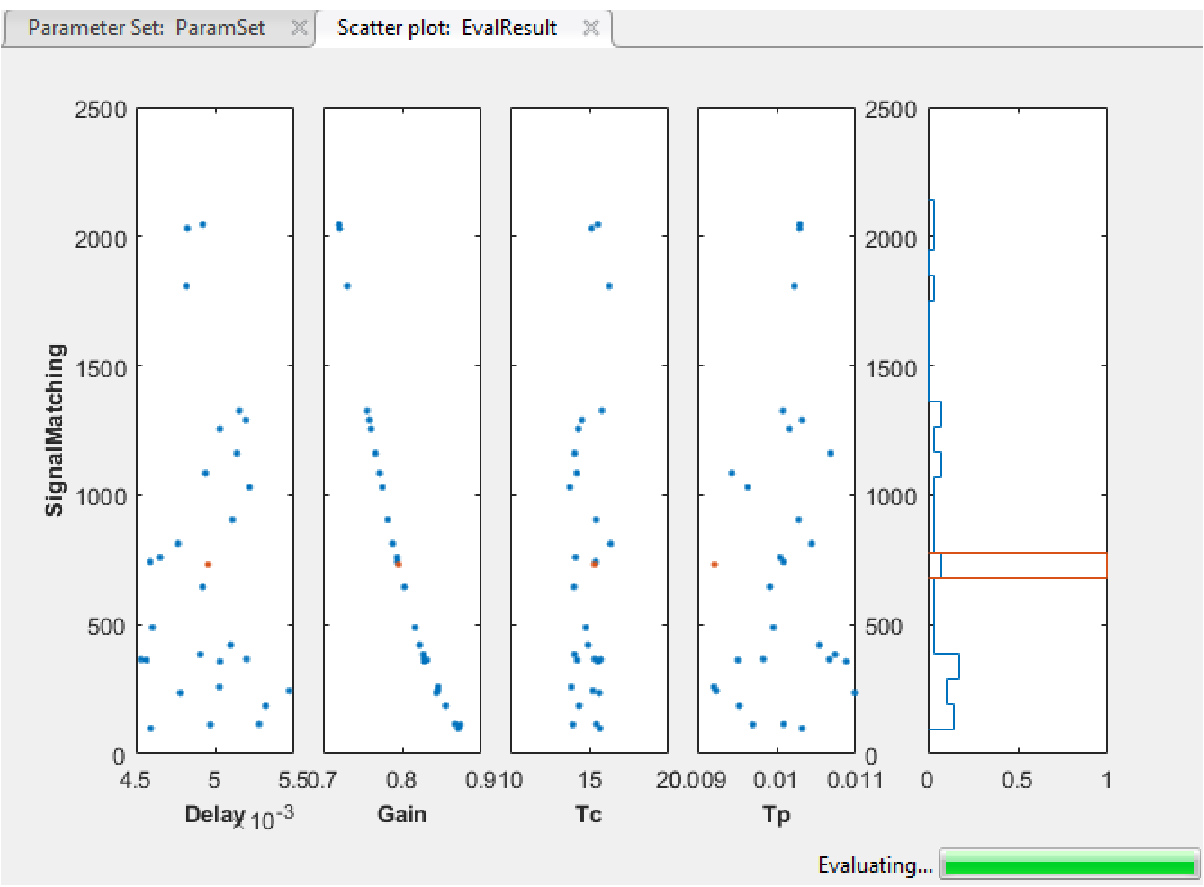
4 Speed up successive evaluations of design requirements that require the same logged signals and parameter values.

Click **Store Intermediate Data**. For more information, see "Store Intermediate Data in the App" on page 4-100.

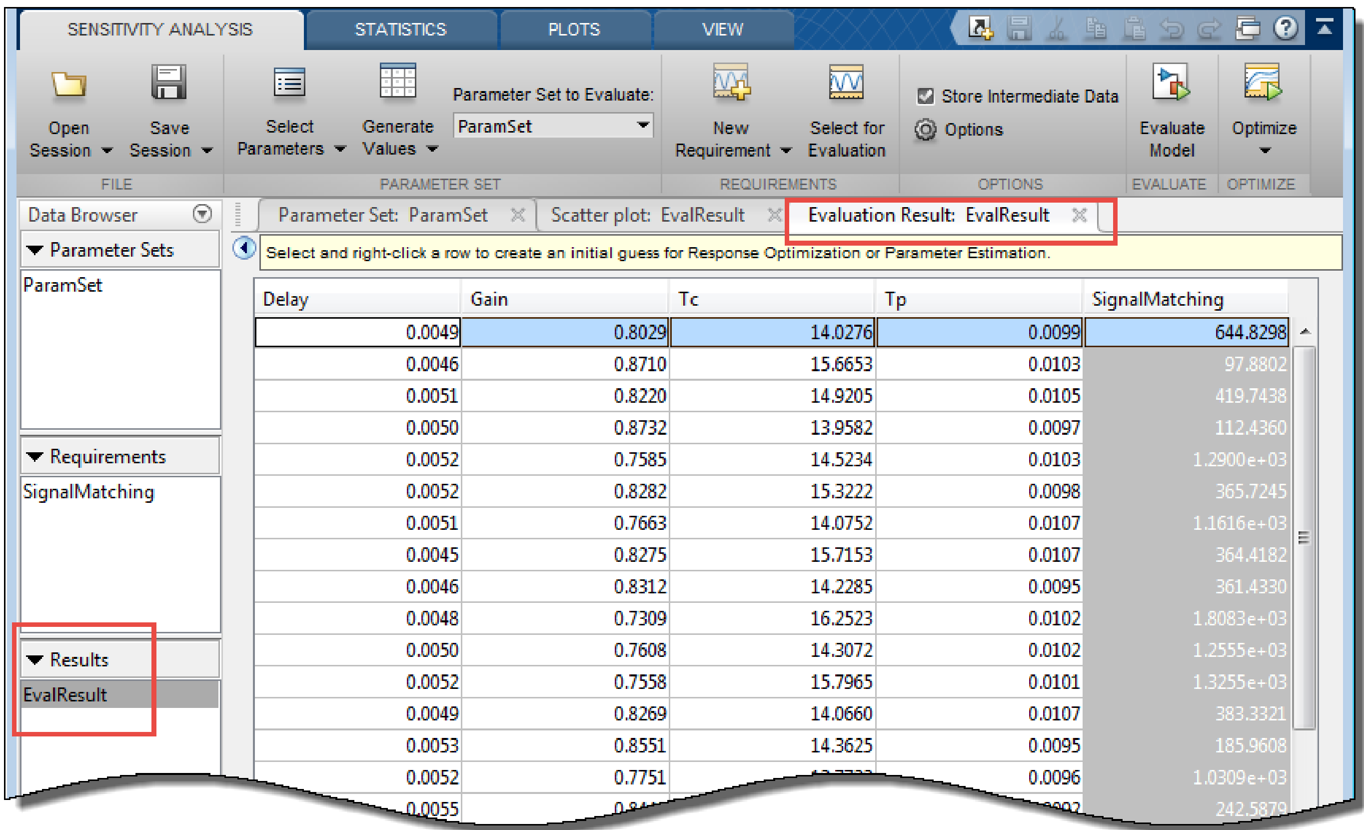
5 Evaluate the design requirements for each sample in your parameter set.

Click **Evaluate Model**. The cost function associated with your design requirement is evaluated using each sample in your parameter set. A sample corresponds to a row of values in the parameter set table.

The app generates an evaluation result scatter plot. The plot updates to display the evaluated cost function value as a function of each parameter in the parameter set. The last column of subplots displays histograms of the probability distribution of the evaluated cost function values.



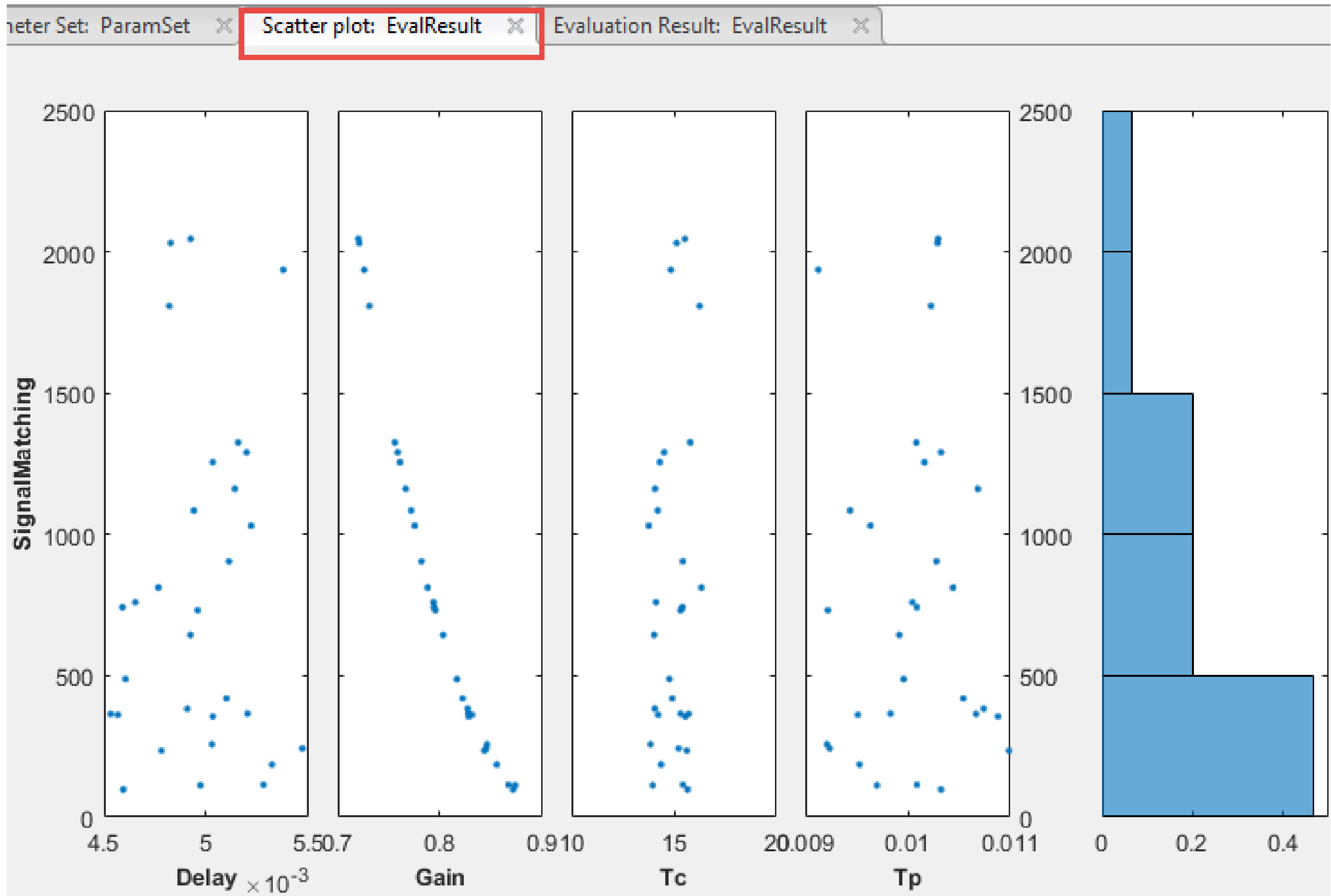
When the evaluation is complete, the app displays the evaluated requirement (normalized cost function value) and the corresponding parameter values in the **Evaluation Result** table. The app also creates a new variable with this information in the **Results** area.



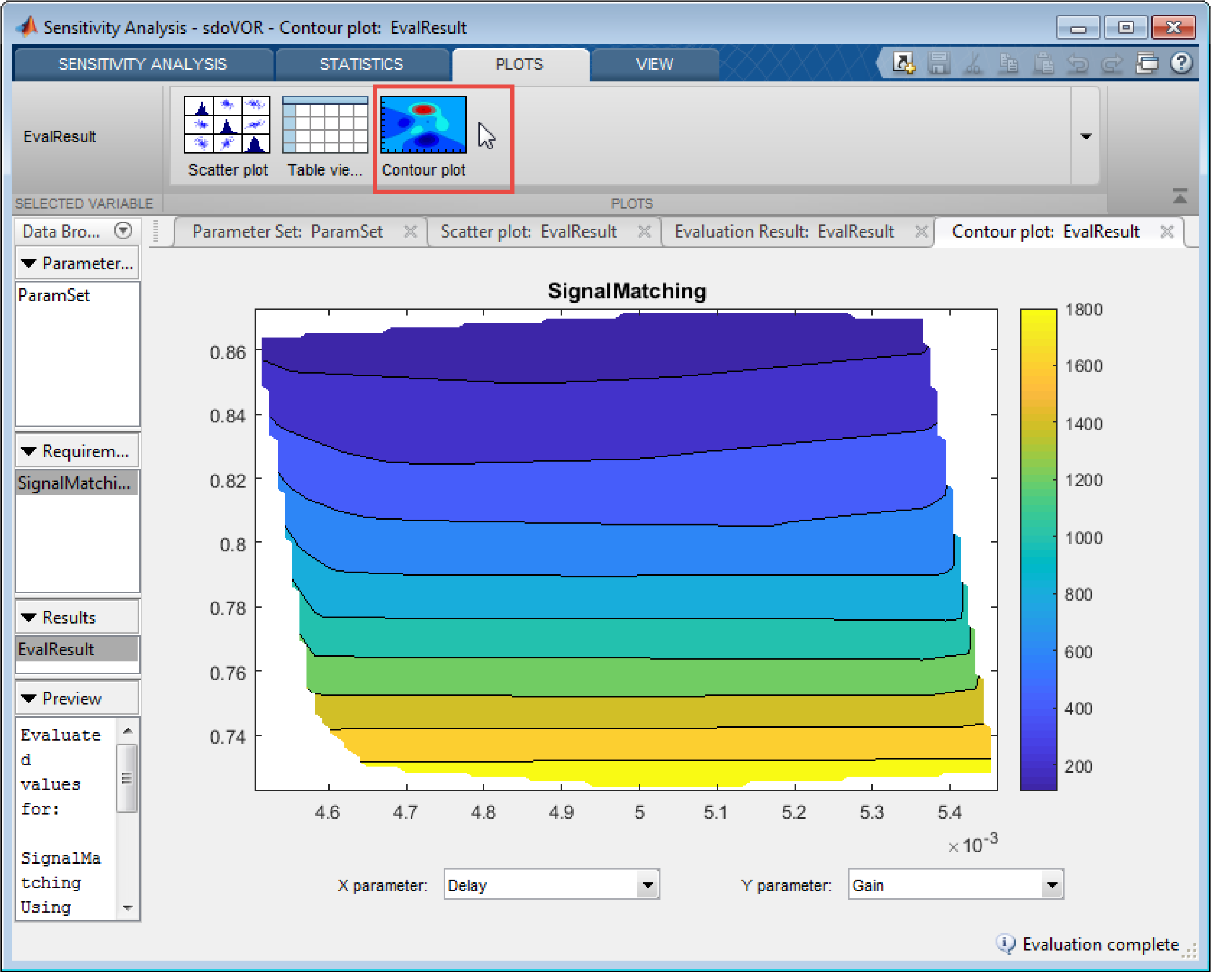
For requirements that involve a bound, a positive requirement value indicates that your requirement was violated, while a negative value indicates that the requirement was satisfied for that sample of parameter values. The parameter sample (row) corresponding to the least requirement value comes closest to satisfying your requirement.

You can employ the evaluation results to configure estimation or optimization of your parameters. For more information, see “Use Sensitivity Analysis to Configure Estimation and Optimization” on page 4-74.

The app displays the final scatter plots and probability distribution histogram. The number of data points in each scatter plot equals the number of samples (rows) in the parameter set table. Use this plot to visually analyze the relation between parameters and requirements. For example, in this case, the `SignalMatching` requirement looks monotonically related to the `Gain` parameter. To learn more about the plot, see “Interact with Plots in the Sensitivity Analyzer” on page 4-79.



You can make a contour plot of the evaluated results. To do so, select the evaluated result in the **Results** area of the app, and choose a contour plot in the **Plots** tab of the app.



The contour plot shows that the requirement does not vary systematically as a function of `Delay`, but it does as a function of `Gain`.

You can also quantify the relation between parameters and requirements. For more information, see "Analyze Relation Between Parameters and Design Requirements" on page 4-67.

See Also

Related Examples

- "Generate Parameter Samples for Sensitivity Analysis" on page 4-8
- "Specify Time-Domain Requirements" on page 4-21
- "Specify Frequency-Domain Requirements" on page 4-48
- "Analyze Relation Between Parameters and Design Requirements" on page 4-67

- “Validate Sensitivity Analysis” on page 4-96
- “Identify Key Parameters for Estimation (GUI)” on page 4-131

Analyze Relation Between Parameters and Design Requirements

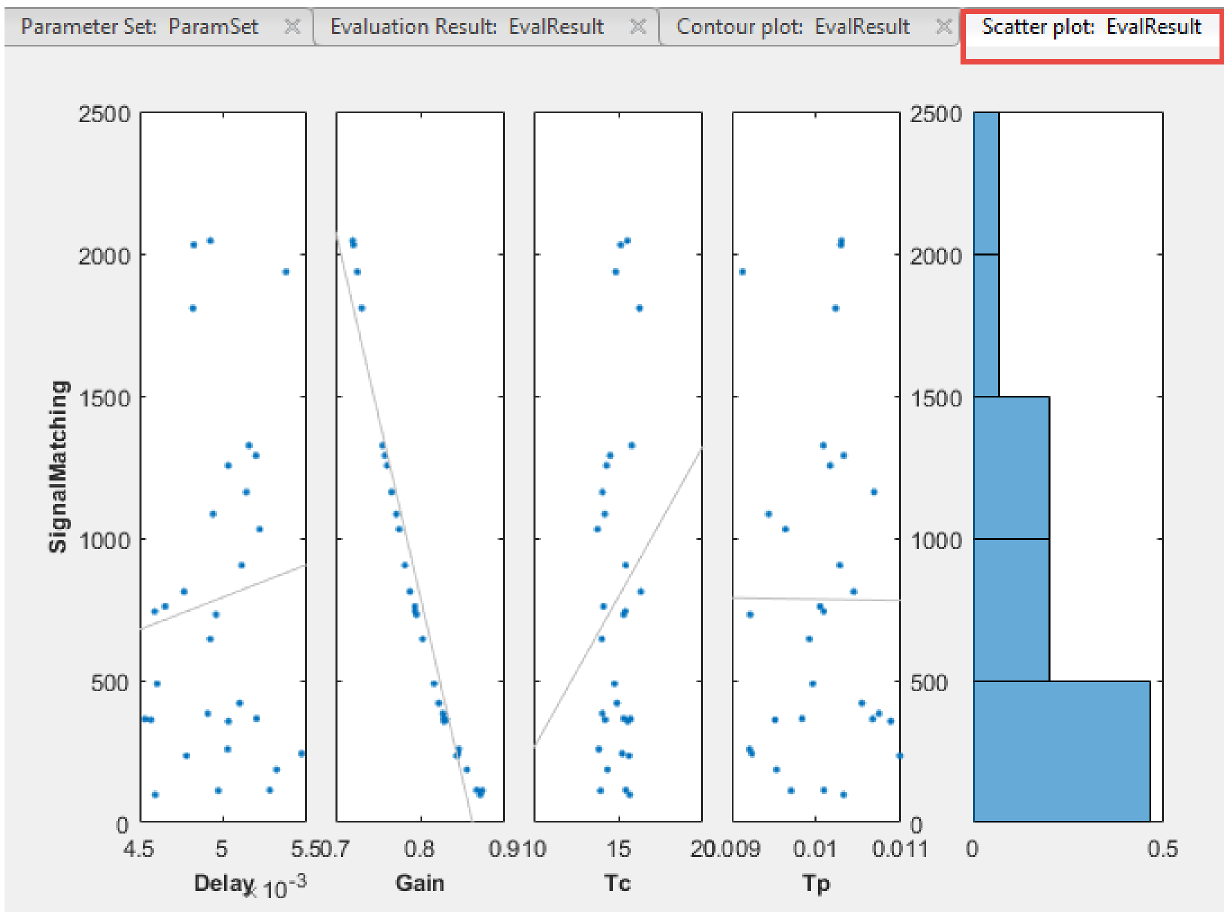
To analyze how the parameters and states (collectively referred to as parameters) of a Simulink model influence the design requirement on the model signals, you first generate samples of the parameters. You then define the cost function by creating a design requirement on the model signals, and evaluate the cost function for each sample. Finally, you analyze the relationship between the parameter variations and the cost function values. You can perform this analysis in the following ways:

- “Visual Analysis” on page 4-67
- “Statistical Analysis” on page 4-68

Visual Analysis

View a plot of the cost function evaluations against the parameter samples to identify trends. This method is informal and provides visual intuition about how the various parameters affect the cost function.

In the **Sensitivity Analyzer**, after the evaluation is complete, an evaluation result scatter plot is generated in the app. The plot displays the evaluated cost function value as a function of each parameter in the parameter set. The last column subplot displays the probability distribution of the evaluated cost function values. You can add a best-fit line to the scatter subplots by right-clicking in the plot, and selecting **Overlay linear fit** in the context menu. In this plot, the best-fit line indicates that the `Gain` parameter has a lot of influence on the requirement.



You can also plot a contour plot of the evaluated results. To learn more about these plots, see "Interact with Plots in the Sensitivity Analyzer" on page 4-79. For an example, see "Identify Key Parameters for Estimation (GUI)" on page 4-131.

At the command line, you can use tools such as:

- `sdo.scatterPlot` — Scatter plot of the parameter samples against the cost function evaluation
- `surf`, `mesh`, `contour` — 3-D plot of samples of two parameters against the cost function evaluation

For an example, see "Identify Key Parameters for Estimation (Code)" on page 4-169.

Statistical Analysis

In addition to visually analyzing the effect of parameters on the cost function, you can also compute statistics to quantify the relation.

Obtain summary statistics about the relationship between cost function evaluations and parameters samples. Available analysis methods include:

Method	Description
Correlation on page 4-70	Use to analyze how a model parameter and the cost function output are correlated.
Partial Correlation on page 4-70	Use to analyze how a model parameter and the cost function are correlated, removing the effects of the remaining parameters.
Standardized Regression on page 4-70	Use when you expect that the model parameters linearly influence the cost function.

For each of these methods, you specify what data to use for the analysis by choosing from the following analysis types:

- Linear analysis, also referred to as Pearson analysis — Uses raw data for analysis. Use linear analysis when you expect a linear relation between the parameters and cost function, and when the residuals about the best-fit line are expected to be normally distributed. Linear analysis is also recommended when the number of samples, and so the number of residual points is large.
- Ranked analysis, also referred to as Spearman analysis and ranked transformation — Uses ranks of data for analysis. Use ranked analysis when you expect a nonlinear monotonic relation between the parameters and the cost function and when the residuals about the best-fit line are not normally distributed. Ranked analysis is also recommended when the number of samples, and so the number of residual points is small.

  Linear analysis retains information about intervals between data values, whereas ranked analysis does not. Suppose that you had the following data set:

x_1	x_2	y
9	20	340
5	60	106
2.3	50.4	870.5

  Here x_1 and x_2 are model parameters, and y is the cost function. Each row represents a sample and the associated cost function evaluation.

  The data is ranked on a per column basis. For example, when you rank the data in column 1 (x_1), which contains the entries 9, 5, and 2.3, the ranked data is equal to 3, 2, and 1. The ranked data set for the samples of x_1, x_2 and y are as follows:

x_1	x_2	y
3	1	2
2	3	1
1	2	3

  The ranked data set can be used for correlation, partial correlation, or standardized regression analysis.
- Kendall — Kendall’s tau rank correlation coefficient is calculated.

  Applicable when the analysis method is Correlation. Requires Statistics and Machine Learning Toolbox software.

Correlation Method

Calculates the correlation coefficients, R. Use this method to analyze how a model parameter and the cost function outputs are correlated.

R is calculated as follows:

$$
\begin{aligned}
R(i,j) &= \frac{C(i,j)}{\sqrt{C(i,i)C(j,j)}} \\
C &= cov(x,y) \\
&= E[(x-\mu_x)(y-\mu_y)] \\
\mu_x &= E[x] \\
\mu_y &= E[y]
\end{aligned}
$$

`x` contains Ns samples of Np model parameters. `y` contains Ns rows, each row corresponds to the cost function evaluation for a sample in `x`.

R values are in the [-1 1] range. The (i,j) entry of R indicates the correlation between $x(i)$ and $y(j)$.

- `R(i,j) > 0` — Variables have positive correlation. The variables increase together.
- `R(i,j) = 0` — Variables have no correlation.
- `R(i,j) < 0` — Variables have negative correlation. As one variable increases, the other decreases.

Partial Correlation Method

Calculates the partial correlation coefficients, R. This method requires Statistics and Machine Learning Toolbox software. Use this method to analyze how a model parameter and the cost function are correlated, adjusting to remove the effect of the other parameters.

R is calculated using `partialcorri` from the Statistics and Machine Learning Toolbox software.

Standardized Regression Method

Calculates the standardized regression coefficients, R. Use this method when you expect that the model parameters linearly influence the cost function.

R is calculated as follows:

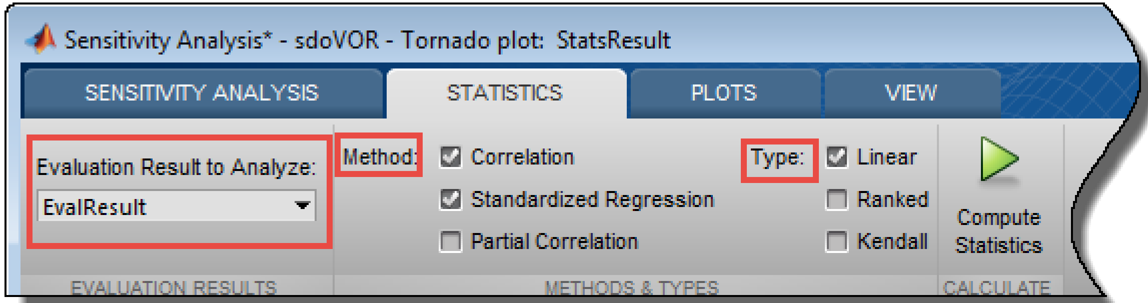
$$R = b_x \frac{\sigma_x}{\sigma_y}$$

Consider a single sample (x_1,...,xNp) and the corresponding single output, y. b_x is the regression coefficient vector calculated using least squares assuming a linear model $\hat{y} = b_0 + \sum_{i=1}^{Np} \hat{b}_{x_i} x_i$. R standardizes each element of b_x by multiplying it with the ratio of the standard deviation of the corresponding x sample (σ_x) to the standard deviation of y (σ_y).

Perform Statistical Analysis

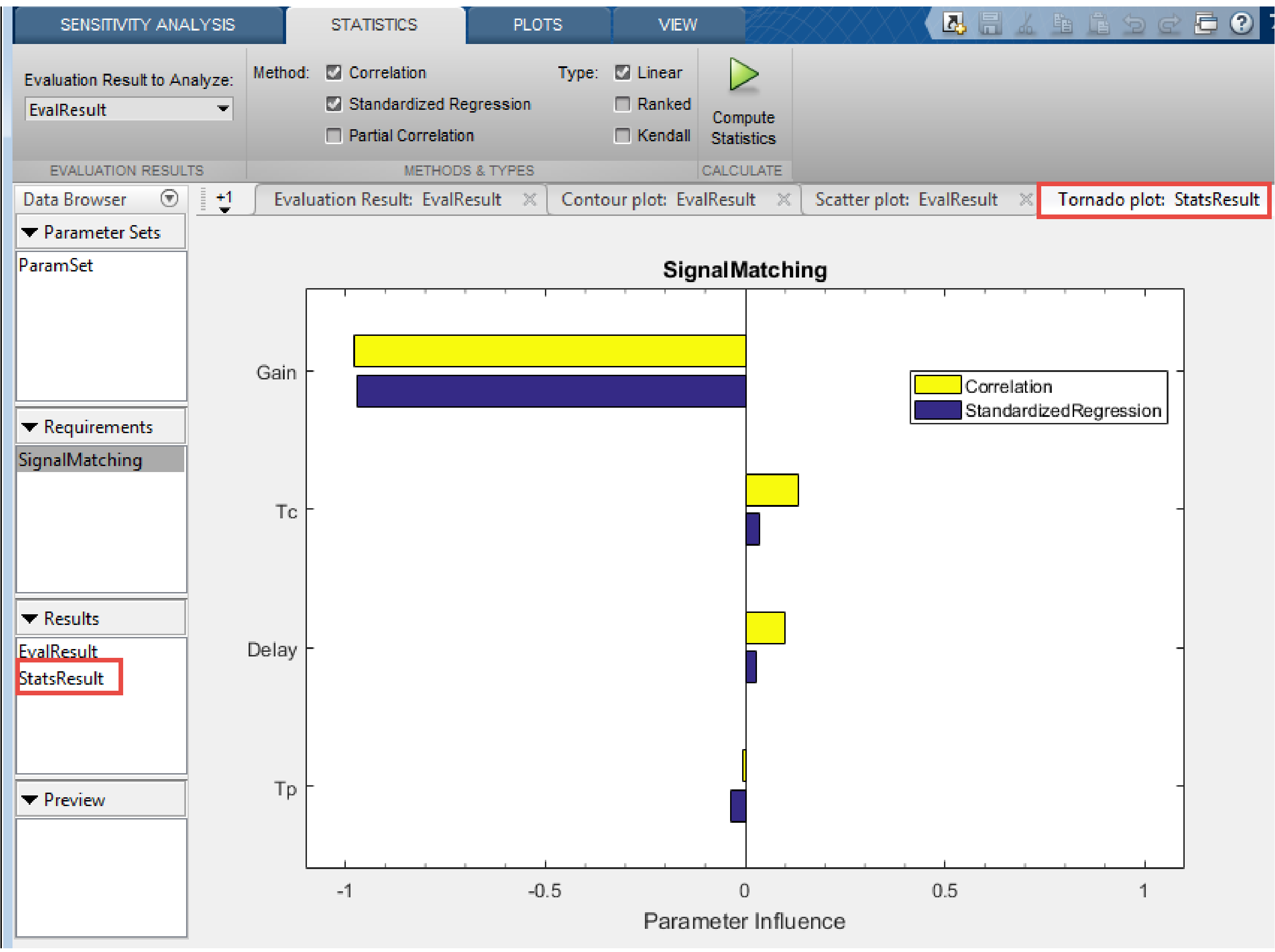
In the **Sensitivity Analyzer**, after you have evaluated the design requirements on page 4-60, specify the analysis methods and types in the **Statistics** tab of the app.

Select the evaluation results you want to analyze in the **Evaluation Results to Analyze** list. After that, you specify the analysis methods and types, and click **Compute Statistics**. You can compute all applicable combinations of analysis methods and types.



The results of the analysis are returned in the `StatsResult` variable, in the **Results** area of the app. In this case, the `StatsResult` variable includes the linear (Pearson) correlation coefficients and linear standardized regression coefficients calculated between the cost function and each parameter. To see the coefficients, right-click `StatsResult`, and select **Open** in the context-menu.

A tornado plot is generated that displays the results of the analysis in order of influence of parameters on the cost function. The parameter that most influences the cost function is displayed on the top. As was seen in the results scatter plot, in this tornado plot the `Gain` parameter has the most influence on the design requirement cost function.



To learn more about tornado plots, see "Interact with Plots in the Sensitivity Analyzer" on page 4-79. For an example, see "Identify Key Parameters for Estimation (GUI)" on page 4-131.

At the command line, specify the analysis methods and types using `sdo.analyze`. This function performs linear correlation analysis by default. To specify other analysis methods, use `sdo.AnalyzeOptions`. For an example, see "Identify Key Parameters for Estimation (Code)" on page 4-169.

See Also

`sdo.AnalyzeOptions` | `sdo.analyze` | `sdo.sample` | `sdo.evaluate`

Related Examples

- "What is Sensitivity Analysis?" on page 4-2
- "Evaluate Design Requirements" on page 4-60
- "Identify Key Parameters for Estimation (GUI)" on page 4-131
- "Identify Key Parameters for Estimation (Code)" on page 4-169

- “Use Sensitivity Analysis to Configure Estimation and Optimization” on page 4-74

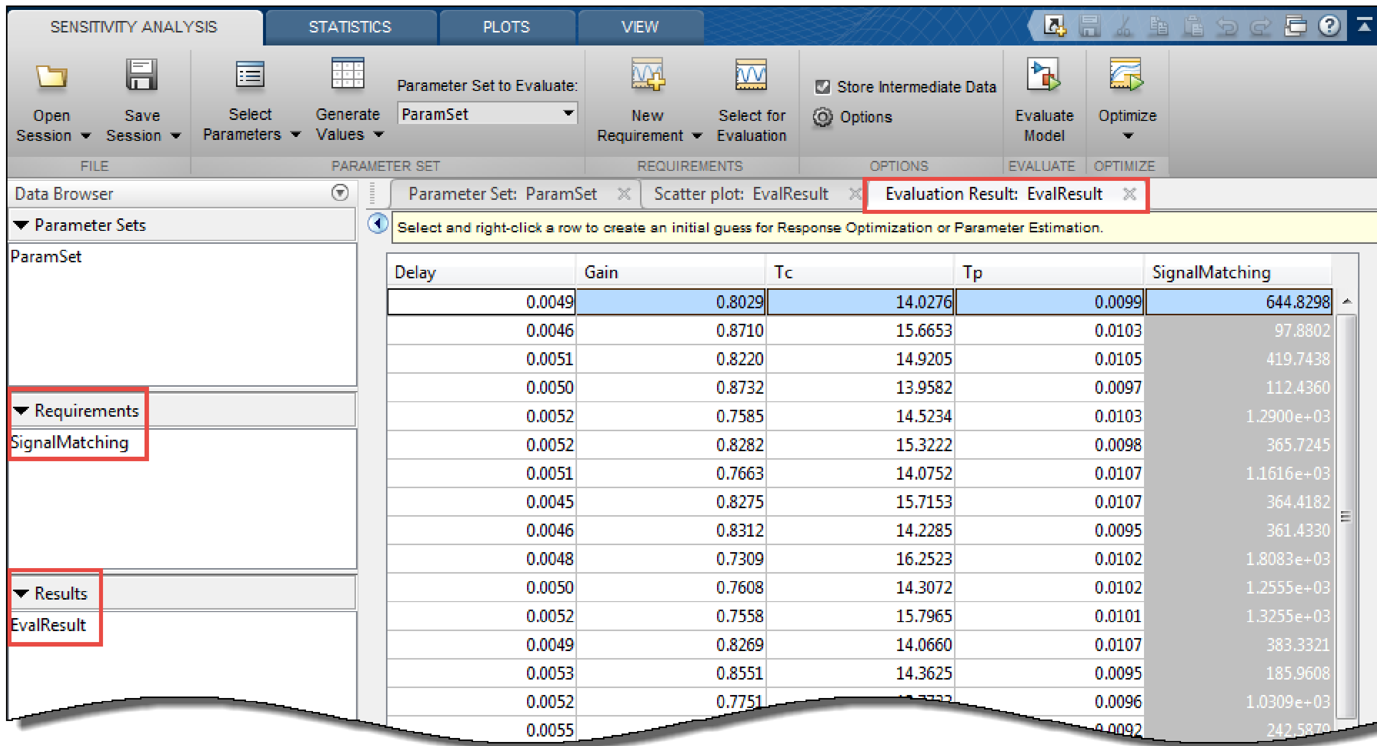
Use Sensitivity Analysis to Configure Estimation and Optimization

This topic shows how to use the results generated in the **Sensitivity Analyzer** to configure parameter estimation or response optimization.

You can use sensitivity analysis to evaluate how the parameters of a Simulink model influence the model output or model design requirements. You first generate samples of the parameters, and then define a cost function by creating a design requirement on the model signals. For more information see, "Generate Parameter Samples for Sensitivity Analysis" on page 4-8, "Specify Time-Domain Requirements" on page 4-21, and "Specify Frequency-Domain Requirements" on page 4-48. You then evaluate the requirement (cost function) for each sample. You can use the evaluated results to configure parameter estimation or response optimization in the following ways:

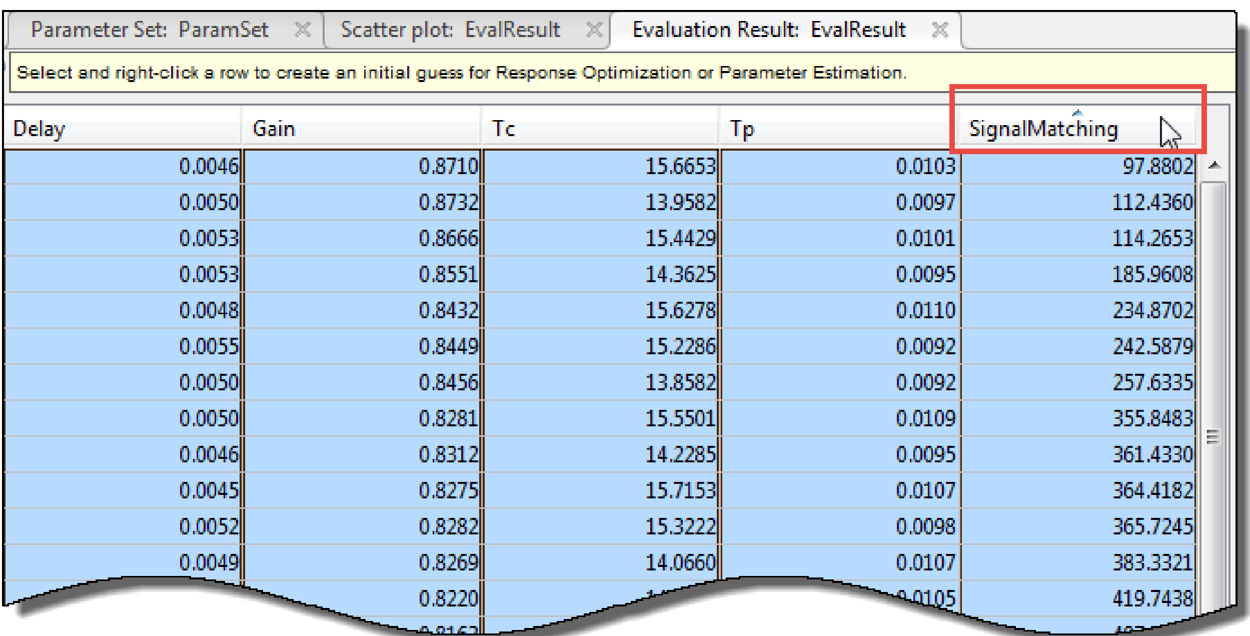
1. Analyze the relationship between the parameters and the evaluated requirement values, and rank parameters in order of influence. For more information, see "Analyze Relation Between Parameters and Design Requirements" on page 4-67. You can then choose to estimate or optimize the more influential parameters.
2. Obtain initial guesses for parameter values for estimation or optimization.

   After you evaluate the requirements in the **Sensitivity Analyzer**, the evaluated requirement (cost function value) and the corresponding parameter values are displayed in the **Evaluation Result** table of the app. A new variable, `EvalResults`, with this information is created in the **Results** area of the app. For example, the table below lists the evaluated signal matching requirement and corresponding values for the parameters `Gain`, `Delay`, `Tc`, and `Tp` of the model, `sdoVOR`.

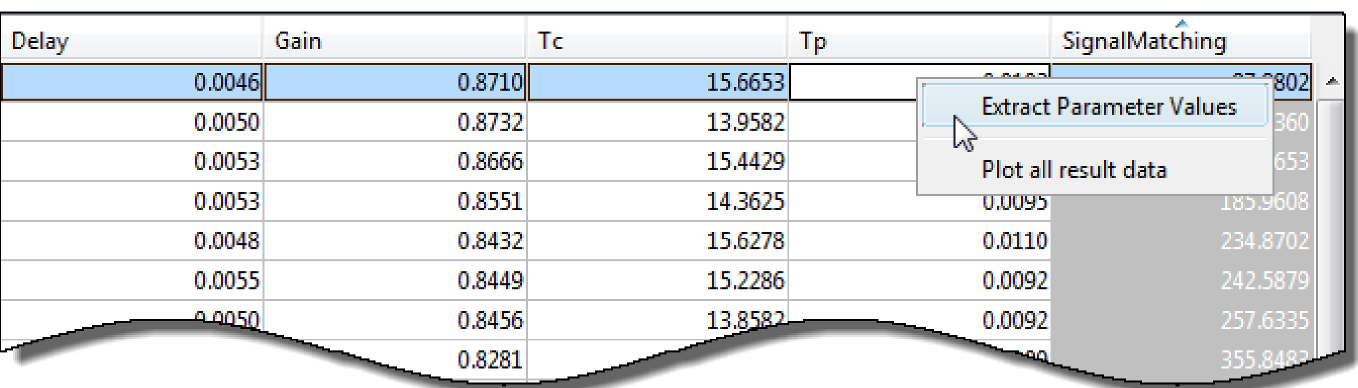


To extract parameter values to use as an initial guess during estimation or optimization:

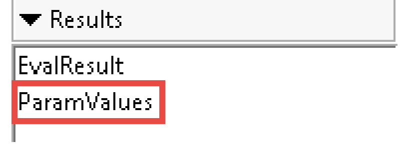
a Sort the evaluated cost function values in ascending order by clicking the evaluated requirement column.



b To choose the parameter values that minimize the cost function, right-click corresponding row, and select **Extract Parameter Values**.



A new variable, `ParamValues`, is created in the **Results** area of the app.



c When exporting to a Parameter Estimator or Response Optimizer app session on page 4-76, choose this variable to specify the initial guess for parameters.

3 To test the robustness of your design during optimization in the **Response Optimizer** app, specify the values for uncertain parameters. For more information, see “Optimizing Parameters for Robustness” on page 3-177.

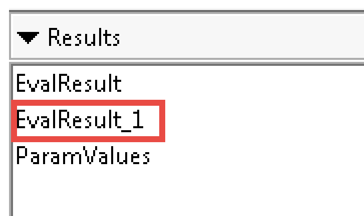
You can specify the values for uncertain parameters using all the parameter values in `EvalResults`. You can also choose a subset of the parameter values:

a Select the relevant rows of parameter values in the **Evaluation Result** table of the app.

Delay	Gain	Tc	Tp	SignalMatching
0.0054	0.8694	15.9519	0.0100	100.2616
0.0046	0.8668	13.9571	0.0098	137.8549
0.0047	0.8687	13.9969	0.0093	138.2714
0.0049	0.8545	13.9865	0.0099	192.0046
0.0052	0.8529	[illegible]	0.0102	196.9189
0.0053	0.8503	[illegible]	0.0094	215.8378
0.0052	0.8447	[illegible]	0.0109	222.4661
0.0055	0.8412	[illegible]	0.0095	266.2807
0.0048	0.8406	16.4884	0.0092	268.3061
[illegible]	0.8186	[illegible]	0.0101	451.3620
[illegible]	0.8136	[illegible]	[illegible]	[illegible]

Create new evaluation result
Plot all result data

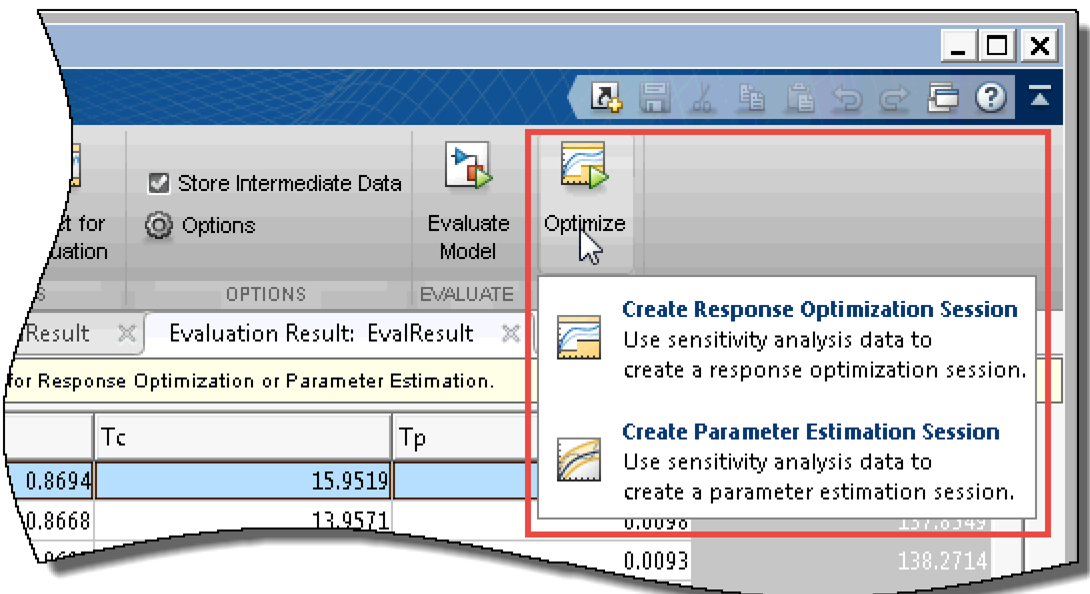
b Right-click, and select **Create new evaluation result**. A new variable is created in the **Results** area of the app.



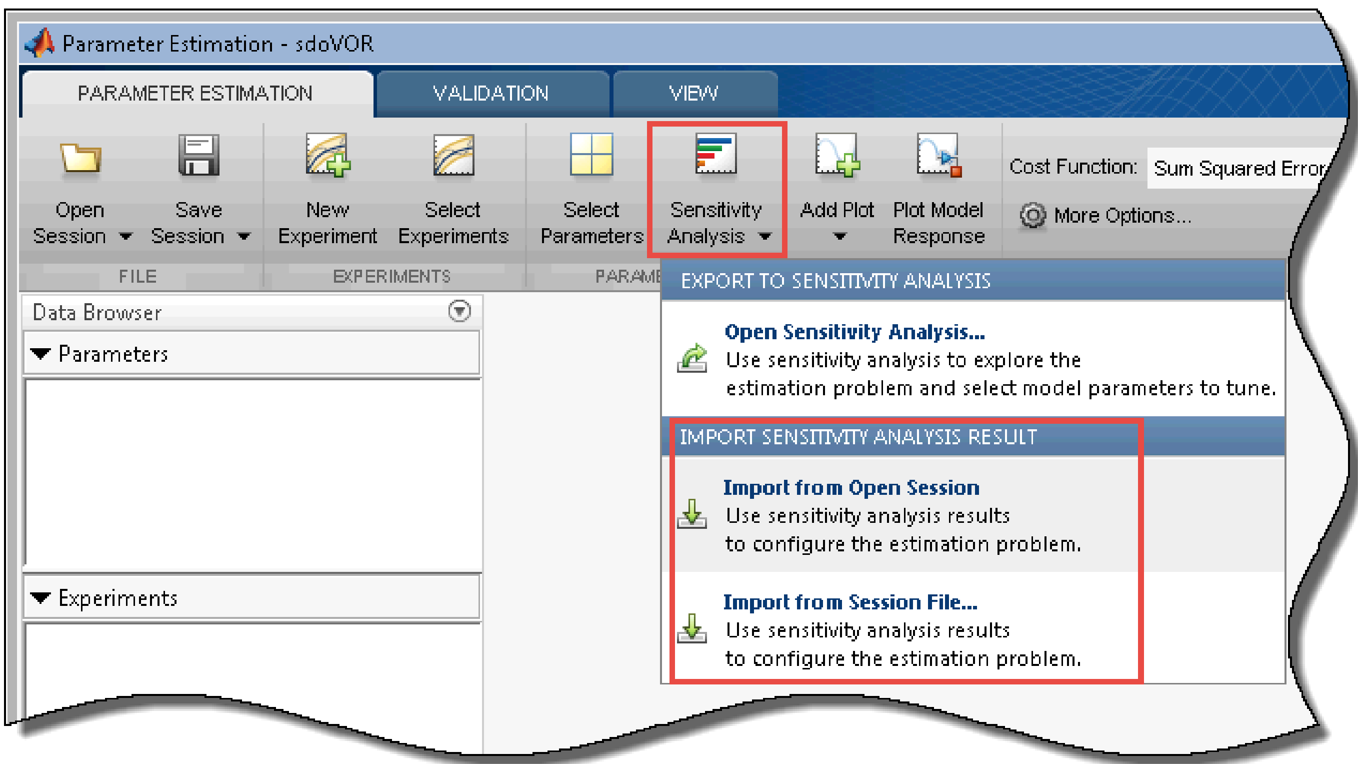
c When exporting to a Response Optimizer app session on page 4-76, choose this variable to specify the uncertain variables.

Export Sensitivity Analysis Results

You can export results from **Sensitivity Analyzer** to the **Parameter Estimator** and **Response Optimizer** apps. To do so, in the **Sensitivity Analyzer**, click **Optimize**. In the drop-down menu, choose the app to export to.



Alternatively, if you have an open **Parameter Estimator** or **Response Optimizer** session, in these apps, click **Sensitivity Analysis**. In the drop-down menu, choose **Import from Open Session** or **Import from Session file**. The latter option loads results from a previously saved **Sensitivity Analyzer** session.



Note

- Only signal matching requirements are exported from Sensitivity Analysis to a **Parameter Estimator** session. In the **Parameter Estimator**, they are referred to as experiments.
- Only requirements other than signal matching requirements are exported from Sensitivity Analysis to a **Response Optimizer** session.

See Also

Related Examples

- “What is Sensitivity Analysis?” on page 4-2
- “Design Exploration Using Parameter Sampling (GUI)” on page 4-112
- “Identify Key Parameters for Estimation (GUI)” on page 4-131

Interact with Plots in the Sensitivity Analyzer

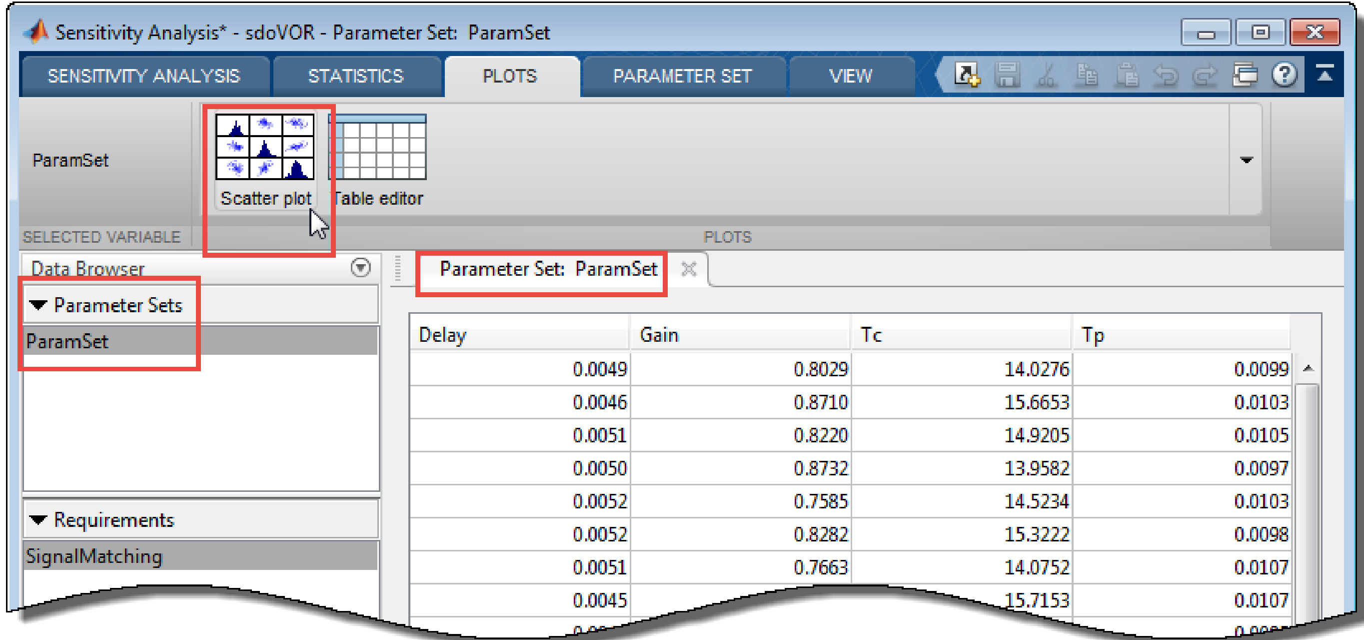
This topic shows how to interact with and interpret plots generated in the **Sensitivity Analyzer** app.

Parameter Set Plots

After you have generated parameter values for sensitivity analysis, you can plot the generated parameter set. For information about parameter generation, see “Generate Parameter Samples for Sensitivity Analysis” on page 4-8.

The app displays the generated parameter set and the corresponding parameter set table. The number of rows in the parameter set table correspond to the number of samples you specified. To plot the generated parameters in the app:

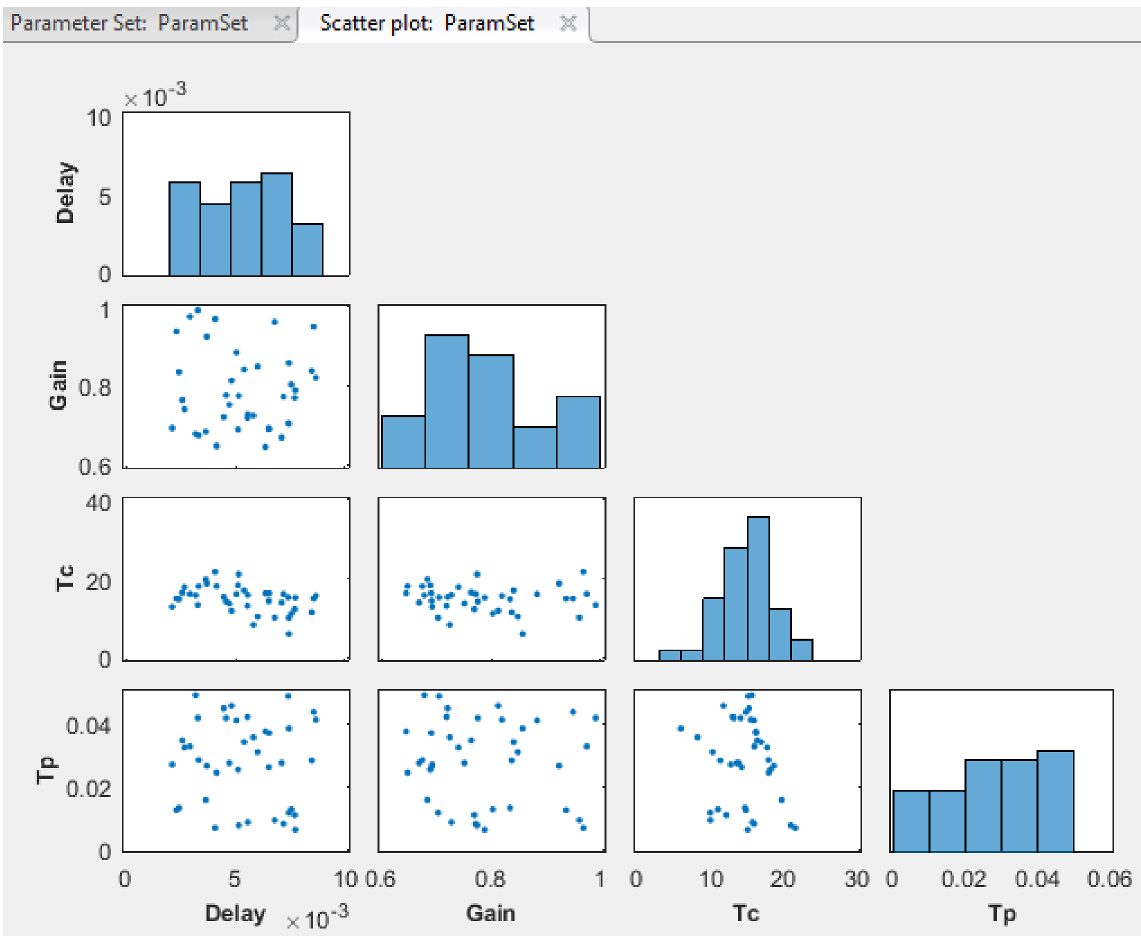
1 Select the generated parameter set in the **Parameter Sets** area of the app.



2 On the **Plots** tab, select **Scatter Plot**.

Alternatively, right-click the parameter set, and select **Plot** in the drop-down menu.

The diagonal subplots display the histograms of generated parameter values. The off-diagonal subplots are pair-wise scatter plots of the parameters. The number of data points in each scatter plot equals the number of rows in the parameter set table.



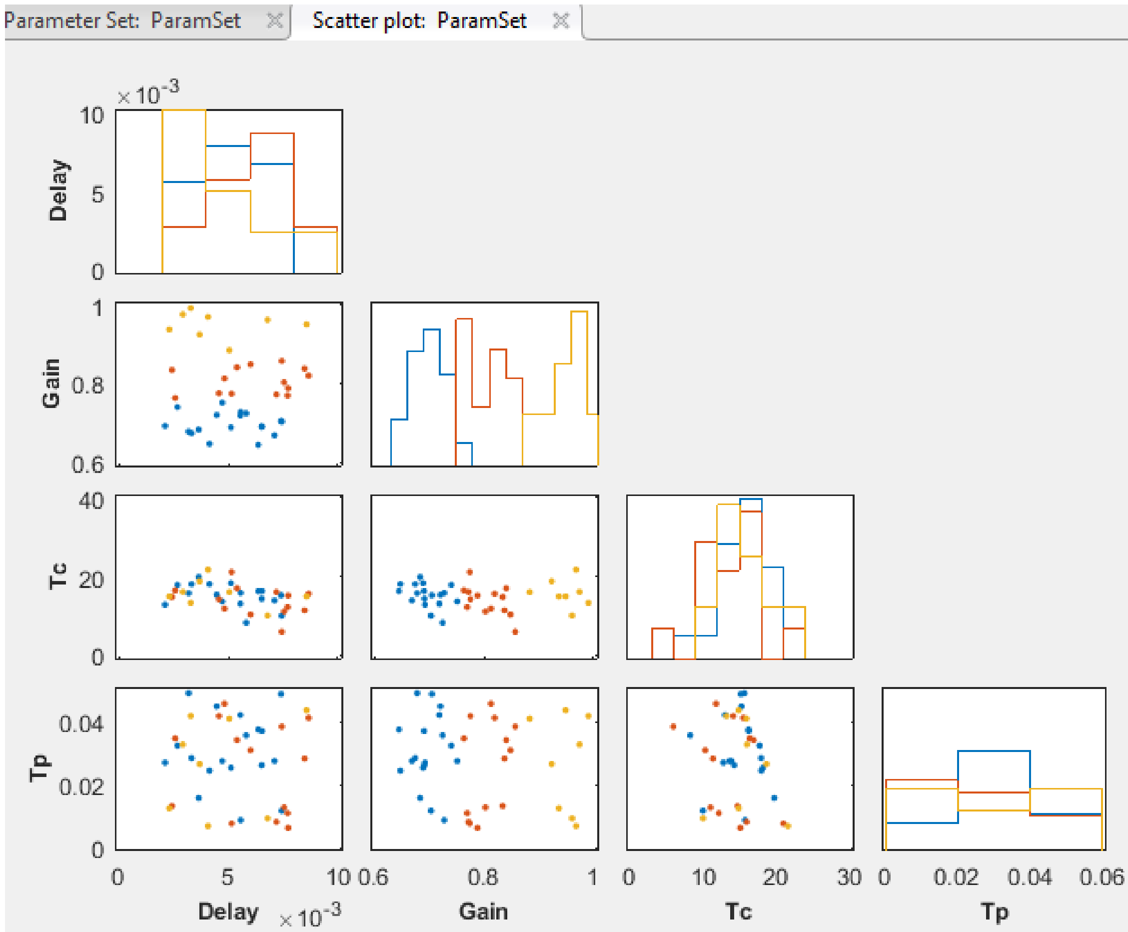
You can inspect the histograms to ensure that the generated parameter values match the desired parameter distributions within the constraints of a finite sample size. Inspect the off-diagonal scatter plots to ensure that any specified correlations between parameters are present. For more information, see “Inspect the Generated Parameter Set” on page 4-96.

3 To access additional plot features, right-click in the white area of any scatter plot.

You can choose from the following options:

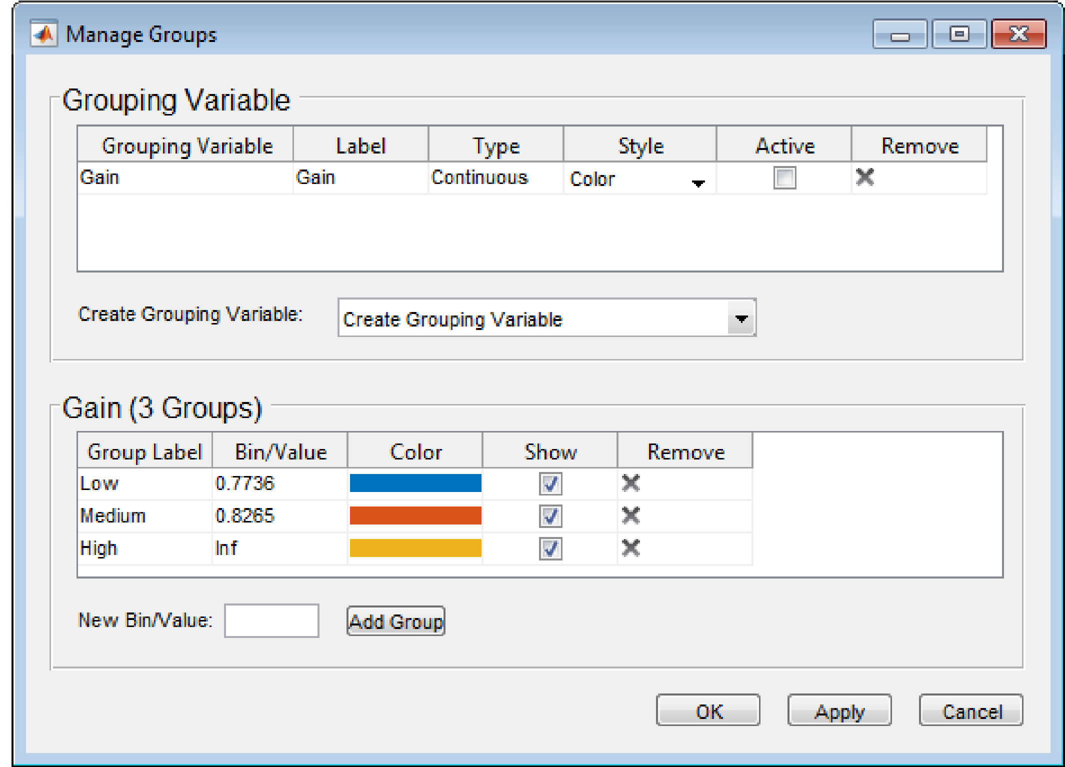
- **Variables** — Select the parameters to plot.
- **Groups** — Select grouping variables for the plots, and configure how the groups are displayed.

  To select a parameter as a grouping variable, click **Groups** > **New Grouping Variable**. For example, the following plot is generated when the grouping variable is `Gain`.



The app creates three groups based on low, medium, and high values of the grouping variable. The app computes these grouping values, but you can change them in the **Manage Groups** dialog box. The second diagonal plot shows the distribution of the gain values in the low (blue), medium (red), and high (yellow) groups. The other diagonal plots show the distribution of the remaining parameters when the corresponding gain value is low, medium, or high. The off-diagonal scatter plots show points belonging to the same group using the same color.

You can demarcate the groups based on marker size and marker type instead of color, add more groups corresponding to the grouping variable, and change the grouping values. You can also add more grouping variables. To do so, click **Groups** > **Manage Groups**.



In the **Manage Groups** dialog box, you configure how the groups are displayed. You can perform tasks such as:

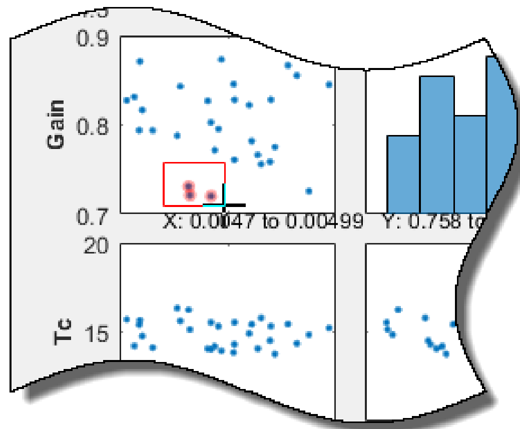
- Select the plotting **Style** as either `Color`, `MarkerSize`, or `MarkerType`. In the plots, the app uses the selected style to demarcate the groups corresponding to a grouping variable.
- Select whether a grouping variable is **Active**. If a grouping variable is inactive, the scatter plot points are not demarcated in groups corresponding to that variable. To delete a grouping variable, click ✕ in the corresponding **Remove** column.
- Add more grouping variables using the **Create Grouping Variable** drop-down list.
- For a grouping variable, specify the range of values for each group in the **Bin/Value** column. For example, currently the dialog box shows that the `Gain` values in the groups are:

  - **Low** — below 0.7736
  - **Medium** — 0.7736–0.8265
  - **High** — above 0.8265

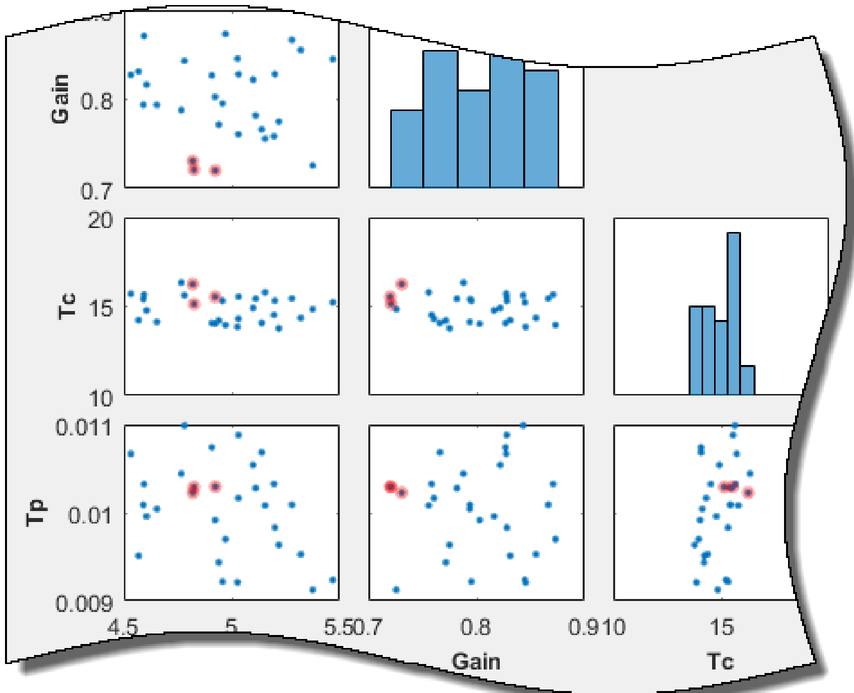
  To change the **Low** group values to be 0.79 or lower, type `0.79` in the corresponding row of the **Bin/Value** column.
- Add more groups corresponding to a grouping variable. For example, to add a group with values from 0.8265 through 0.9, type `0.9` in **New Bin/Value**, and click **Add Group**.

- **Upper triangle plot** — Plot the off-diagonal subplots above the diagonal in addition to the existing plots.
- **Marginal Box Plots** — Requires Statistics and Machine Learning Toolbox software. Plot box plots for each of the parameters in the parameter set, and choose the position of the plots.

- **Histograms** — Plot the probability distribution of the parameters, and choose the position of the plots.
- **Kernel Density Plots** — Requires Statistics and Machine Learning Toolbox software. Plot the probability distribution of the parameters using a kernel density estimator, and choose the position of the plots. For more information, see "Kernel Distribution" (Statistics and Machine Learning Toolbox).
- **Overlay linear fit** — Plot the best-fit line on the scatter subplots. You can choose to plot the best-fit lines for one, all, a row, or a column of scatter subplots.
- **Enable brushing/data selection** — Enable selection of data points in the scatter subplots.



When you highlight parameter values in one plot, the values corresponding to other parameters from the same row in the parameter set table are also highlighted. In addition, the rows in the parameter set table that correspond to these values are highlighted.



Delay	Gain	Tc	Tp
0.0049	0.8029	14.0276	0.0099
0.0046	0.8710	15.6653	0.0103
0.0051	0.8220	14.9205	0.0105
0.0050	0.8732	13.9582	0.0097
0.0052	0.7585	14.5234	0.0103
0.0052	0.8282	15.3222	0.0098
0.0051	0.7663	14.0752	0.0107
0.0045	0.8275	15.7153	0.0107
0.0046	0.8312	14.2285	0.0095
0.0048	0.7309	16.2523	0.0102
0.0050	0.7608	14.3072	0.0102
0.0052	0.7558	15.7965	0.0101
0.0049	0.8269	14.0660	0.0107
0.0053	0.8551	14.3625	0.0095
0.0052	0.7751	13.7733	0.0096
0.0055	0.8449	15.2286	0.0092
0.0050	0.8281	15.5501	0.0109
0.0048	0.7211	15.1398	0.0103
0.0046	0.8163	14.7772	0.0100
0.0051	0.7819	15.4333	0.0103
0.0053	0.8666	15.4429	0.0101
0.0049	0.7202	15.5371	0.0103
0.0046	0.7940	15.4074	0.0101
0.0048	0.7879	16.3355	0.0104

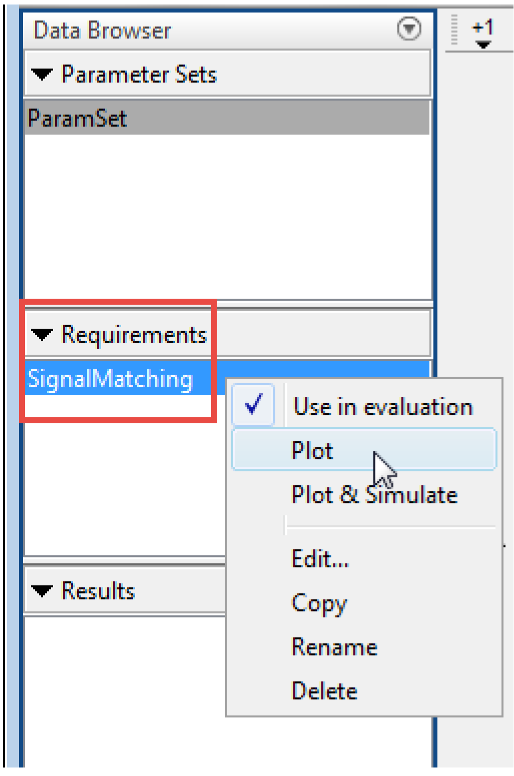
To remove the highlighting, invert the selection to all other data points in the plot, or disable the feature, right-click the highlighted data points, and choose from the context-menu.

- **Pop-out plot** — View a subplot in a new window.

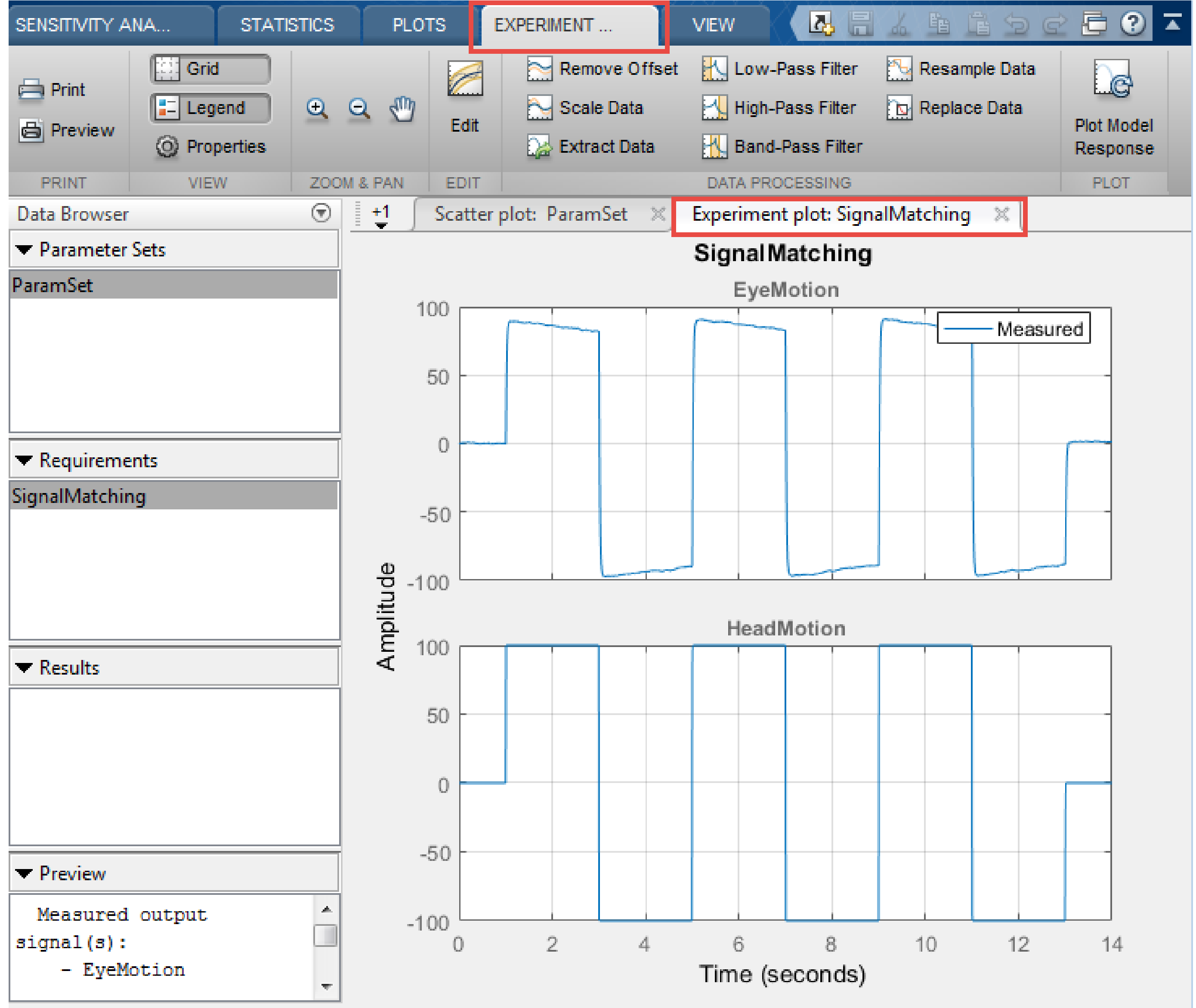
Requirement Plots

After you have specified design requirements, you can plot the requirements and associated model response. For information about specifying the requirements, see “Specify Time-Domain Requirements” on page 4-21 and “Specify Frequency-Domain Requirements” on page 4-48.

The specified requirements are displayed in the **Requirements** area of the app. To plot the requirement in the app, right-click the requirement, and select **Plot**.

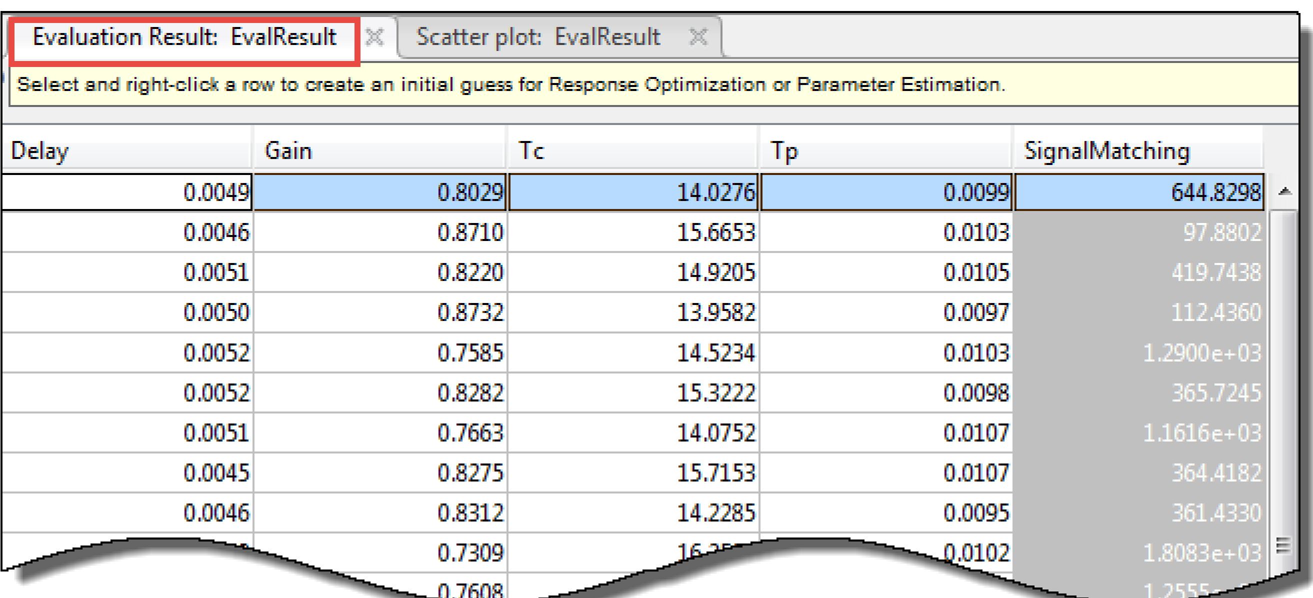


Alternatively, select the requirement, and in the **Plots** tab of the app, select the plot type. A plot is generated and a new tab associated with the plot appears in the app. In the new tab, you can perform additional tasks such as preprocessing imported data on page 1-13 (for signal matching requirement only), zooming, and plotting the associated model response. The model response is the signal or system on which the requirement is applied. The response is plotted using the parameter values specified in the model workspace and is not updated during evaluation.



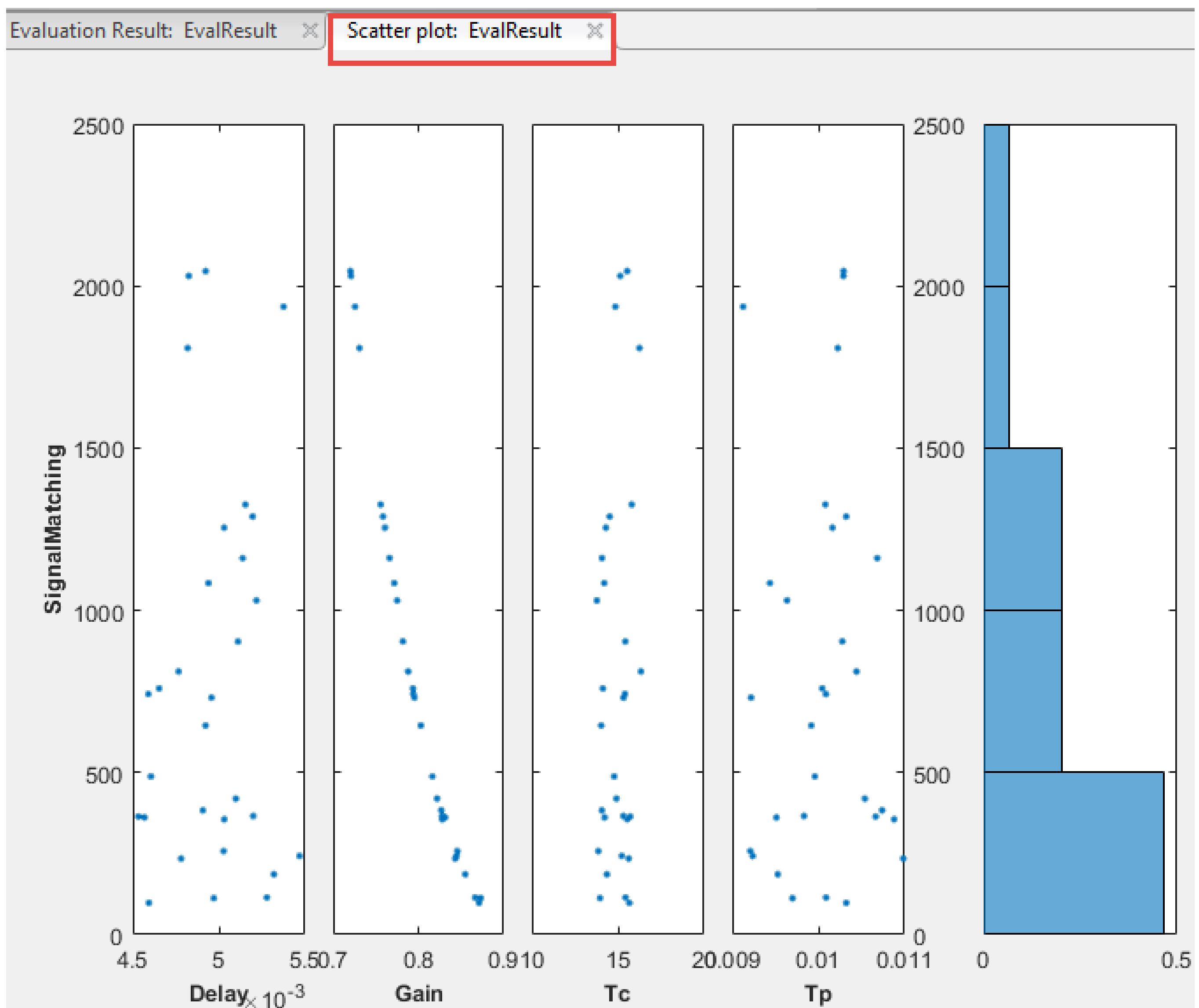
Evaluated Result Scatter Plots

After you have evaluated your design requirements on page 4-60, an evaluation results table lists the samples in the parameter set and the corresponding evaluated requirement (cost function) values. For requirements that involve a bound, a positive requirement value indicates that your requirement was violated, while a negative value indicates that the requirement was satisfied for that sample of parameter values.



Delay	Gain	Tc	Tp	SignalMatching
0.0049	0.8029	14.0276	0.0099	644.8298
0.0046	0.8710	15.6653	0.0103	97.8802
0.0051	0.8220	14.9205	0.0105	419.7438
0.0050	0.8732	13.9582	0.0097	112.4360
0.0052	0.7585	14.5234	0.0103	1.2900e+03
0.0052	0.8282	15.3222	0.0098	365.7245
0.0051	0.7663	14.0752	0.0107	1.1616e+03
0.0045	0.8275	15.7153	0.0107	364.4182
0.0046	0.8312	14.2285	0.0095	361.4330
[illegible]	0.7309	[illegible]	0.0102	1.8083e+03
[illegible]	0.7608	[illegible]	[illegible]	[illegible]

An evaluation result plot is also generated. The scatter subplots display the evaluated requirement (cost function value) as a function of each parameter in the parameter set. The number of points in each scatter plot equals the number of rows in the parameter set. The last column of subplots displays histograms of the probability distribution of the evaluated cost function values.



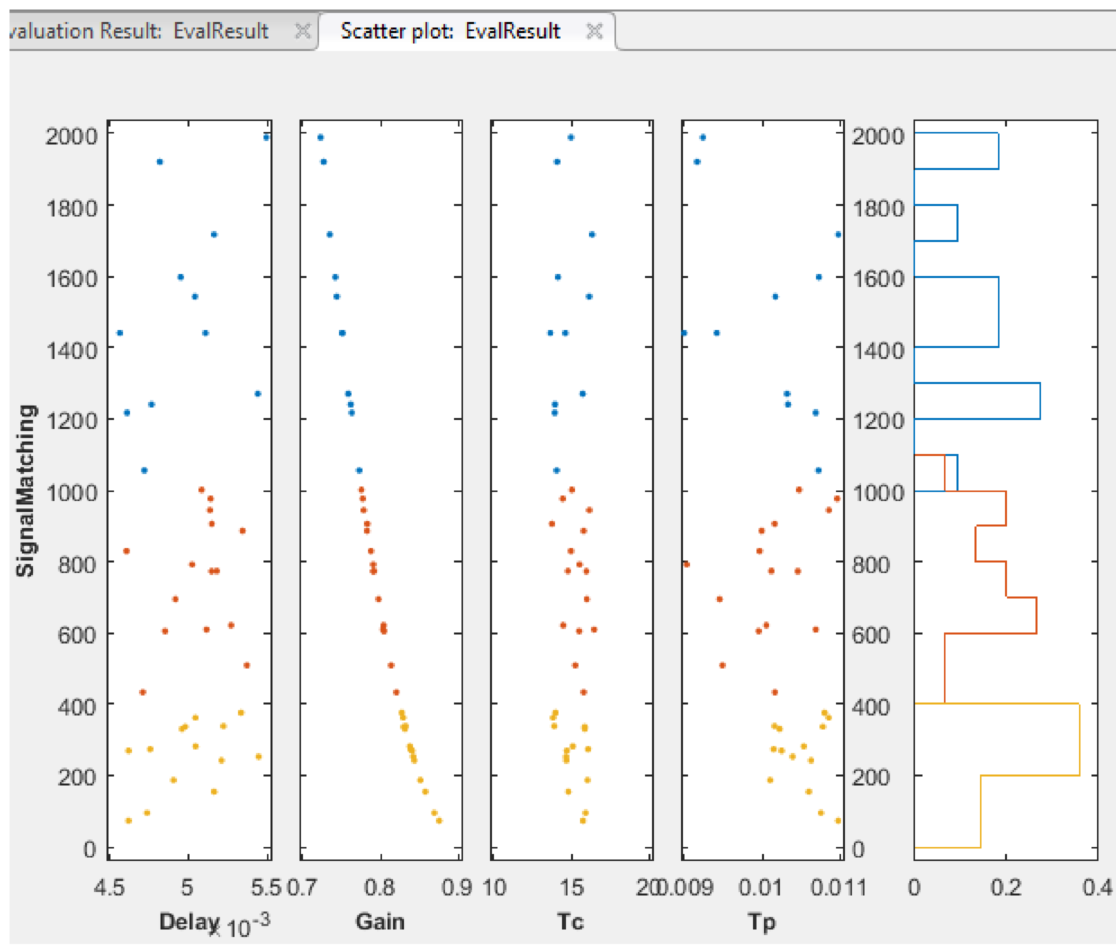
Use this plot to visually analyze the relation between parameters and requirements on page 4-67. For example, in this case, the `SignalMatching` requirement looks monotonically related to the `Gain` parameter.

You can also plot best-fit lines on the scatter subplots. To do so, and to access additional plot features, right-click in the white area of any scatter subplot.

You can choose from the following options:

- **X-Variables** — Select the parameters and requirements to use as x-variables in the scatter subplots.
- **Y-Variables** — Select the parameters and requirements to use as y-variables in the scatter subplots.
- **Grouping** — Select grouping variables for the subplots, and configure how the groups are displayed.

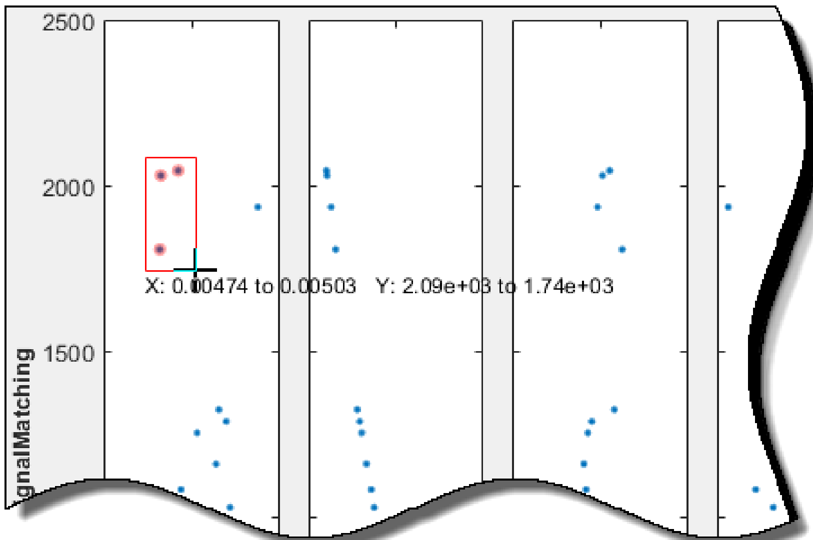
To select a parameter or evaluated requirement as a grouping variable, click **Groups > New Grouping Variable**. For example, the following plot is generated when the grouping variable is `Gain`. The app creates three groups based on low, medium, and high values of the grouping variable. The app computes these grouping values, but you can change them in the **Manage Groups** dialog box. The scatter subplots display the evaluated requirement values when the corresponding gain value is low (blue), medium (red), and high (yellow). The histogram plots the probability distribution of the evaluated requirement corresponding to the groups.



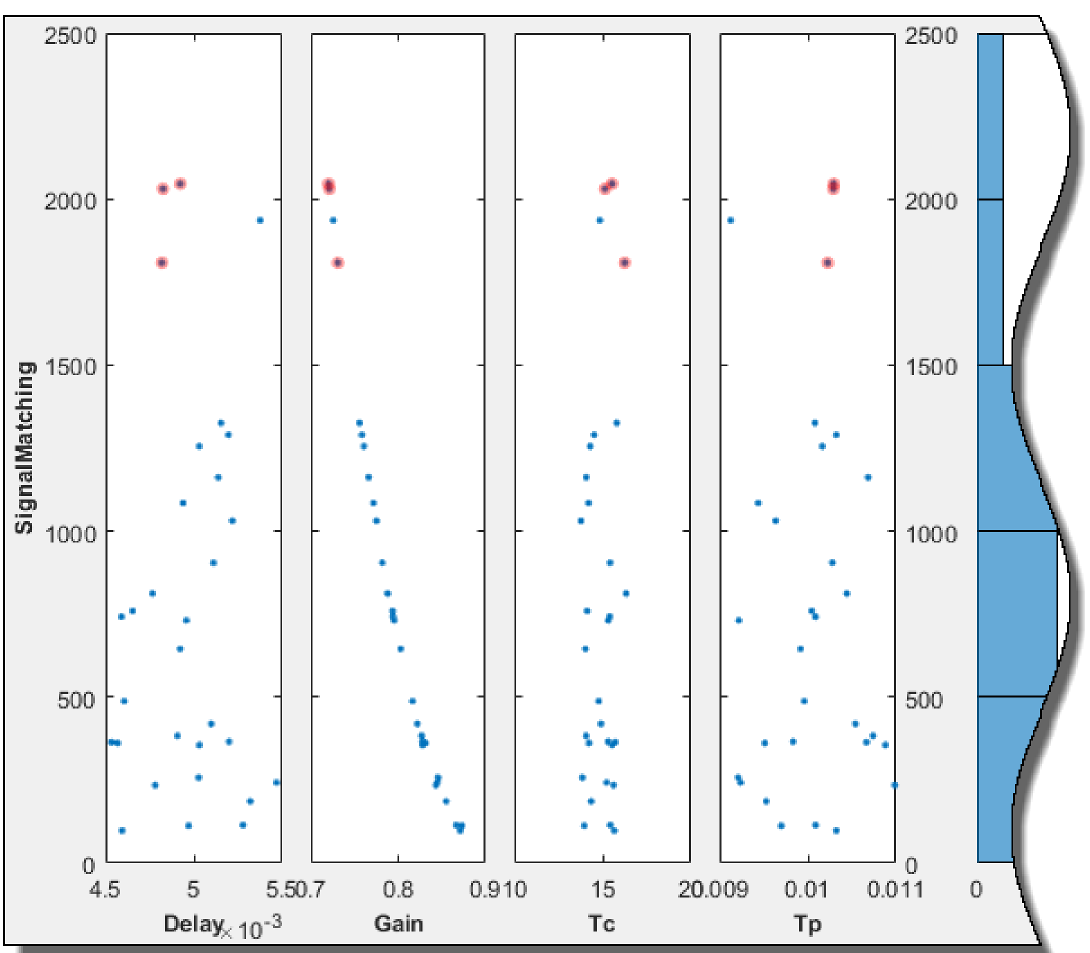
You can demarcate the groups based on marker size and marker type instead of color, add more groups corresponding to the grouping variable, and change the grouping values. You can also add more grouping variables. To do so, click **Groups > Manage Groups**. For more information, see “Parameter Set Plots” on page 4-79.

- **Marginal Box Plots** — Requires Statistics and Machine Learning Toolbox software. Plot box plots for each of the parameters in the parameter set, and choose the position of the plots.
- **Histograms** — Plot the probability distribution of the parameters, and choose the position of the plots.
- **Kernel Density Plots** — Requires Statistics and Machine Learning Toolbox software. Plot the probability distribution of the parameters using a kernel density estimator, and choose the position of the plots. For more information, see “Kernel Distribution” (Statistics and Machine Learning Toolbox).

- **Overlay linear fit** — Plot the best-fit line on the scatter subplots. You can choose to plot the best-fit lines for one, all, a row, or a column of scatter plots.
- **Enable brushing/data selection** — Enable selection of data points in the scatter subplots.



When you highlight parameter values in one scatter subplot, the values corresponding to other parameters from the same row in the evaluated results table are also highlighted. In addition, the rows in the evaluated results table that correspond to these values are highlighted.


SignalMatching
2500
2000
1500
1000
500
0
4.5
5
5.5
Delay
× 10-3
0.7
0.8
0.9
Gain
10
15
20
Tc
0.009
0.01
0.011
Tp
0

Delay	Gain	Tc	Tp	SignalMatching
0.0049	0.8029	14.0276	0.0099	644.8298
0.0046	0.8710	15.6653	0.0103	97.8802
0.0051	0.8220	14.9205	0.0105	419.7438
0.0050	0.8732	13.9582	0.0097	112.4360
0.0052	0.7585	14.5234	0.0103	1.2900e+03
0.0052	0.8282	15.3222	0.0098	365.7245
0.0051	0.7663	14.0752	0.0107	1.1616e+03
0.0045	0.8275	15.7153	0.0107	364.4182
0.0046	0.8312	14.2285	0.0095	361.4330
0.0048	0.7309	16.2523	0.0102	1.8083e+03
0.0050	0.7608	14.3072	0.0102	1.2555e+03
0.0052	0.7558	15.7965	0.0101	1.3255e+03
0.0049	0.8269	14.0660	0.0107	383.3321
0.0053	0.8551	14.3625	0.0095	185.9608
0.0052	0.7751	13.7733	0.0096	1.0309e+03
0.0055	0.8449	15.2286	0.0092	242.5879
0.0050	0.8281	15.5501	0.0109	355.8483
0.0048	0.7211	15.1398	0.0103	2.0309e+03
0.0046	0.8163	14.7772	0.0100	487.9127
0.0051	0.7819	15.4333	0.0103	904.3621
0.0053	0.8666	15.4429	0.0101	114.2653
0.0049	0.7202	15.5371	0.0103	2.0458e+03
0.0046	0.7940	15.4074	0.0101	742.1060
0.0048	0.7879	16.3355	0.0104	811.8904

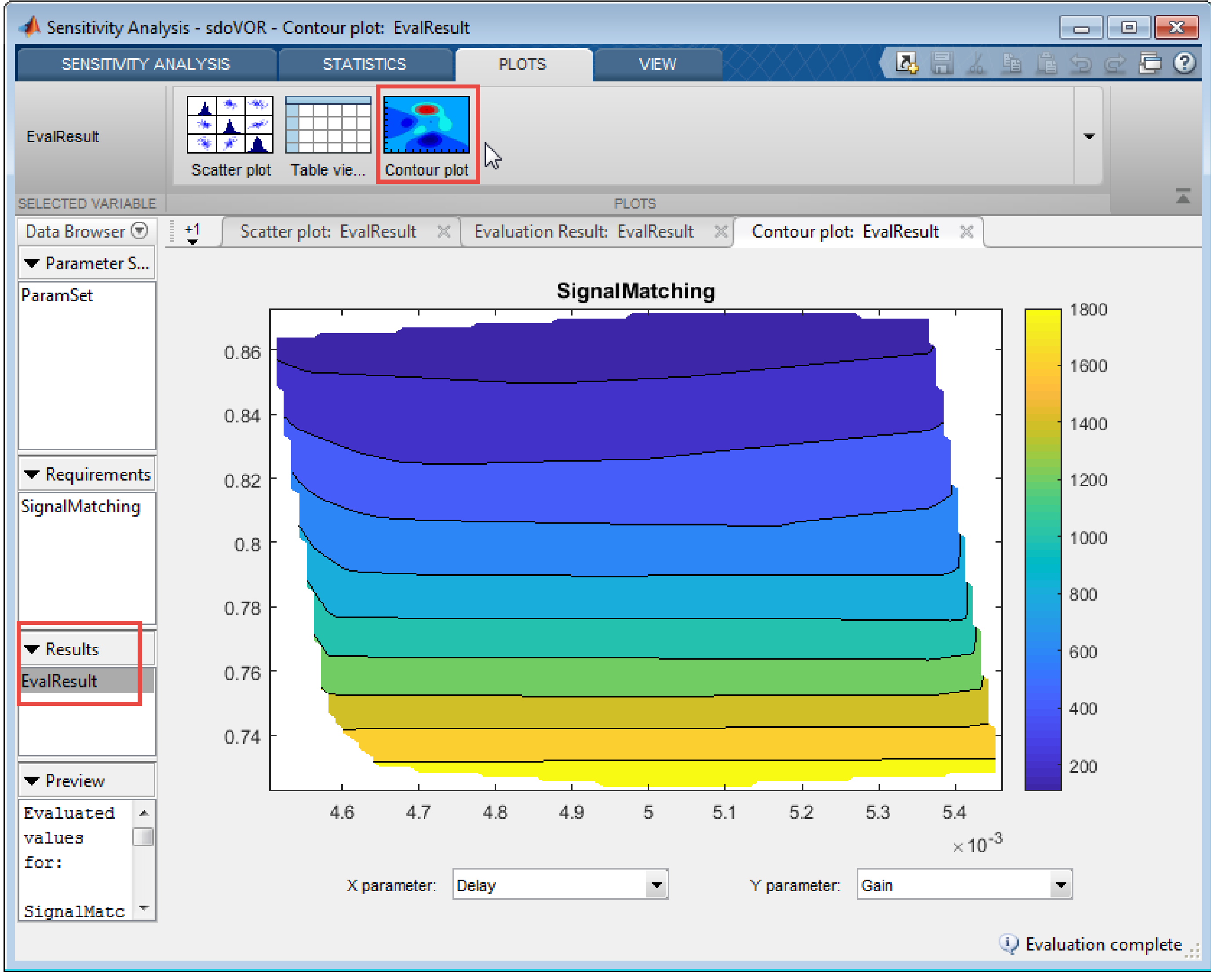
To remove the highlighting, invert the selection to all other data points in the plot, or disable the feature, right-click the highlighted data points, and choose from the context-menu.

- **Pop-out plot** — View a subplot in a new window.

Evaluated Result Contour Plots

After you have evaluated your design requirements, an evaluation results table lists the samples in the parameter set and the corresponding evaluated requirement (cost function) values. For information about evaluation, see “Evaluate Design Requirements” on page 4-60.

You can plot a contour plot of the evaluated results. To do so, select the evaluated result in the **Results** area of the app, and choose a contour plot in the **Plots** tab of the app.



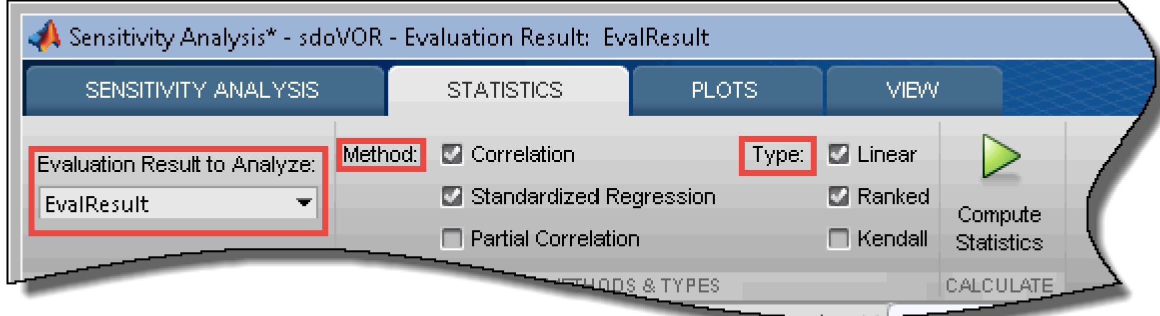
Use this plot to visually analyze the relation between parameters and design requirements. Select the parameters to plot in the **X parameter** and **Y parameter** drop-down lists. The evaluated requirement value is plotted as a function of these parameters.

Statistical Analysis Tornado Plots

After you have evaluated the design requirements for each parameter, you can perform statistical analysis to analyze how the parameters of your Simulink model influence the requirements.

To generate a tornado plot ranking the influence of parameters on requirements:

1 In the **Statistics** tab of the app, select the evaluation results you want to analyze in the **Evaluation Results to Analyze** list.



2 Specify the statistical analysis methods.

You can choose to calculate a correlation coefficient, standardized regression coefficient, and partial correlation coefficient (requires Statistics and Machine Learning Toolbox software).

For more information, see "Analyze Relation Between Parameters and Design Requirements" on page 4-67.

3 For each of these methods, specify what data to use for the analysis. You can choose from **Linear** (Pearson), **Ranked** (Spearman), and **Kendall** analysis types. **Kendall** is applicable when the analysis method is **Correlation**, and requires Statistics and Machine Learning Toolbox software.

You can compute all applicable combinations of analysis methods and types.

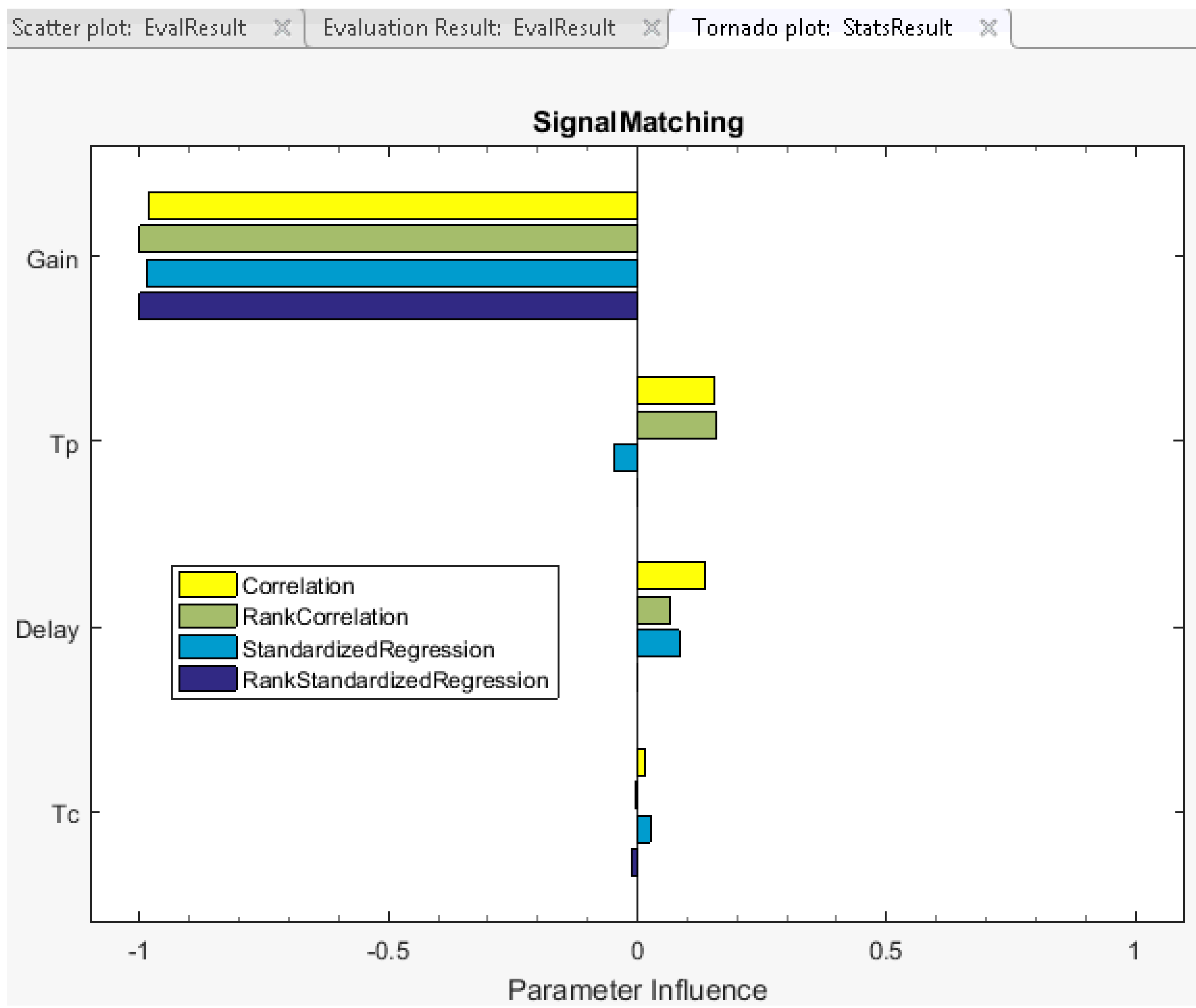
4 Calculate the coefficients, and generate a tornado plot.

Click **Compute Statistics**.

The resulting tornado plot displays the calculated coefficients for each specified analysis method and type. The coefficients are plotted in order of influence of parameters on the cost function. The parameter with the greatest magnitude of influence on the cost function is displayed on the top, giving the plot a tornado shape. When more than one type of coefficient is calculated, the tornado plot sorts the parameters based on the first calculated coefficient. The coefficients are calculated in the following order:

- Correlation
- Rank correlation
- Kendall correlation
- Partial correlation
- Rank partial correlation
- Standardized regression
- Rank Standardized Regression

In this tornado plot, the parameters are sorted based on the Correlation coefficient. For all calculated coefficients, the `Gain` parameter has the most influence on the design requirement cost function.



See Also

Related Examples

- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Specify Time-Domain Requirements” on page 4-21
- “Specify Frequency-Domain Requirements” on page 4-48
- “Evaluate Design Requirements” on page 4-60
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67

Validate Sensitivity Analysis

You can validate sensitivity analysis by checking generated parameter values, evaluation results, and analysis results.

Inspect the Generated Parameter Set

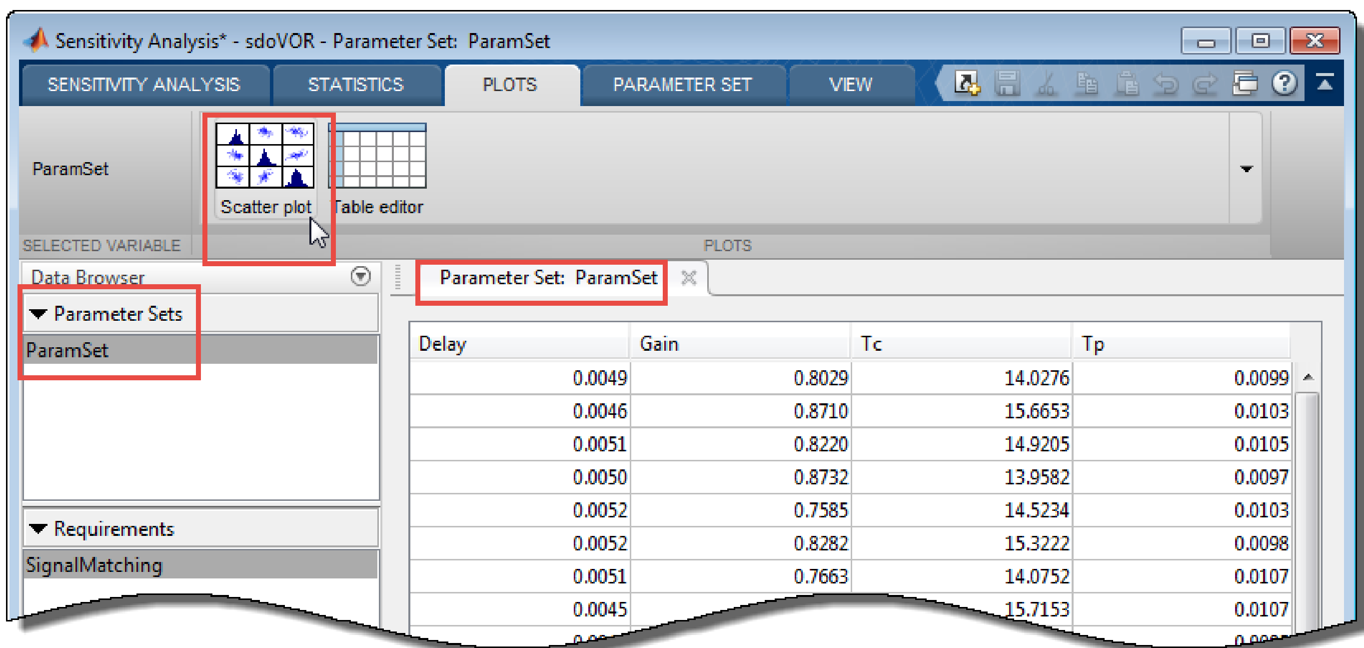
To perform sensitivity analysis, you select model parameters for evaluation, and generate a representative set of parameter values to explore the design space. You create the parameter set by specifying parameter distributions such as normal or uniform. You can also specify correlations between parameters. For more information, see "Generate Parameter Samples for Sensitivity Analysis" on page 4-8. After generating the parameter values, plot them to check if generated parameter values match the desired specifications. This is particularly important if you generate a small number of random samples for each parameter set.

If you see a discrepancy in the generated parameters and the specified distribution and correlations, you can try one of the following:

- Generate the random samples again, until you achieve the specified distributions and correlations.
- Increase the sample size at the expense of increasing the evaluation time.
- Specify different sampling methods. Use Latin hypercube sampling method for a more systematic space-filling approach than random sampling. If you have Statistics and Machine Learning Toolbox software, use the Sobol and Halton quasirandom sampling methods for a more space-filling approach than the Latin hypercube method.

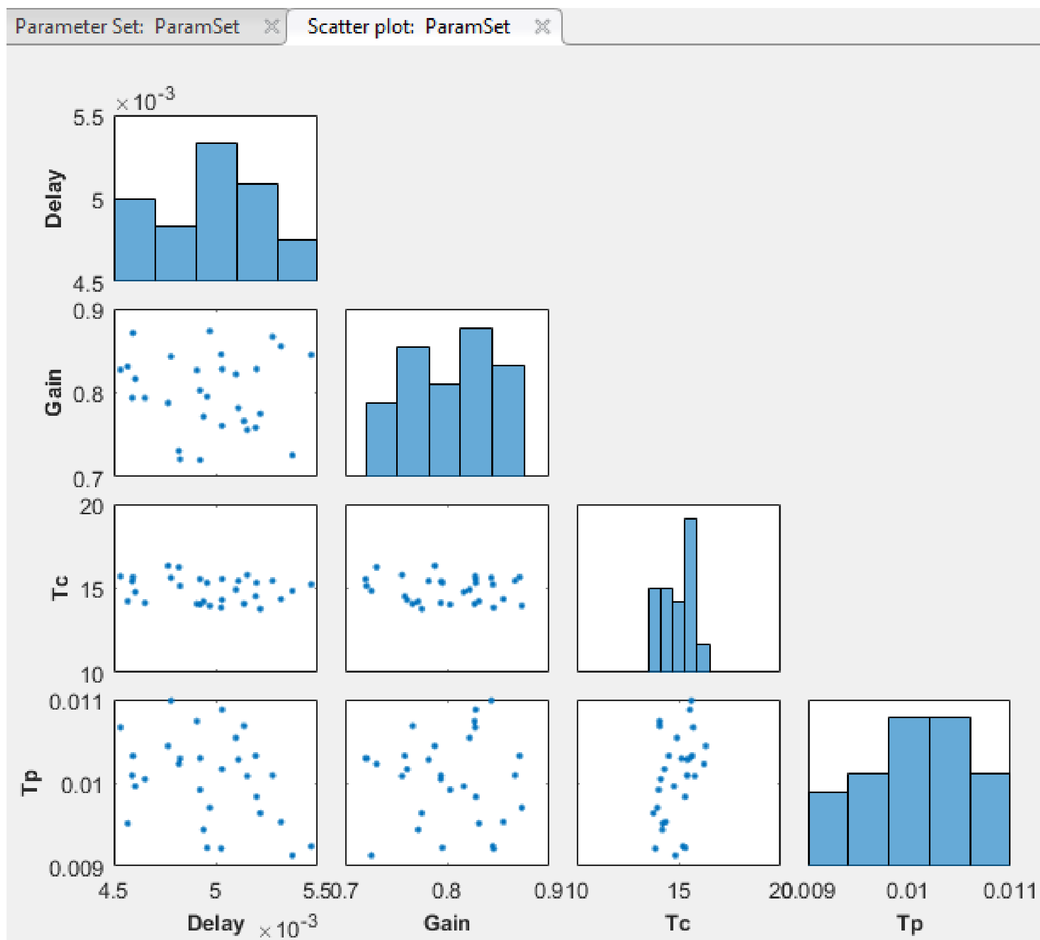
To plot the generated parameters in the **Sensitivity Analyzer**:

1 Select the generated parameter set in the **Parameter Sets** area of the app.



2 In the **Plots** tab, select **Scatter Plot**.

The generated plot displays histograms of generated values for each parameter on the diagonal, and the pairwise scatter plot of the parameters on the off-diagonals. For more information about the scatter plot, see "Interact with Plots in the Sensitivity Analyzer" on page 4-79.



3 Inspect the histograms to ensure that the generated parameter values match the intended parameter distributions. Inspect the off-diagonal scatter plots to ensure that any specified correlations between parameters are present.

To plot the generated parameter values at the command line, use `sdo.scatterPlot`. Use functions such as `mean` to check the sample statistics.

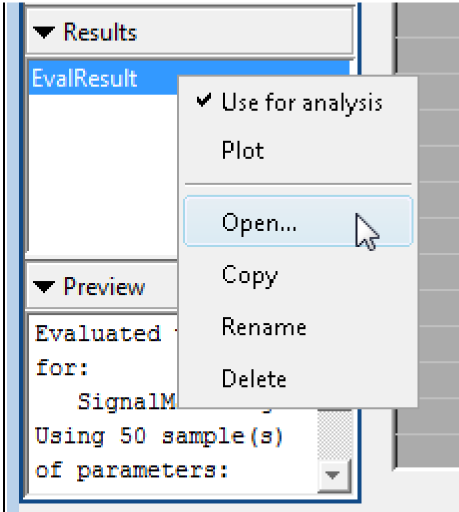
Check Evaluation Results

After generating a parameter set, you define a cost function by creating a design requirement on the model signals. You then evaluate the cost function at each set of parameter values on page 4-60. To validate the evaluation results, inspect the evaluated cost function values. If the cost function evaluations contain `NaN` values, that could indicate an issue.

To check for `NaN` values in the **Sensitivity Analyzer** after the evaluation is complete:

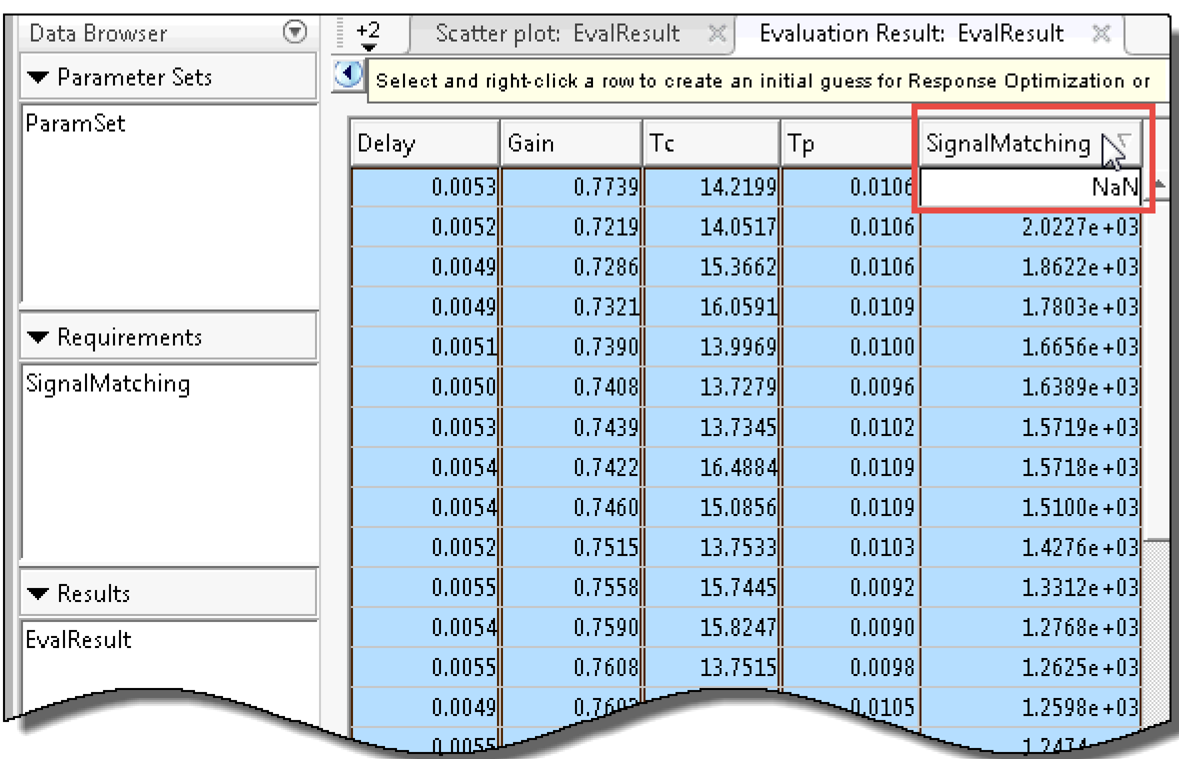
1 Open the evaluation results table if it is not already open.

In the **Results** area of the app, right-click the evaluated result, and select **Open** in the menu.



In the **Evaluation Results** table, each row of the table lists the parameter set values and the corresponding evaluated design requirement cost function values.

2 Sort the evaluated requirement values in descending order. To do so, click twice on the evaluated requirement column. Any `NaN` values are listed at the top of the evaluated requirement column.



3 Inspect the parameter values that resulted in the `NaN` values for evaluated requirements. If you do not expect an `NaN` result for that row of parameter values, investigate your model further.

To view the evaluated results at the command line, inspect the cost function evaluation output of `sdo.evaluate`.

Perform Sensitivity Analysis with Different Parameter Set

After evaluation, you analyze the effect of the parameters on the design requirements, and identify most influential parameters. For more information, see “Analyze Relation Between Parameters and Design Requirements” on page 4-67. To validate the analysis results, generate a different parameter set and reevaluate the design requirements. If the analysis results are not consistent, consider increasing the number of samples in your parameter set.

See Also

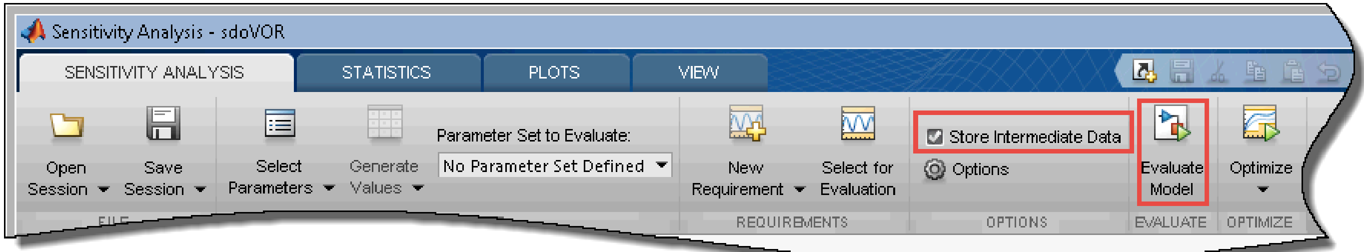
Related Examples

- “What is Sensitivity Analysis?” on page 4-2
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67

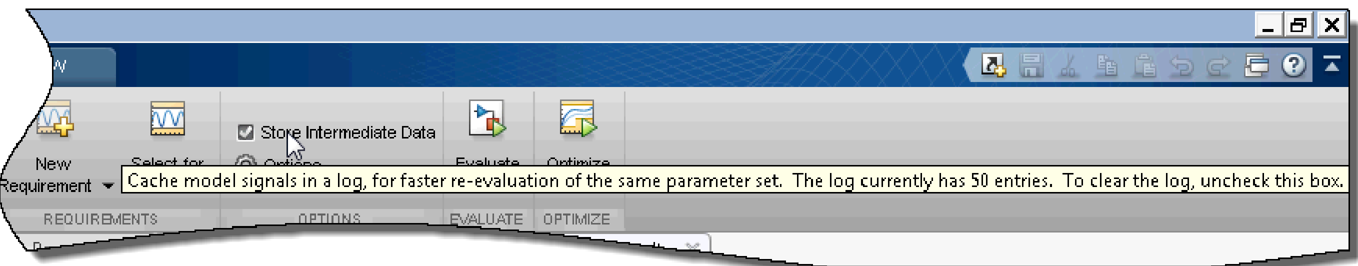
Store Intermediate Data in the App

This topic shows how to speed up successive evaluations of design requirements in the **Sensitivity Analyzer** by storing intermediate data during evaluation. Use this option when memory usage is not a concern. Choosing this option results in a memory-time trade-off.

To store intermediate data during evaluation, in the **Sensitivity Analysis** tab, click **Store Intermediate Data**.



After creating a parameter set and specifying design requirements, you can evaluate your model. When you click **Evaluate Model**, the app saves the logged signals that are used to compute the design requirements at each combination of parameter values in your parameter set. The logged signal values are stored in the RAM. After the evaluation is complete, you can view the number of logged entries by hovering over **Store Intermediate Data**.



If you now evaluate your model for a different design requirement that uses the same logged signals and parameter set values, the app uses the stored signal values. As a result, successive evaluations take less time.

If your system is running out of memory during evaluation, stop the evaluation, and clear **Store Intermediate Data**. Doing so will delete the stored data from memory.

See Also

Related Examples

- “Specify Parameters for Design Exploration” on page 4-4
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Specify Time-Domain Requirements” on page 4-21
- “Specify Frequency-Domain Requirements” on page 4-48

- “Evaluate Design Requirements” on page 4-60
- “Ways to Speed Up Design Optimization Tasks”

Specify Steady-State Operating Point for Sensitivity Analysis

What is a Steady-State Operating Point?

An *operating point* of a dynamic system defines the states and root-level input signals of the model at a specific time. For example, in a car engine model, variables such as engine speed, throttle angle, engine temperature, and surrounding atmospheric conditions typically describe the operating point.

A *steady-state operating point* of a model, also called an equilibrium or *trim* condition, includes state variables that do not change with time.

A model can have several steady-state operating points. For example, a hanging damped pendulum has two steady-state operating points at which the pendulum position does not change with time. A *stable steady-state operating point* occurs when a pendulum hangs straight down. When the pendulum position deviates slightly, the pendulum always returns to equilibrium. In other words, small changes in the operating point do not cause the system to leave the region of good approximation around the equilibrium value.

When using optimization search to compute operating points for nonlinear systems, your initial guesses for the states and input levels must be near the desired operating point to ensure convergence.

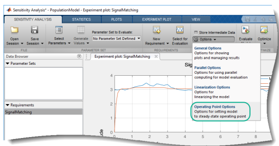
When linearizing a model with multiple steady-state operating points, it is important to have the right operating point. For example, linearizing a pendulum model around the stable steady-state operating point produces a stable linear model, whereas linearizing around the unstable steady-state operating point produces an unstable linear model.

For more information on operating points, see “What Is an Operating Point?” (Simulink Control Design) and “What Is a Steady-State Operating Point?” (Simulink Control Design).

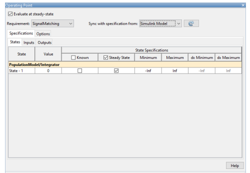
Setting up a Steady-State Operating Point

This topic shows how to setup a steady-state operating point in the **Sensitivity Analyzer**. To improve the fit between the model and measured data, the model must be set to steady-state when parameters are evaluated.

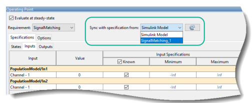
1. Open the **Sensitivity Analyzer** and setup your requirements using the steps outlined in “Identify Key Parameters for Estimation (GUI)” on page 4-131.
2. In the toolstrip, click **Options** and select `Operating Point Options` from the drop down menu.



3. The following **Operating Point** dialog box opens.

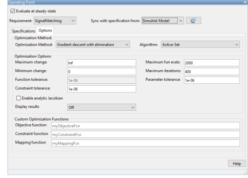


The **Evaluate at steady-state** option is checked by default when you open the operating point dialog. Select the appropriate requirement to change the parameters for from the `Requirement:` drop down menu. Use the **States**, **Inputs** and **Outputs** tabs to specify the known parameters, bounds and deviations. For instance, there is one state in the above figure. Use the operating point dialog to specify that this state should be treated as an unknown, and it should be set to steady state. During sensitivity analysis, the operating point computation will vary this state to set it at steady-state.



You can also sync operating point specifications from your Simulink model or another requirement using the `Sync with specification from:` drop-down list. After you make your selection, click on the button to copy the parameters.

4. The Simulink Design Optimization software uses optimization methods to search for operating points in a model. Use the **Options** tab of the dialog to specify these optimization methods. These options specify the optimization algorithm, tolerances, and stopping conditions. For instance, the option `Gradient descent with projection` is often used to find the operating point for systems that use physical modeling. For more information, click on the button.



5. Having specified the operating point parameters, continue with the sensitivity analysis workflow as described in “Identify Key Parameters for Estimation (GUI)” on page 4-131.

See Also

More About

- “What Is an Operating Point?” (Simulink Control Design)
- “What Is a Steady-State Operating Point?” (Simulink Control Design)
- “Set Model to Steady-State When Estimating Parameters (Code)” on page 2-97
- “Set Model to Steady-State When Estimating Parameters (GUI)” on page 2-118

Use Parallel Computing for Sensitivity Analysis

Configure Your System for Parallel Computing

To perform global sensitivity analysis, you sample the model parameters and states, define a cost function by creating a design requirement on the model signals, and evaluate the cost function for each sample. Evaluating the model for many samples can be time consuming. You can speed up evaluation in the **Sensitivity Analyzer**, or at the command line, using parallel computing on multicore processors or multiprocessor networks.

When you evaluate the cost function with the parallel computing option enabled, the software uses the available parallel pool. If none is available, and **Automatically create a parallel pool** is selected in your Parallel Computing Toolbox preferences, the software starts a parallel pool using the settings in those preferences. To open a parallel pool that uses a specific cluster profile, use:

```
parpool(MyProfile);
```

`MyProfile` is the name of a cluster profile.

For information regarding creating a cluster profile, see “Add and Modify Cluster Profiles” (Parallel Computing Toolbox).

Model Dependencies

Model dependencies are any referenced models, data such as model variables, S-functions, or additional files necessary to run the model. Before starting the parallel model evaluation, verify that the model dependencies are complete. Otherwise, you may get unexpected results.

Making Model Dependencies Accessible to Remote Workers

When you use parallel computing, the Simulink Design Optimization software helps you identify model dependencies. To do so, the software uses the Dependency Analyzer. The dependency analysis may not find all the files required by your model. To learn more, see “Dependency Analyzer Scope and Limitations”. If your model has dependencies that are undetected or inaccessible by the parallel pool workers, then add them to the list of model dependencies.

The dependencies are made accessible to the parallel pool workers by specifying one of the following:

- File dependencies: the model dependency files are copied to the parallel pool workers.
- Path dependencies: the paths to the model dependencies are added to the paths of the parallel pool workers. If you are working in a multi-platform scenario, ensure that the paths are compatible across platforms.

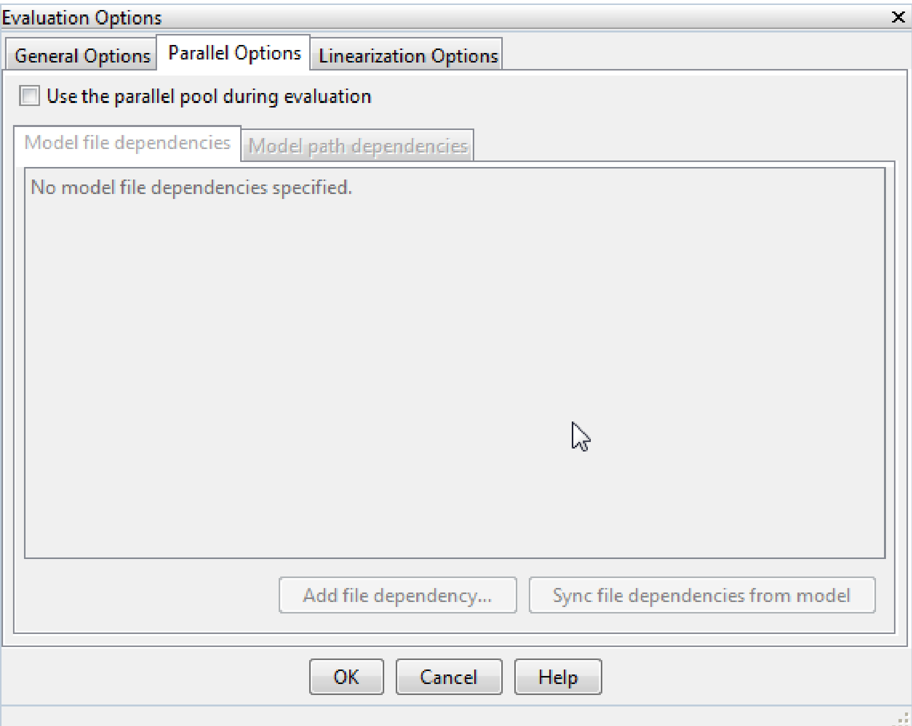
Using file dependencies is recommended, however, in some cases it can be better to choose path dependencies. For example, if parallel computing is set up on a local multi-core computer, using path dependencies is preferred as using file dependencies creates multiple copies of the dependent files on the local computer.

Perform Sensitivity Analysis Using Parallel Computing (GUI)

To perform sensitivity analysis using parallel computing in the **Sensitivity Analyzer**:

1. Ensure that the software can access parallel pool workers that use the appropriate cluster profile.

   For more information, see “Configure Your System for Parallel Computing” on page 4-104.
2. Open the **Sensitivity Analyzer** for the Simulink model.
3. Specify the parameter set, generate parameter samples, and specify the requirements for sensitivity analysis. For example, see “Design Exploration Using Parameter Sampling (GUI)” on page 4-112 and “Identify Key Parameters for Estimation (GUI)” on page 4-131.
4. On the **Sensitivity Analysis** tab, click **Options** to open the **Evaluation Options** dialog box.
5. Select the **Parallel Options** tab.

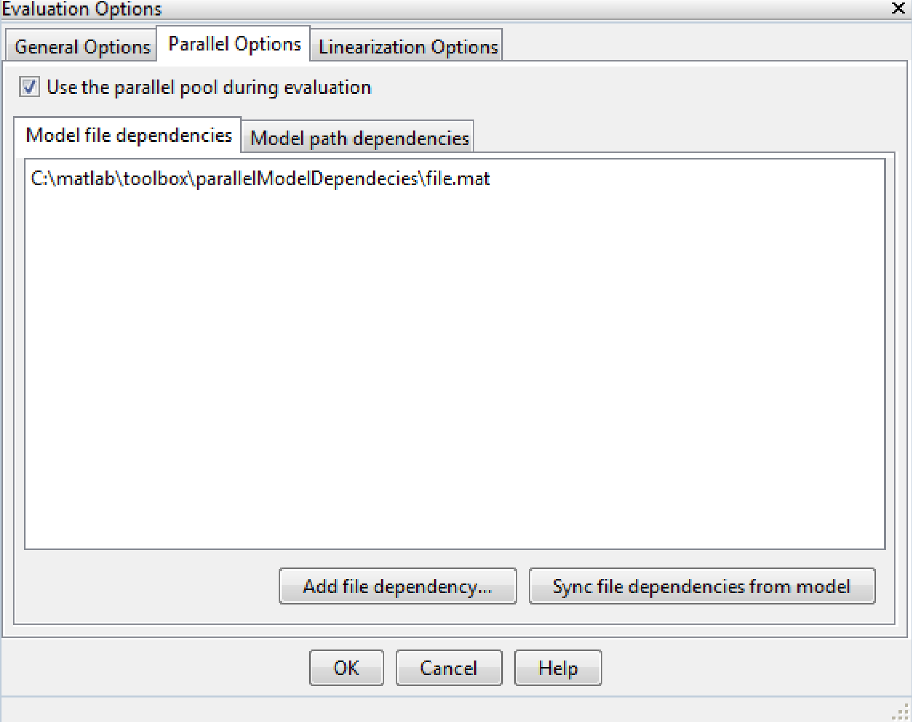


6. Select the **Use the parallel pool during evaluation** check box.

   This option checks for dependencies in your Simulink model. The file dependencies are displayed in the **Model file dependencies** list box, and corresponding path to the files in **Model path dependencies**. The files listed in **Model file dependencies** are copied to the remote workers.

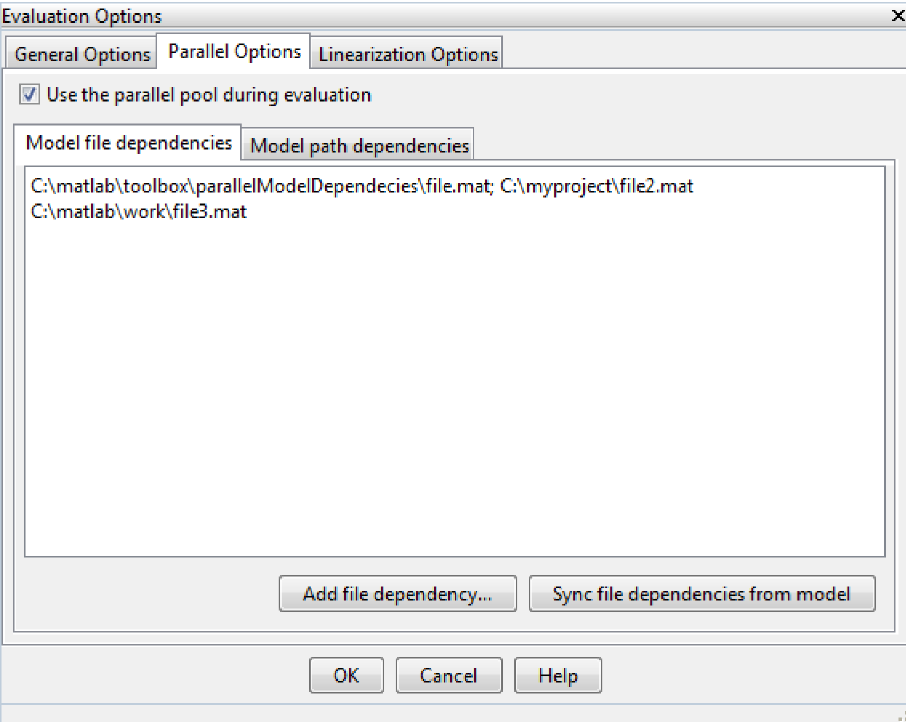
Note The automatic dependencies check may not detect all the dependencies in your model.

For more information, see “Model Dependencies” on page 4-104. In this case, add the undetected dependencies manually.



7 Add any file dependencies that the automatic check does not detect.

Specify the files in the **Model file dependencies** list box separated by semicolons or on separate lines.



Alternatively, click **Add file dependency** to open a dialog box, and select the file to add.

Note If you do not want to copy the files to the remote workers, delete all entries in the **Model file dependencies** list box. Populate the **Model path dependencies** list box by clicking the **Sync path dependencies from model**, and add any undetected path dependencies. In addition, in the list box, update the paths on local drives to make them accessible to remote workers. For example, change `C:\` to `\\\\hostname\\C$\\`.

---

8. If you modify the Simulink model, resync the dependencies to ensure that any new dependencies are detected. Click **Sync file dependencies from model** in the **Parallel Options** tab to rerun the automatic dependency check for your model.

   This action updates the **Model file dependencies** list box with any new file dependency found in the model.
9. Click **OK**.
10. In the **Sensitivity Analyzer**, click **Evaluate** to perform sensitivity analysis using parallel computing. The design requirements are evaluated for each combination of parameter values in your parameter set.

This functionality is not supported in Simulink Online.

Perform Sensitivity Analysis Using Parallel Computing (Code)

To evaluate a model using parallel computing:

1. Ensure that the software can access parallel pool workers that use the appropriate cluster profile.

   For more information, see “Configure Your System for Parallel Computing” on page 4-104.
2. Open the model.
3. Specify the cost function and generate parameter samples for sensitivity analysis. For example, see “Design Exploration Using Parameter Sampling (Code)” on page 4-157.
4. Enable parallel computing using an evaluation option set.

```
opt = sdo.EvaluateOptions;
opt.UseParallel = true;
```

5. Find the model dependencies.

```
[dirs,files] = sdo.getModelDependencies(modelname)
```

Note `sdo.getModelDependencies` may not detect all the dependencies in your model. For more information, see “Model Dependencies” on page 4-104. In this case, add the undetected dependencies manually.

---

6. Modify `files` to include any file dependencies that `sdo.getModelDependencies` does not detect.

```
files = vertcat(files,'C:\matlab\work\filename.m')
```

Note If you do not want to copy the files to the remote workers, add any undetected path dependencies to `dirs` and update the paths on local drives to make them accessible to remote workers. See `sdo.getModelDependencies` for more details.

---

7. Add the file dependencies for evaluation.

   ```
   opt.ParallelFileDependencies = files;
   ```
8. Specify the name of the model to be evaluated in parallel.

   ```
   opt.EvaluatedModel = modelname;
   ```
9. Evaluate the model.

   ```
   [pOpt,opt_info] = sdo.evaluate(fcn,samples,opt);
   ```

Troubleshooting

Why Don’t I See the Evaluation Speed up I Expected Using Parallel Computing?

When you evaluate a model that does not require a large number of evaluations or does not take long to simulate, you might not see a speedup in the evaluation time. In such cases, the overhead associated with creating and distributing the parallel tasks outweighs the benefits of running the evaluation in parallel.

See Also

`sdo.evaluate` | `sdo.EvaluateOptions` | `sdo.getModelDependencies` | `parpool`

More About

- “Ways to Speed Up Design Optimization Tasks”
- “Store Intermediate Data in the App” on page 4-100

Use Fast Restart Mode During Sensitivity Analysis

This topic shows how to speed up sensitivity analysis using Simulink fast restart. You can use the fast restart feature to speed up sensitivity analysis of tunable parameters of a model.

Fast restart enables you to perform iterative simulations without compiling a model or terminating the simulation each time. Using fast restart, you compile a model only once. You can then tune parameters and simulate the model again without spending time on compiling. Fast restart associates multiple simulation phases with a single compile phase to make iterative simulations more efficient. You see a speedup of design optimization tasks using fast restart in models that have a long compilation phase. See “How Fast Restart Improves Iterative Simulations”.

When you enable fast restart, you can only change tunable properties of the model during simulation. For more information about the limitations, see “Limitations”.

You can perform sensitivity analysis using fast restart in the **Sensitivity Analyzer** or at the command line on page 4-109.

Sensitivity Analyzer Workflow for Fast Restart

To evaluate a model using fast restart in the **Sensitivity Analyzer**:

1. Open the Simulink model.
2. Enable fast restart in the model.

   Click **Fast Restart** in the model window.
3. Open the **Sensitivity Analyzer** for the model.
4. Specify the parameter set, generate parameter samples, and specify the requirements for sensitivity analysis. Optionally, specify evaluation settings. For example, see “Design Exploration Using Parameter Sampling (GUI)” on page 4-112 and “Identify Key Parameters for Estimation (Code)” on page 4-169.
5. Click **Evaluate** to evaluate the model in fast restart mode. The design requirements are evaluated for each combination of parameter values in your parameter set.
6. Disable fast restart.

   In the model window, click **Fast Restart** .

This functionality is not supported in Simulink Online.

Command-Line Workflow for Fast Restart

You can use sensitivity analysis to evaluate which model parameters most influence a cost function. You can use these parameters during parameter estimation or response optimization. Suppose that you want to use sensitivity analysis to reduce the number of parameters that you need to estimate to fit a model.

To evaluate the model in fast restart mode using a cost function aimed at parameter estimation:

1. Open the Simulink model.
2. Specify the model parameter values, `params`, to estimate and generate parameter samples, `params_samples`. For an example, see "Identify Key Parameters for Estimation (Code)" on page 4-169.
3. Create an experiment object, `Exp`.

   ```
   Exp = sdo.Experiment('model');
   ```

   Store the measured input-output data in `Exp`. For an example, see "Identify Key Parameters for Estimation (Code)" on page 4-169.
4. Create a model simulator from the experiment.

   ```
   Simulator = createSimulator(Exp);
   ```

   `Simulator` is an `sdo.SimulationTest` object.

   Note You must create a simulation scenario with logging information before configuring the model for fast restart. You cannot modify logging information once the model has been compiled for fast restart.

   ---
5. Configure the model and simulator for fast restart.

   ```
   Simulator = fastRestart(Simulator,'on');
   ```
6. Create a cost function, `myCostfcn`, and pass `Simulator` to the cost function as an input. For more information, see "Write a Cost Function" on page 2-49. In the cost function, the simulator configured for fast restart is used to update the model parameters, simulate the model, and log signals.

   Use an anonymous function with one argument that calls `myCostfcn`.

   ```
   evalfcn = @(param) myCostfcn(param,Simulator,Exp);
   ```
7. Evaluate the model.

   ```
   [param_opt,opt_info] = sdo.evaluate(evalfcn,param,param_samples);
   ```
8. Restore the simulator fast restart settings.

   ```
   Simulator = fastRestart(Simulator,'off');
   ```

The fast restart workflow is similar for sensitivity analysis that identifies design variables using a cost function aimed at response optimization. See "Use Fast Restart Mode During Response Optimization" on page 3-196.

Troubleshooting

Why Don't I See the Evaluation Speedup I Expected Using Fast Restart?

You see a speedup of design optimization tasks using fast restart in models that have a long compilation phase. If the compilation phase of your model is not long, you do not see a significant change in estimation speed.

See Also

`sdo.SimulationTest` | `sdo.evaluate` | `fastRestart`

More About

- “Ways to Speed Up Design Optimization Tasks”
- “Store Intermediate Data in the App” on page 4-100

Design Exploration Using Parameter Sampling (GUI)

This example shows how to sample and explore a design space using the **Sensitivity Analyzer**. You explore the design of a Continuously Stirred Tank Reactor (CSTR) to minimize product concentration variation and production cost. The design must also account for the uncertainty in the temperature and concentration of the input feed to the reactor.

You explore the CSTR design by characterizing model parameters using probability distributions. You use the distributions to generate random samples and perform Monte-Carlo evaluation of the design at these sample points. You then create plots to visualize the design space and select the best design. You then use the best design as an initial guess for optimization of the design.

Continuously Stirred Tank Reactor (CSTR) Model

Continuously Stirred Tank Reactors (CSTRs) are common in the process industry. The Simulink® model, `sdoCSTR`, models a jacketed diabatic (i.e., non-adiabatic) tank reactor described in [1]. The CSTR is assumed to be perfectly mixed, with a single first-order exothermic and irreversible reaction, $A \rightarrow B$. A, the reactant, is converted to B, the product.

In this example, you use the following two-state CSTR model, which uses basic accounting and energy conservation principles:

$$\frac{dC_A}{dt} = \frac{F}{A*h}(C_{feed} - C_A) - r*C_A$$

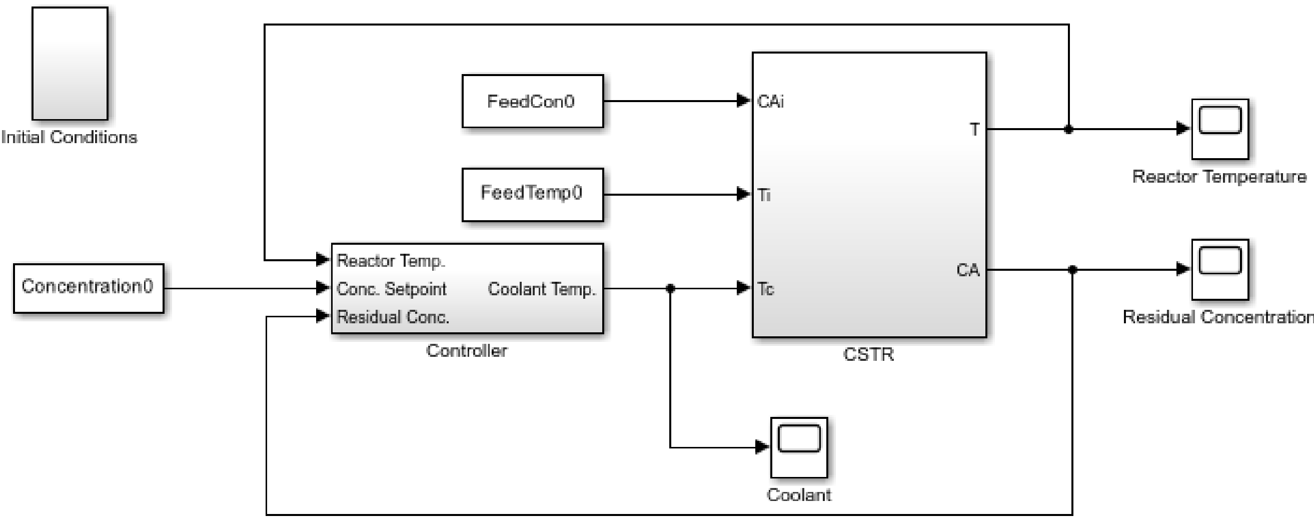
$$\frac{dT}{dt} = \frac{F}{A*h}(T_{feed} - T) - \frac{H}{c_p\rho}r - \frac{U}{c_p*\rho*h}(T - T_{cool})$$

$$r = k_0 * e^{\frac{-E}{R*T}}$$

- C_A, and C_{feed} - Concentrations of A in the CSTR and in the feed [kgmol/m^3]
- T, T_{feed}, and T_{cool} - CSTR, feed, and coolant temperatures [K]
- F and ρ - Volumetric flow rate [m^3/h] and the density of the material in the CSTR [1/m^3]
- h and A - Height [m] and heated cross-sectional area [m^2] of the CSTR.
- k_0 - Pre-exponential non-thermal factor for reaction $A \rightarrow B$ [1/h]
- E and H - Activation energy and heat of reaction for $A \rightarrow B$ [kcal/kgmol]
- R - Boltzmann's gas constant [kcal/(kgmol * K)]
- c_p and U - Heat capacity [kcal/K] and heat transfer coefficients [kcal/(m^2 * K * h)]

Open the Simulink model.

```
open_system('sdoCSTR');
```



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CSTR Design Problem

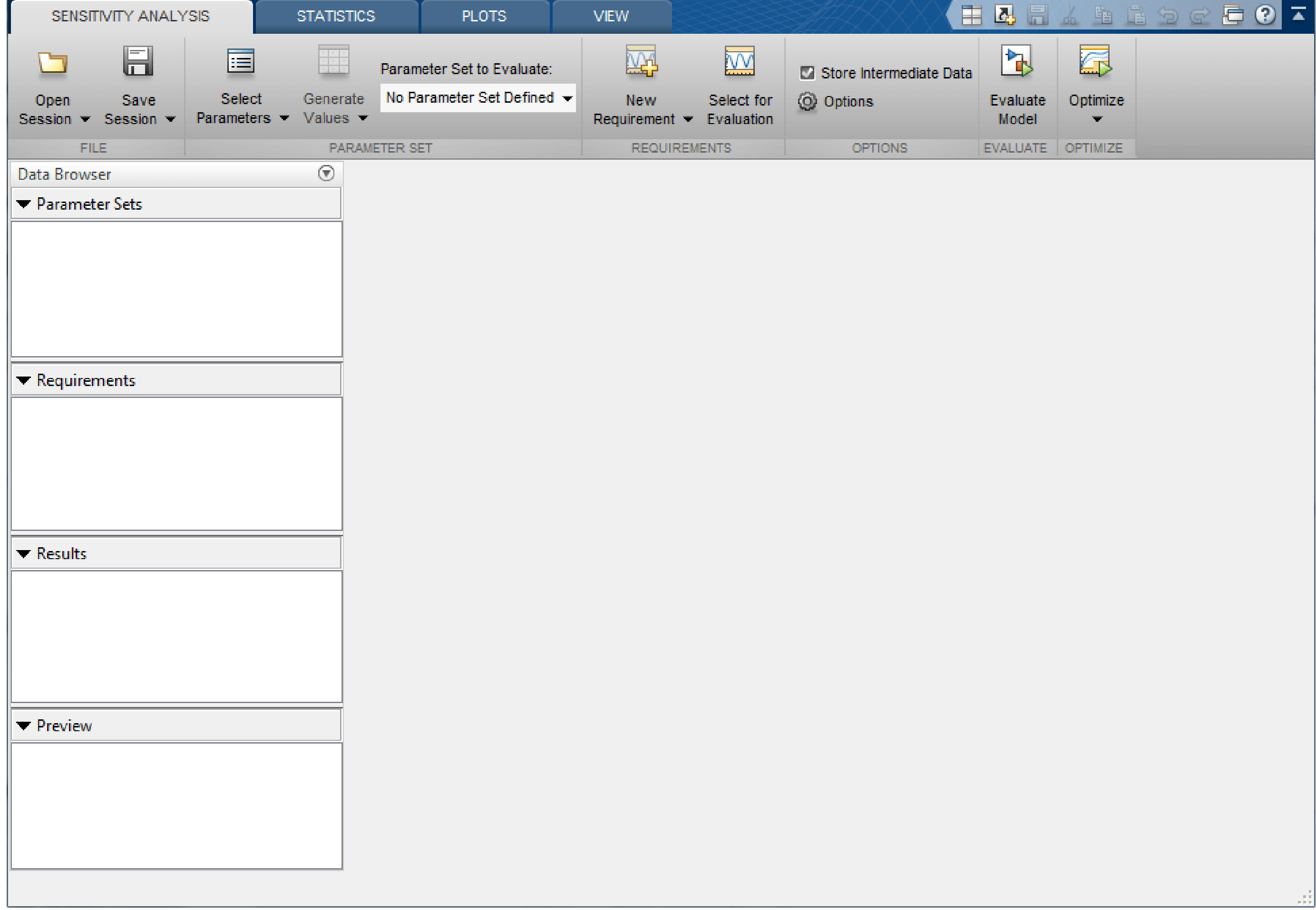
Assume that the CSTR is cylindrical, with the coolant applied to the base of the cylinder. Tune the CSTR cross-sectional area, A, and CSTR height, h, to meet the following design goals:

- Minimize the variation in residual concentration, C_A. Variations in the residual concentration negatively affect the quality of the CSTR product. Minimizing the variations also improves CSTR profit.
- Minimize the mean coolant temperature T_{cool}. Heating or cooling the jacket coolant is expensive. Minimizing the mean coolant temperature improves CSTR profit.

The quality of the feed to the reactor can differ among suppliers. Thus, the design must allow for variations in the supply feed concentration, C_{feed}, and feed temperature, T_{feed}. The quality of the feed differs from supplier to supplier and also varies within each supply batch.

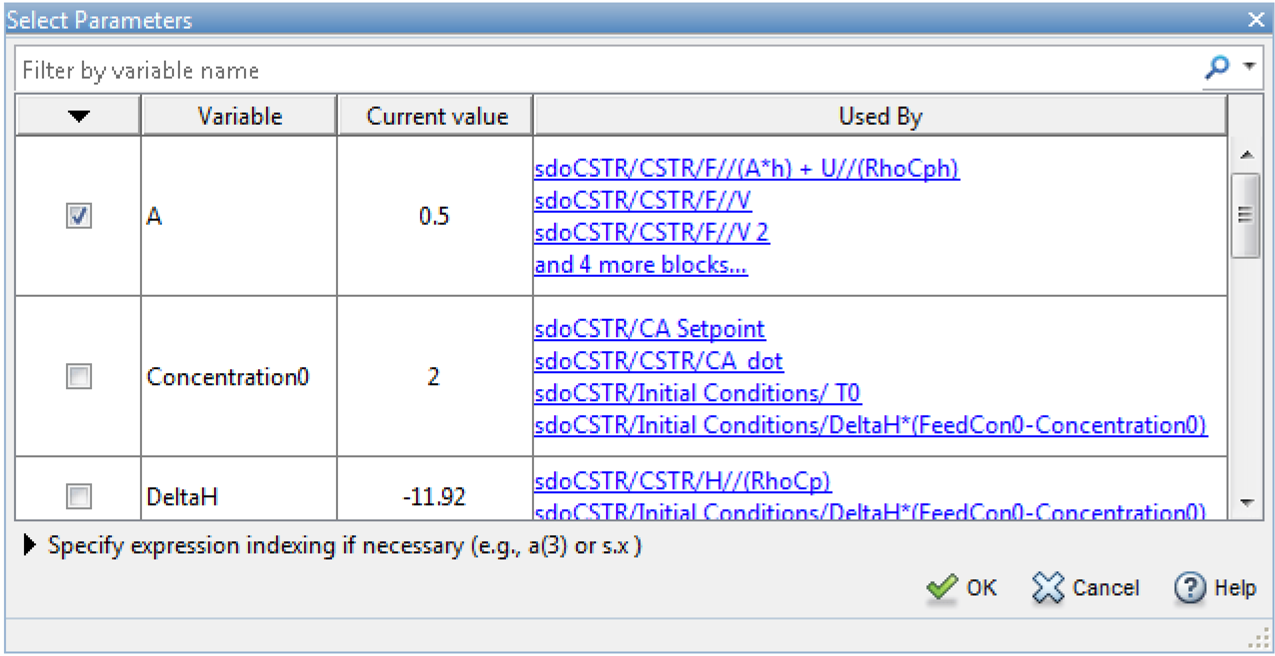
Specify Design Variables

Open the **Sensitivity Analyzer**. In the Simulink model from the **Apps** tab, click **Sensitivity Analyzer** under **Control Systems**. The app opens with an empty Sensitivity Analysis session.



Create a parameter set that includes the CSTR design variables `A` and `h` and the feed variation parameters `FeedConc0` and `FeedTemp0`. You randomly generate multiple values for these parameters to evaluate the CSTR design.

- In the **Sensitivity Analysis** tab, in the **Select Parameters** drop-down menu, select **New**.
- In the dialog box, select `A`, `FeedCon0`, `FeedTemp0`, and `h`.
- Click **OK**. An empty parameter set, `ParamSet` is created in the **Parameter Set** area of the app browser.



Specify the parameter distributions and correlations. `ParamSet` will be populate with parameter values selected randomly from the specified distributions:

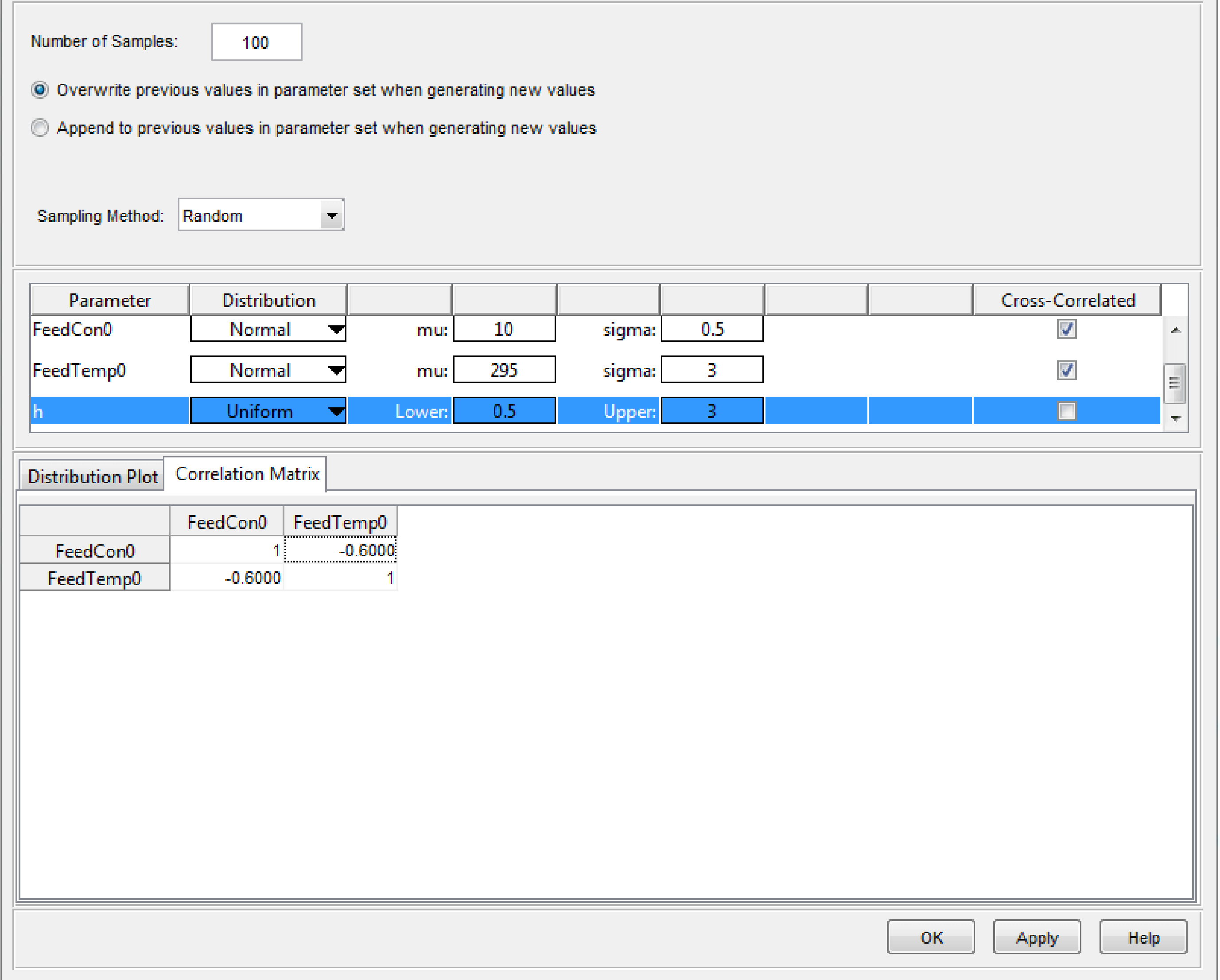
- Sample `A` from a uniform distribution with lower bound 0.2 m^2 and upper bound 2 m^2.
- Sample `h` from a uniform distribution with lower bound 0.5 m and upper bound 3 m.
- Sample `FeedConc0` from a normal distribution with mean 10 kgmol/m^3 and standard deviation 0.5 kgmol/m^3.
- Sample `FeedTemp0` from a normal distribution with mean 295 K and standard deviation 3 K.
- Specify `FeedCon0` and `FeedTemp0` as negatively correlated with covariance 0.6.

To generate 100 parameter values using the above distribution and correlation information, click **Generate Values**, and select **Generate Random Values**. For repeatability of the example reset the random number generator.

```
rng('default')
```

In the **Generate Random Parameter Values** dialog box, specify the following:

- Set the number of samples to 100
- For parameter `A` select **Uniform** distribution, set the lower bound to 0.2 and upper bound to 2.
- For parameter `FeedCon0` select **Normal** distribution, set `mu` to 10 and `sigma` to 0.5, and check `cross-correlated`.
- For parameter `FeedTemp0` select **Normal** distribution, set `mu` to 295 and `sigma` to 3, and check `cross-correlated`.
- For parameter `h` select **Uniform** distribution, set the lower bound to 0.5 and upper bound to 3.
- In the **Correlation Matrix** tab, set the `FeedCon0`, `FeedTemp0` covariance to -0.6.
- Click **OK** to generate the parameter values.

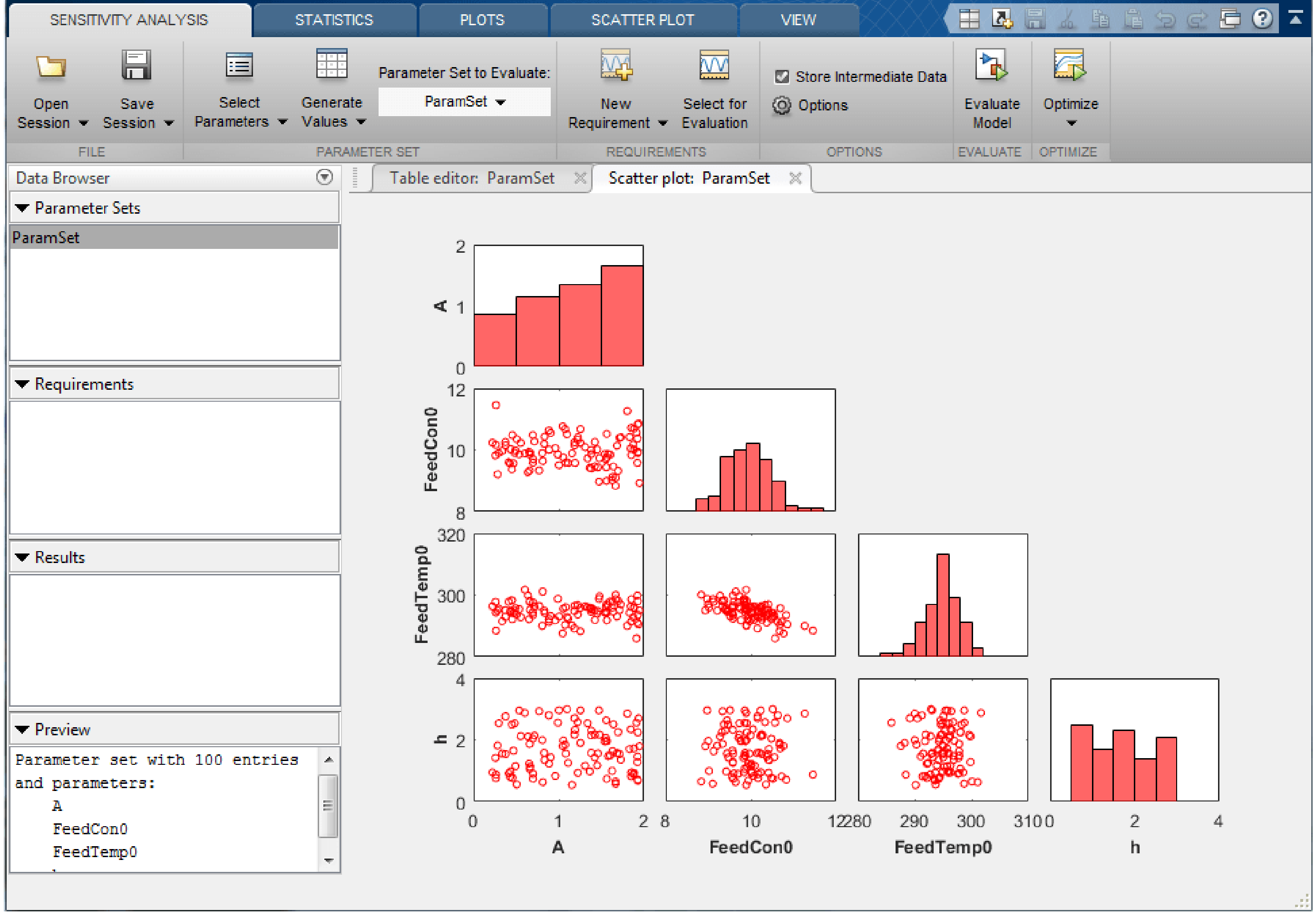


The `ParamSet` table is updated with the generated parameter values. Note that you can manually edit the generated parameter values in the `ParamSet` table.

To plot the parameter set click `ParamSet` in the **Parameter Sets** area of the app browser. In the **Plots** tab, select **Scatter Plot** in the plots gallery. The plot shows the histogram of the generated parameters on the diagonal and pair-wise parameter values on the off-diagonal.

Note that due to the random number generator the specific values in the plots and tables below may differ from what you get when running the example.

Each marker on the plot represents one row of the `ParamSet` table, with each row being simultaneously displayed on all the plots. The correlation between `FeedCon0` and `FeedTemp0` can be seen on the plot.

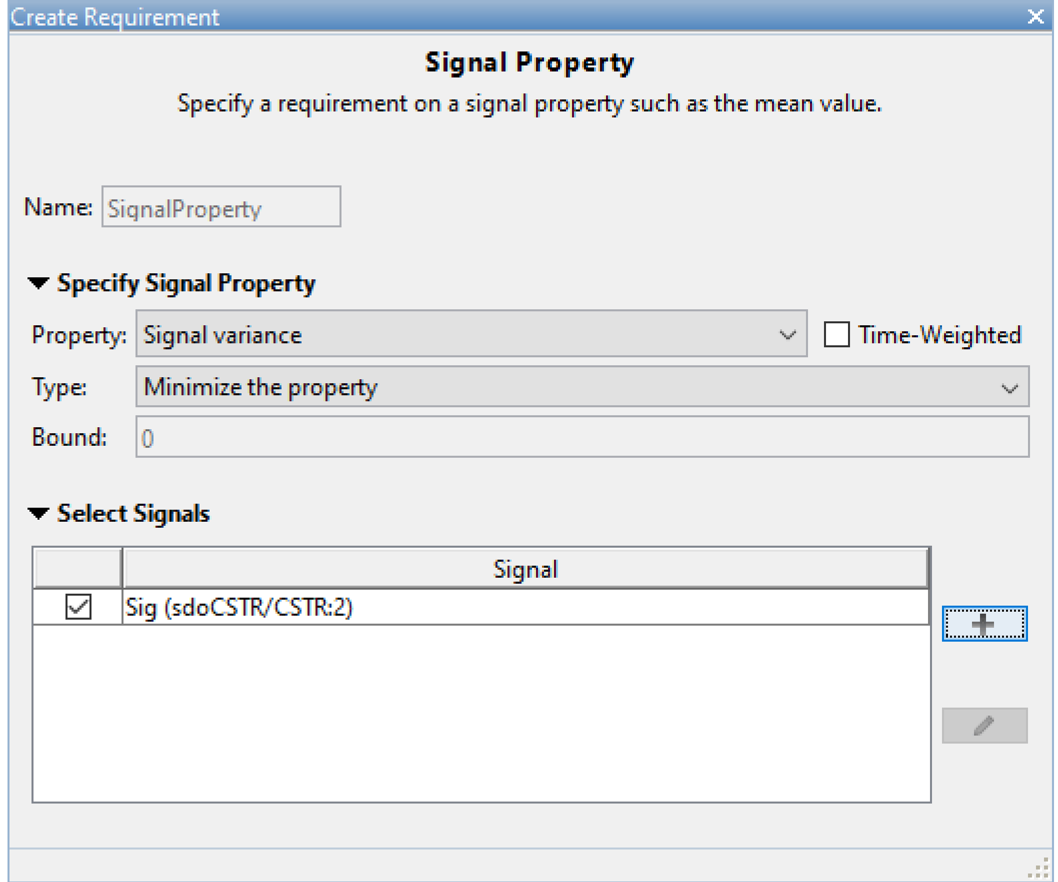


Specify Requirements for Evaluation

The CSTR design is required to minimize the variation in residual concentration and minimize the mean coolant temperature. Select **New Requirement** and click **Signal Property** to create a requirement to minimize the residual concentration variation.

In the **Create Requirement** dialog box, specify the following fields:

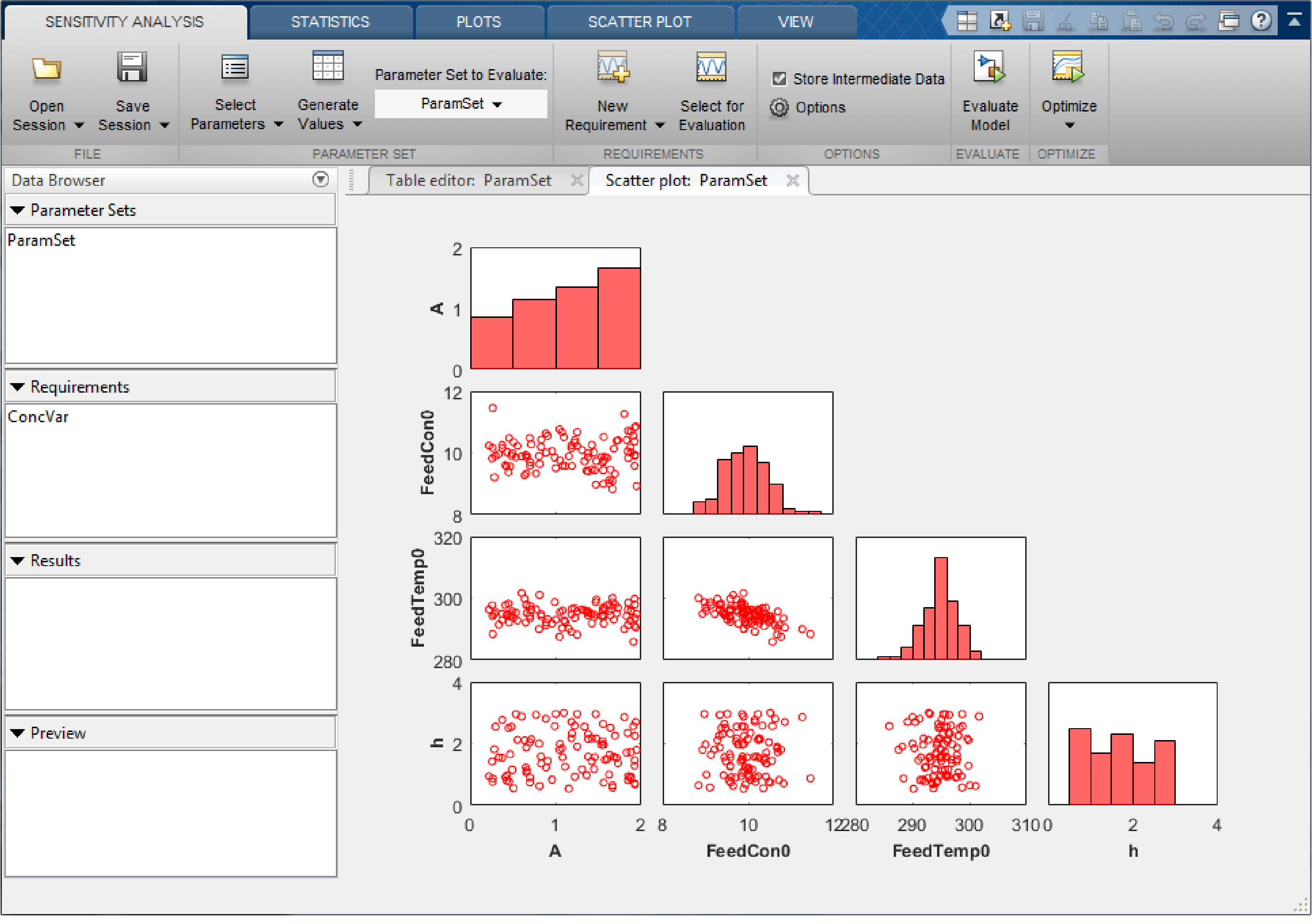
- In the **Property** drop-down list, select **Signal Variance**.
- In the **type** drop-down list, select **Minimize**.
- In the **Select Signals** area, select a logged signal to apply the requirement to. To do so click **+**. A `Create Signal Set` dialog box opens where you specify the logged signal. In the Simulink model, click the signal at the CA output of the CSTR block. The dialog box now displays this signal. Add the signal to the signal set and click **OK**.



- Close the Signal Property requirement dialog by clicking the x in the upper right dialog corner.

Close the **Create Requirement** dialog box. A new requirement, `SignalProperty` is listed in the **Requirements** area of the app browser

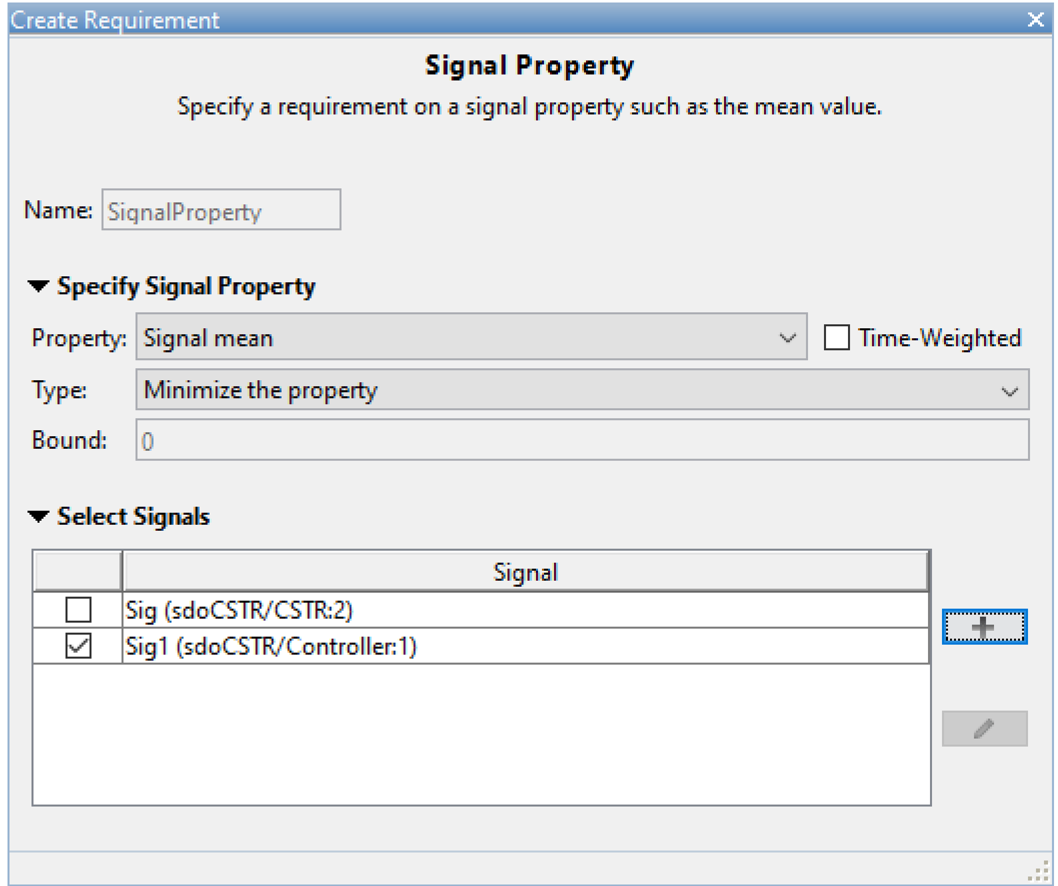
- Right-click `SignalProperty`, select **Rename**; rename the requirement to `ConcVar`.



Select **New Requirement** and click **Signal Property** to create a requirement to minimize the coolant mean (output of block `sdoCSTR/Controller`) temperature.

In the **Create Requirement** dialog box, specify the following fields:

- In the **Property** drop-down list, select **Signal Mean**.
- In the **Type** drop-down list, select **Minimize**.
- In the **Select Signals** area, add the `sdoCSTR/Controller` signal to the requirement.

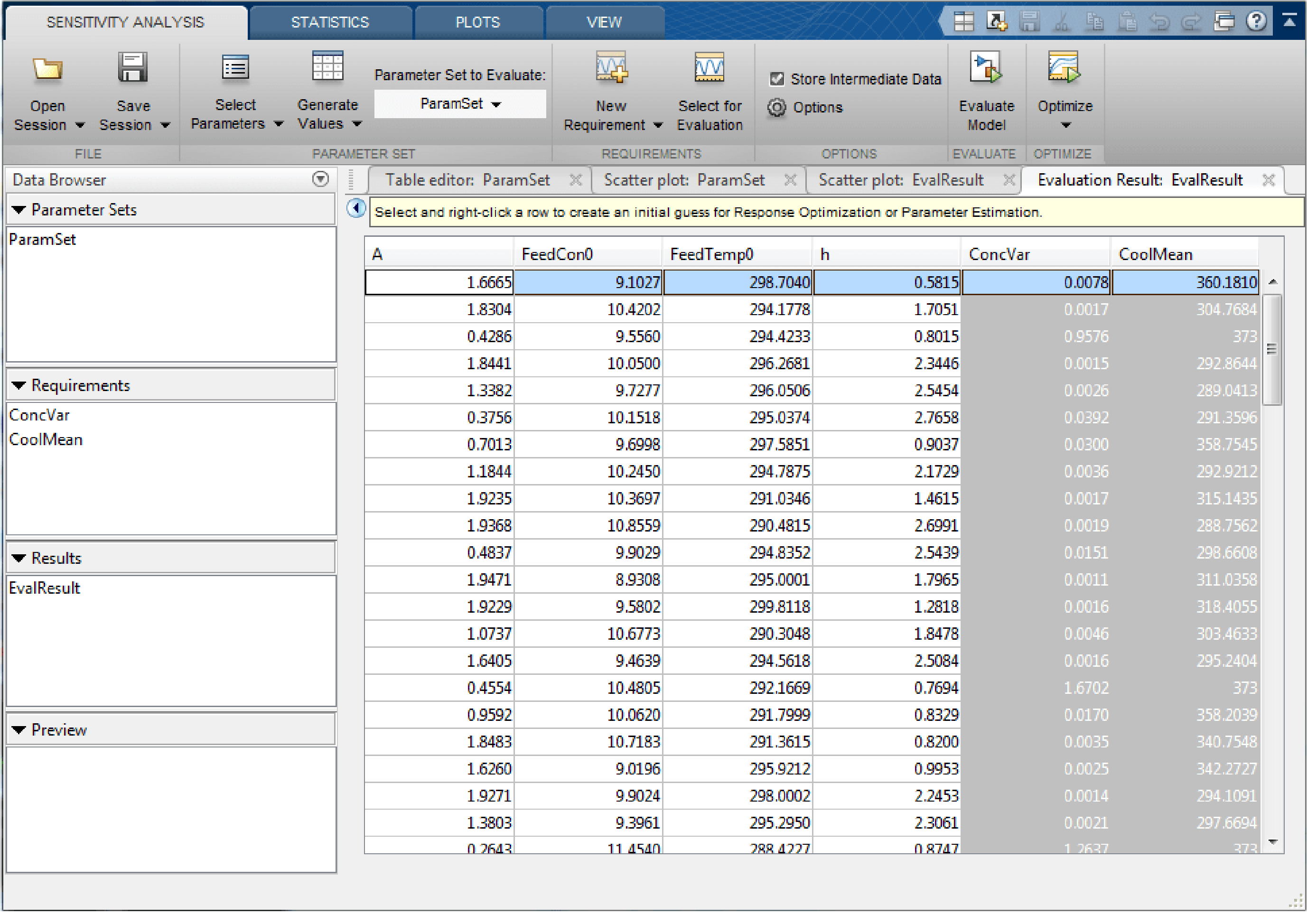


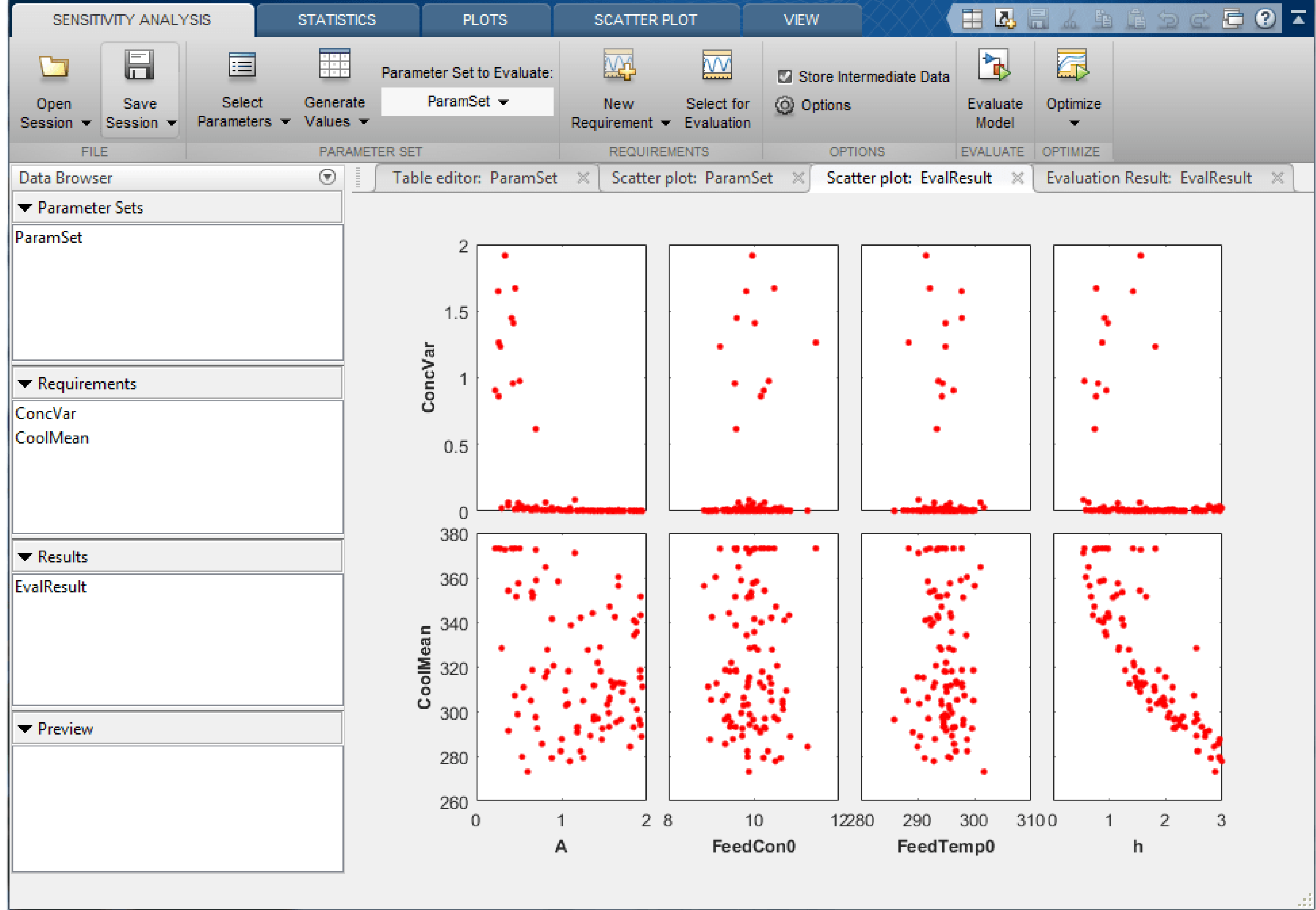
Close the **Create Requirement** dialog box. A new requirement, `SignalProperty` is created in the **Requirements** area of the app browser. Rename the requirement `CoolMean`.

Evaluate

In the **Sensitivity Analysis** tab, click **Select for Evaluation**. By default, all requirements are selected to be evaluated. Click **Evaluate Model** to evaluate the `ConcVar` and `CoolMean` requirements for each row of parameter values in `ParamSet`. Note you can speed up evaluation by using parallel computing if you have the Parallel Computing Toolbox (TM), or by using fast restart. For more information, see "Use Parallel Computing for Sensitivity Analysis" and "use Fast Restart Mode During Sensitivity Analysis" in the Simulink Design Optimization™ documentation.

A results scatter plot showing each parameter vs each requirement is updated during model evaluation. At the end of evaluation a table with the evaluation results is created, each row in the evaluation result table contains values for `A`, `FeedCon0`, `FeedTemp0`, `h` and the resulting requirement values `ConcVar` and `CoolMean`. The evaluation results are stored in the `EvalResult` variable in the **Results** area of the app.

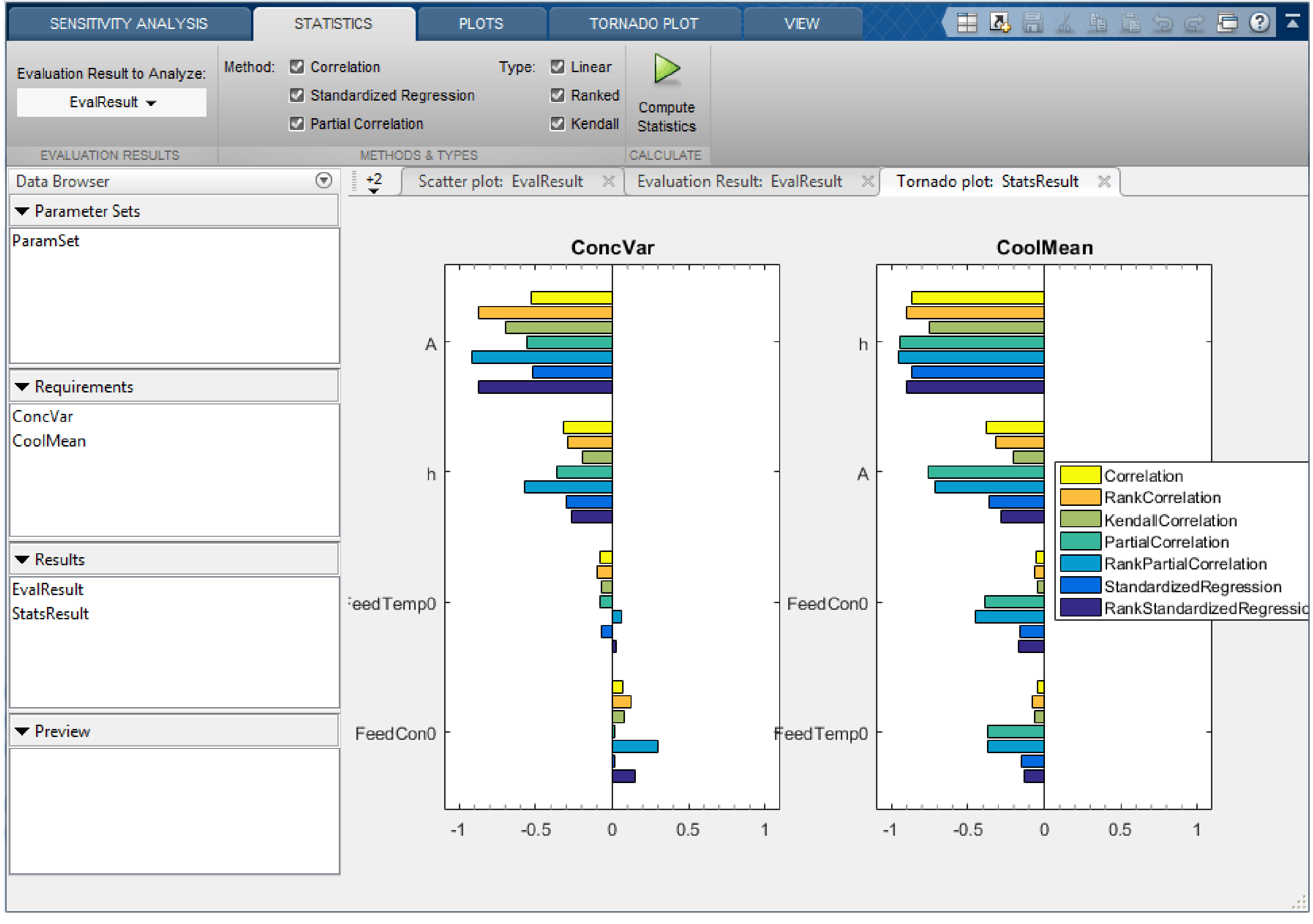

SENSITIVITY ANALYSIS
STATISTICS
PLOTS
VIEW
Open Session
Save Session
Select Parameters
Generate Values
Parameter Set to Evaluate:
ParamSet
New Requirement
Select for Evaluation
Store Intermediate Data
Options
Evaluate Model
Optimize
Data Browser
Parameter Sets
ParamSet
Requirements
ConcVar
CoolMean
Results
EvalResult
Preview
Table editor: ParamSet
Scatter plot: ParamSet
Scatter plot: EvalResult
Evaluation Result: EvalResult
Select and right-click a row to create an initial guess for Response Optimization or Parameter Estimation.
A FeedCon0 FeedTemp0 h ConcVar CoolMean
1.6665 9.1027 298.7040 0.5815 0.0078 360.1810
1.8304 10.4202 294.1778 1.7051 0.0017 304.7684
0.4286 9.5560 294.4233 0.8015 0.9576 373
1.8441 10.0500 296.2681 2.3446 0.0015 292.8644
1.3382 9.7277 296.0506 2.5454 0.0026 289.0413
0.3756 10.1518 295.0374 2.7658 0.0392 291.3596
0.7013 9.6998 297.5851 0.9037 0.0300 358.7545
1.1844 10.2450 294.7875 2.1729 0.0036 292.9212
1.9235 10.3697 291.0346 1.4615 0.0017 315.1435
1.9368 10.8559 290.4815 2.6991 0.0019 288.7562
0.4837 9.9029 294.8352 2.5439 0.0151 298.6608
1.9471 8.9308 295.0001 1.7965 0.0011 311.0358
1.9229 9.5802 299.8118 1.2818 0.0016 318.4055
1.0737 10.6773 290.3048 1.8478 0.0046 303.4633
1.6405 9.4639 294.5618 2.5084 0.0016 295.2404
0.4554 10.4805 292.1669 0.7694 1.6702 373
0.9592 10.0620 291.7999 0.8329 0.0170 358.2039
1.8483 10.7183 291.3615 0.8200 0.0035 340.7548
1.6260 9.0196 295.9212 0.9953 0.0025 342.2727
1.9271 9.9024 298.0002 2.2453 0.0014 294.1091
1.3803 9.3961 295.2950 2.3061 0.0021 297.6694



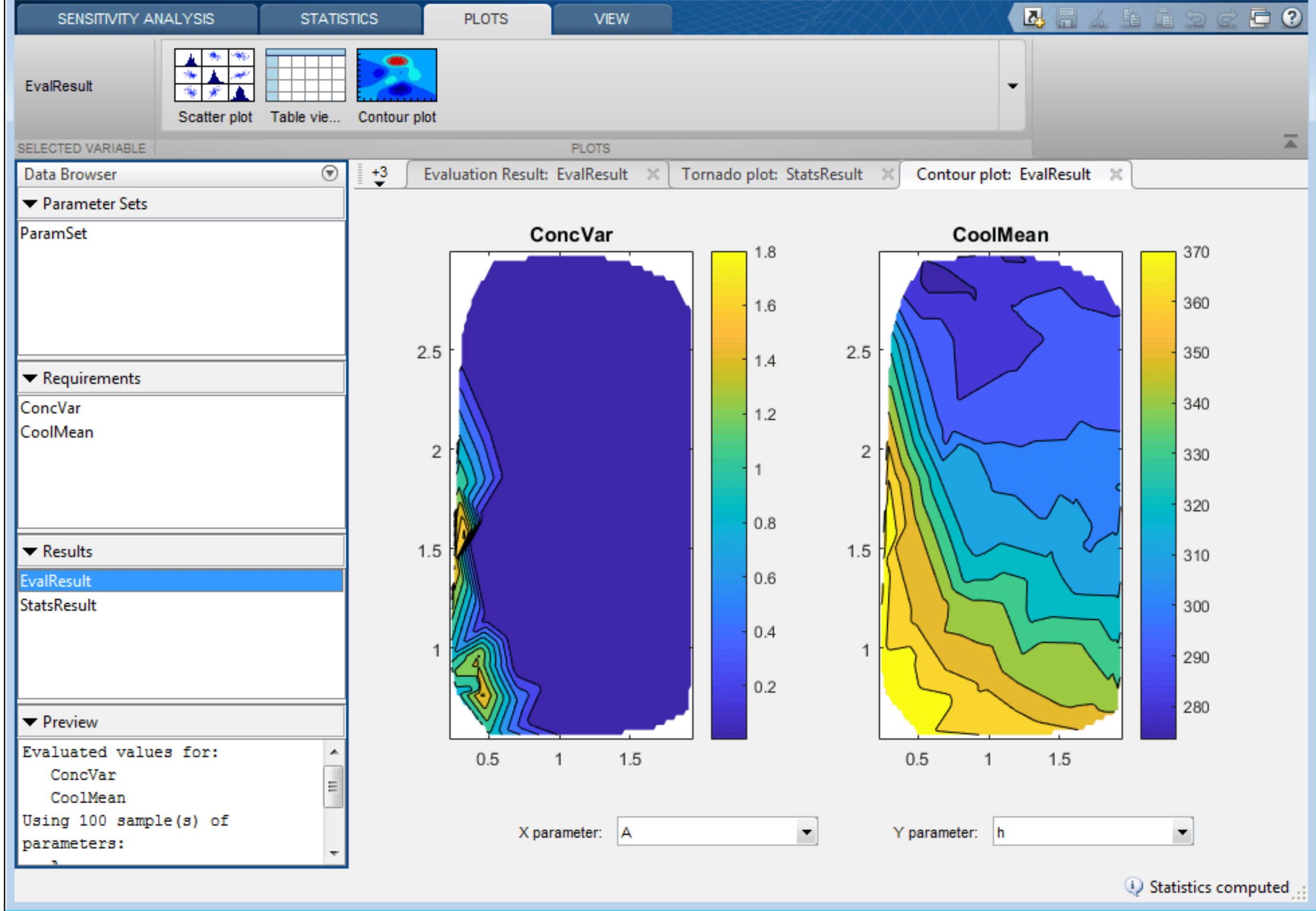
Analyze the Evaluation Results

The results scatter plot for `EvalResult` shows that `CoolMean` is inversely correlated with `h` (increasing `h` decreases `CoolMean`) and that low values of `h` can result in high values for `ConcVar`. The plot shows that low values of `A` can result in high values for `ConcVar`, but it is not clear from the plot how `A` is correlated with `ConcVar` or `CoolMean` or which parameter influences `ConcVar` the most. To investigate further, in the **Statistics** tab, select all the analysis methods and types and click **Compute Statistics**. This performs analysis on the evaluation results and creates a tornado plot. The tornado plot shows the influence of each parameter on each requirement:

- `h` is inversely correlated with `CoolMean`, and is the parameter that influences `CoolMean` the most.
- `A` is inversely correlated with `CoolMean`.
- `FeedCon0` and `FeedTemp0` are inversely correlated with `CoolMean`.
- `A` is inversely correlated with `ConcVar`, and is the parameter that influences `ConcVar` the most.
- `h` is inversely correlated with `ConcVar`.
- `FeedCon0` and `FeedTemp0` have mixed correlation with `ConVar`, but have minimal correlation with `ConcVar`.

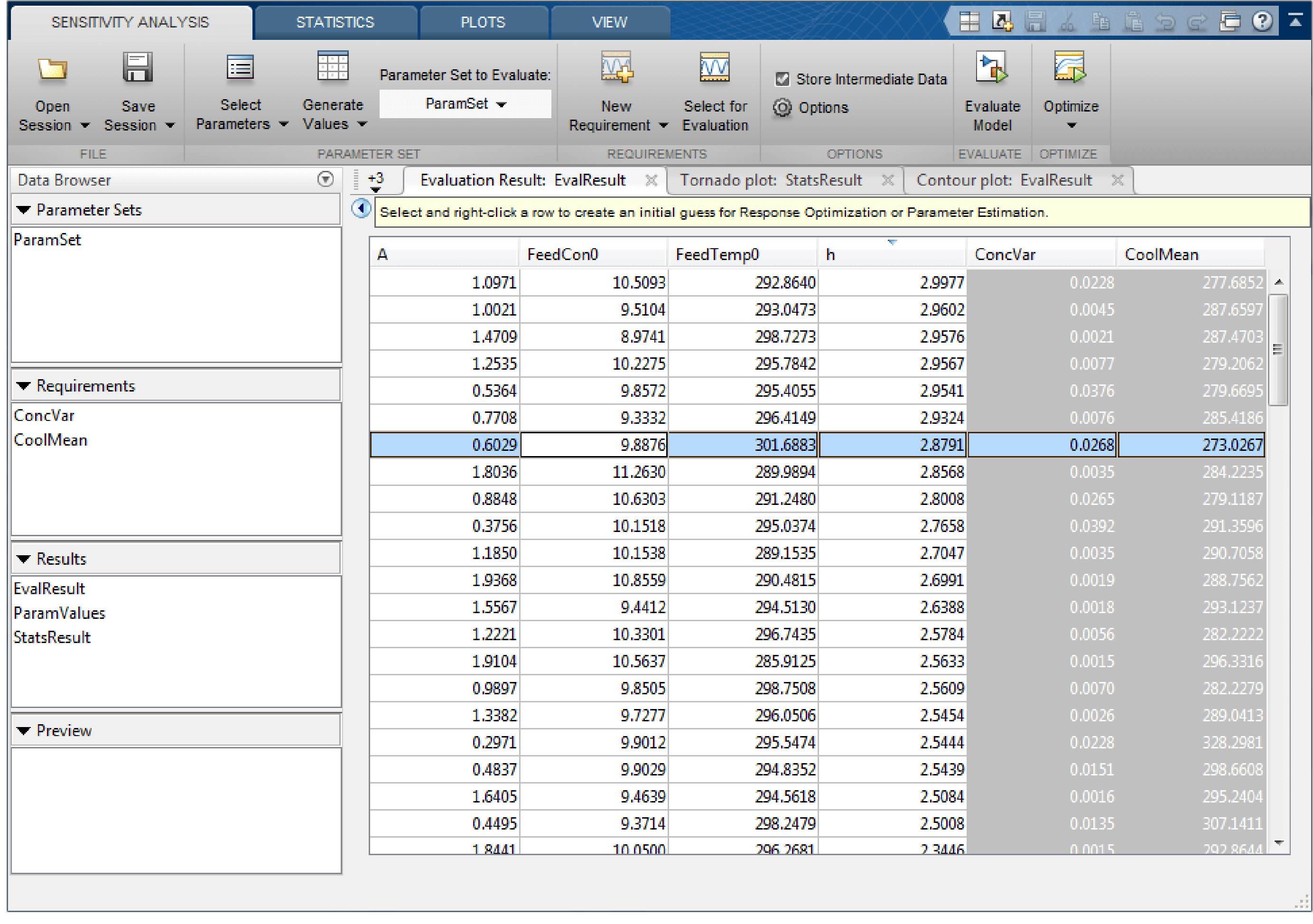


The analysis shows that choosing a large h, to reduce `CoolMean` and choosing a large A to reduce `CoolVar` would appear to be a good design choice. You can confirm this by creating a contour plot of `CoolMean` and `CoolVar` versus h and A. Select `EvalResult` from the **Results** area of the app browser, and in the **Plots** tab, in the plots gallery click **Contour plot**. On the contour plot select h for the **Y parameter**, note that large h medium values of A give low values for both `ConcVar` and `CoolMean`.



Choose an Initial Guess for Optimization

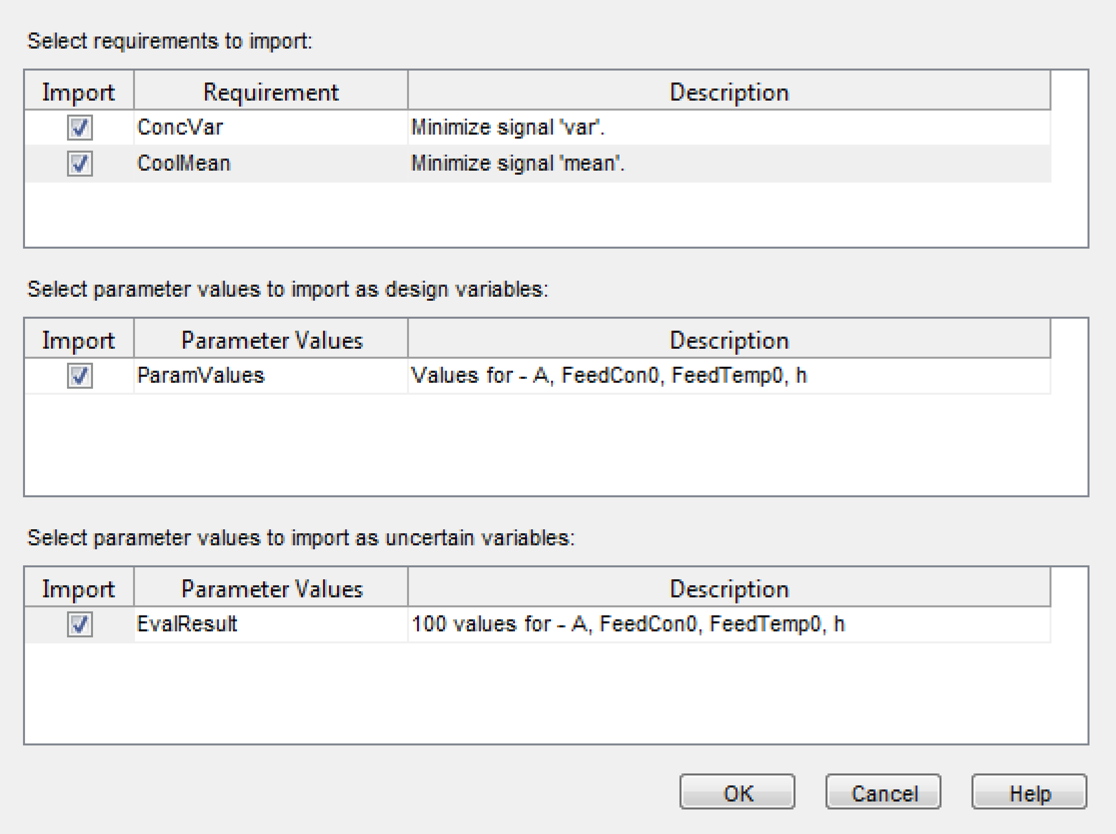
Sort the Evaluation Result table by decreasing `h`, and select a row that has low `ConcVar` and `CoolMean` values. Right-click the selected row and click **Extract Parameter Values**. The extracted parameter values are saved in the `ParamValues` variable in the **Results** area of the app browser. These parameter values are used as the initial guess for optimization.



Optimize

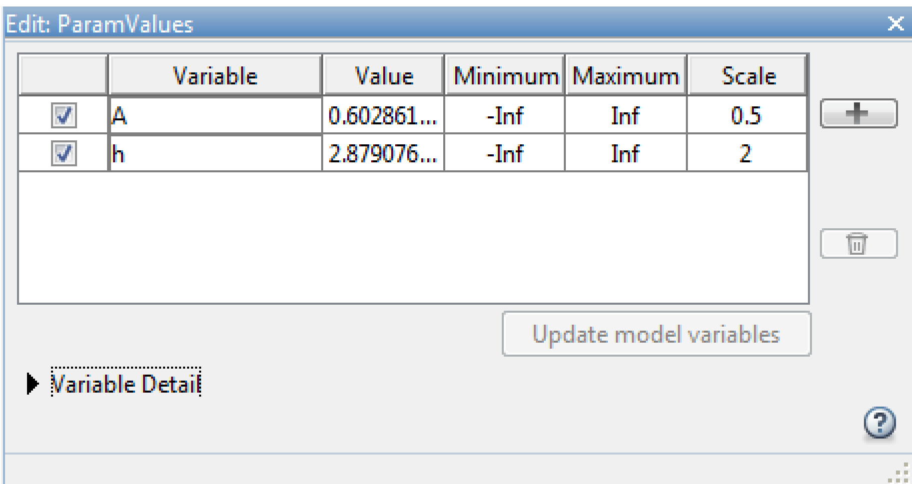
Use the data in the **Sensitivity Analyzer** to create an optimization problem to optimize A and h. In the **Sensitivity Analysis** tab click **Optimize**, and select **Create Response Optimization Session**. This opens a dialog to import data from Sensitivity Analysis to Response Optimizer.

- Select both the `ConcVar` and `CoolMean` requirements to import.
- Select `ParamValues` to import as design variables for optimization.
- Select `EvalResult` to import as uncertain variables to use during optimization.
- Click **OK** to import the data to the **Response Optimizer**

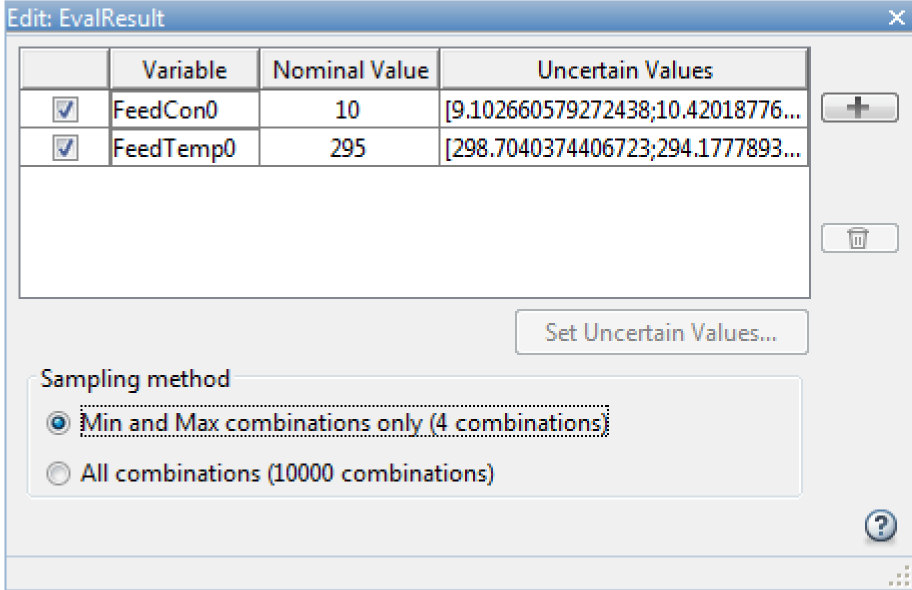

Select requirements to import:
Import
Requirement
Description
ConcVar
Minimize signal 'var'.
CoolMean
Minimize signal 'mean'.
Select parameter values to import as design variables:
Import
Parameter Values
Description
ParamValues
Values for - A, FeedCon0, FeedTemp0, h
Select parameter values to import as uncertain variables:
Import
Parameter Values
Description
EvalResult
100 values for - A, FeedCon0, FeedTemp0, h
OK
Cancel
Help

Configure the **Response Optimizer** to optimize the CSTR design:

- Click the pencil icon to edit the `ParamValues` design variable set, and remove the `FeedCon0` and `FeedTemp0` variables from the design variable set.

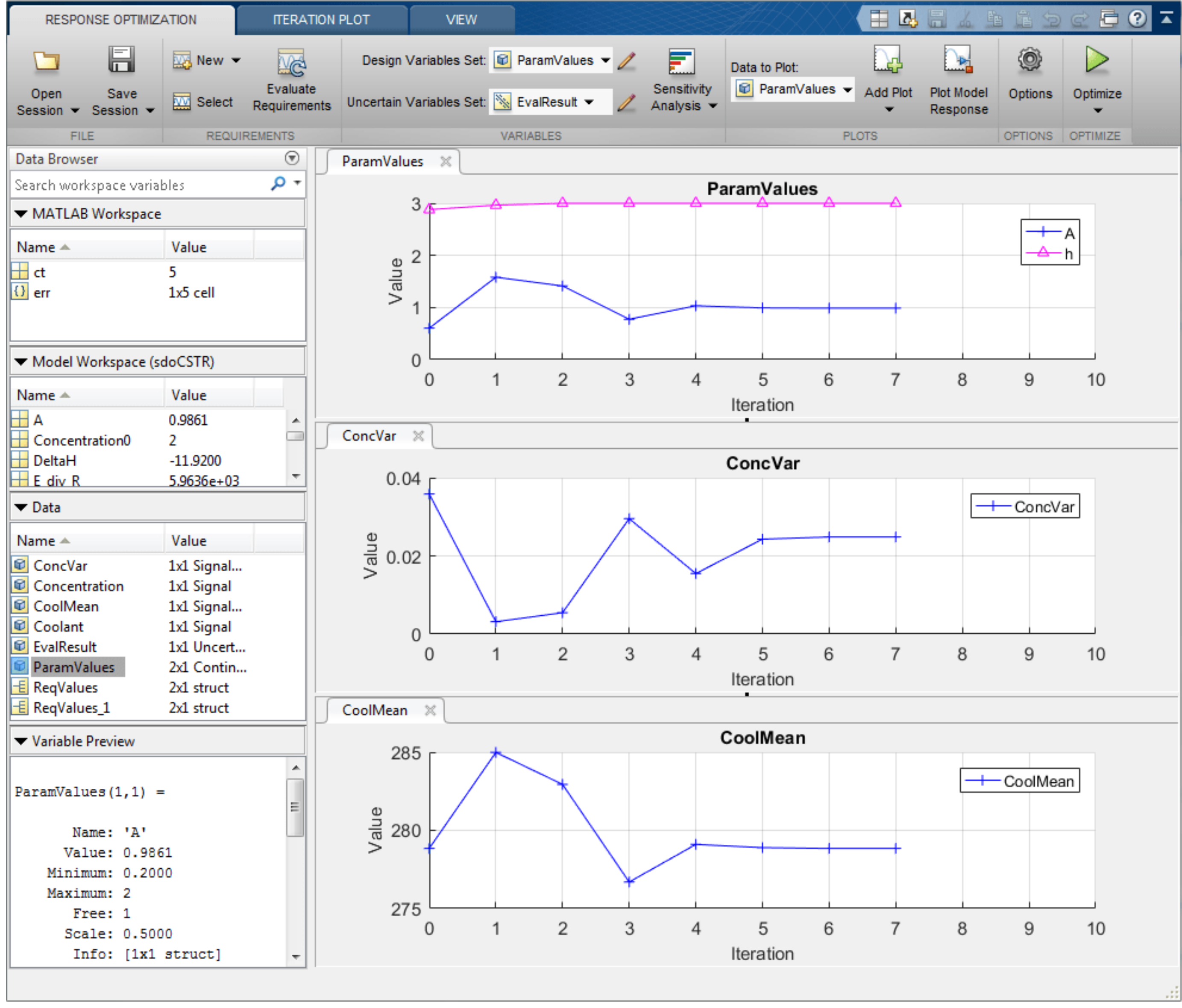


- Select `EvalResult` as the uncertain variable set, click the pencil icon to edit `EvalResult`, and remove `A` and `h` from the uncertain variable set.



Add iteration plots to see how the variables `ParamValues` (`A` and `h`), and optimization requirements `ConcVar` and `CoolMean` change during optimization.

- Select the variables in the `Data to Plot` drop-down list, and select `Iteration Plot` in the `Add Plot` drop-down list.
- Click **Optimize**.



The optimization minimizes `CoolMean` and `ConcVar` in the presence of varying `FeedCon0` and `FeedTemp0`.

Related Examples

To learn how to explore the CSTR design space using the `sdo.evaluate` command, see "Design Exploration Using Parameter Sampling (Code)" on page 4-157.

References

[1] Bequette, B.W. *Process Dynamics: Modeling, Analysis and Simulation*. 1st ed. Upper Saddle River, NJ: Prentice Hall, 1998.

Close the model

```
bdclose('sdoCSTR')
```

See Also

More About

- “Design Exploration Using Parameter Sampling (Code)” on page 4-157
- “Use Parallel Computing for Sensitivity Analysis” on page 4-104
- “Use Fast Restart Mode During Sensitivity Analysis” on page 4-109
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67
- “Validate Sensitivity Analysis” on page 4-96

Identify Key Parameters for Estimation (GUI)

This example shows how to use sensitivity analysis to narrow down the number of parameters that you need to estimate when fitting a model. This example uses a model of the vestibulo-ocular reflex, which generates compensatory eye movements.

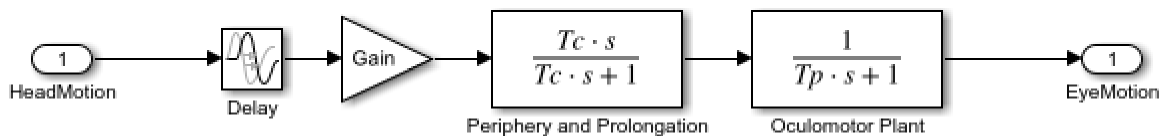
Model Description

The vestibulo-ocular reflex (VOR) enables the eyes to move at the same speed and in the opposite direction as the head, so that vision is not blurred when the head moves during normal activity. For example, if the head turns to the right, the eyes turn to the left at the same speed. This happens even in the dark. In fact, the VOR is most easily characterized by measurements in the dark, to ensure that eye movements are predominantly driven by the VOR.

Head rotation is sensed by organs in the inner ears, known as semicircular canals. These detect head motion and transmit signals about head motion to the brain, which sends motor commands to the eye muscles, so that eye movements compensate for head motion. We would like to use eye movement data to estimate model parameters for these various stages. The model we will use is shown below. There are four parameters in the model: `Delay`, `Gain`, `Tc`, and `Tp`.

```
open_system('sdoVOR')
```

Vestibulo-Ocular Reflex



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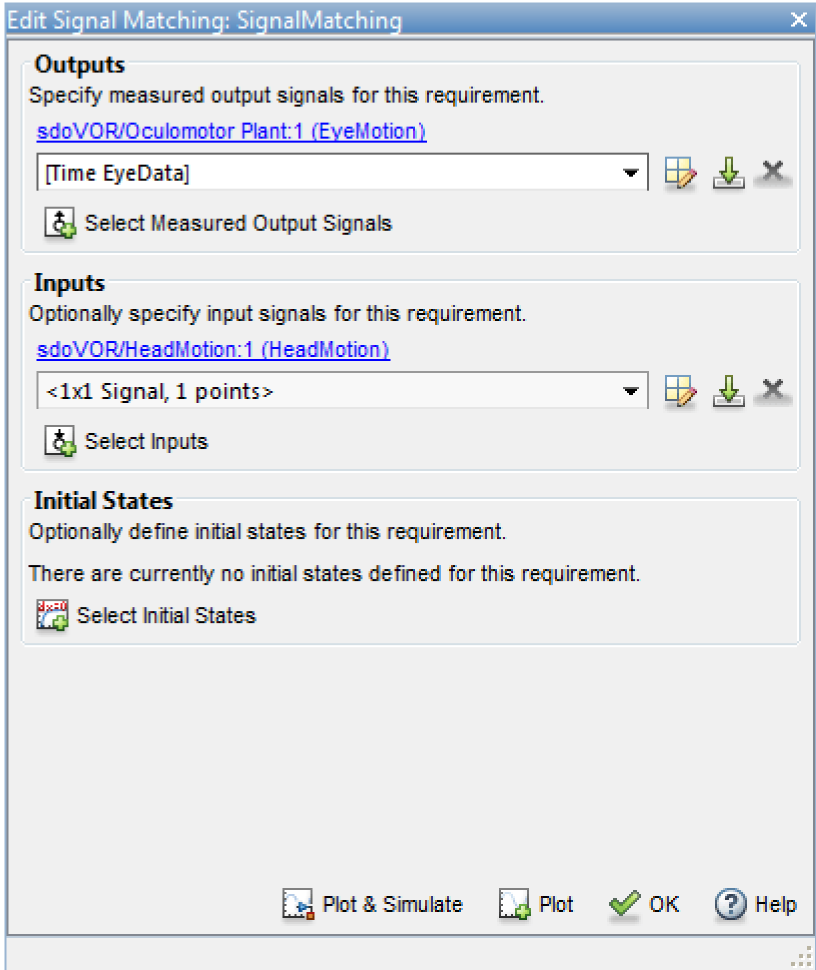
The file `sdoVOR_Data.mat` contains uniformly sampled data of stimulation and eye movements. If the VOR were perfectly compensatory, then a plot of eye movement data, when flipped vertically, would overlay exactly on top of a plot of head motion data. Such a system would be described by a gain of 1 and a phase of 180 degrees. However, real eye movements are close, but not perfectly compensatory.

```
load sdoVOR_Data.mat;   % Column vectors:   Time  HeadData  EyeData
```

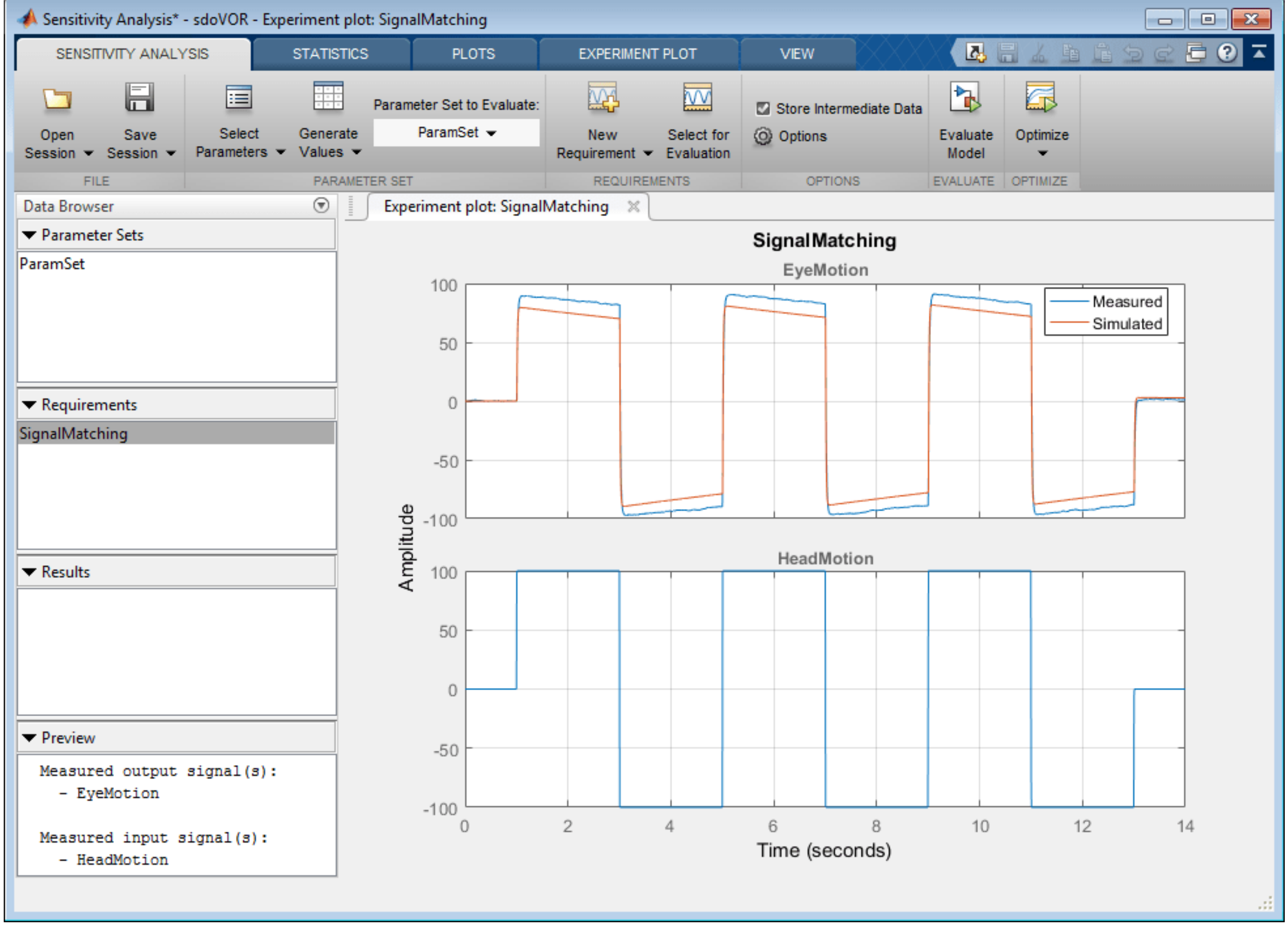
We will use Sensitivity Analysis UI to see how well the model output fits the data, and explore which model parameters have the most influence on the goodness of fit. To open Sensitivity Analysis UI, in the **Apps** tab, click **Sensitivity Analyzer** under **Control Systems** to launch the **Sensitivity Analyzer**.

To associate the data with the model, click **New Requirement** and select a Signal Matching requirement. This specifies an objective function consisting of the sum of squared error between the

data and model output. In the Signal Matching dialog, specify the output as `[Time EyeData]`, and specify the input as `[Time HeadData]`.

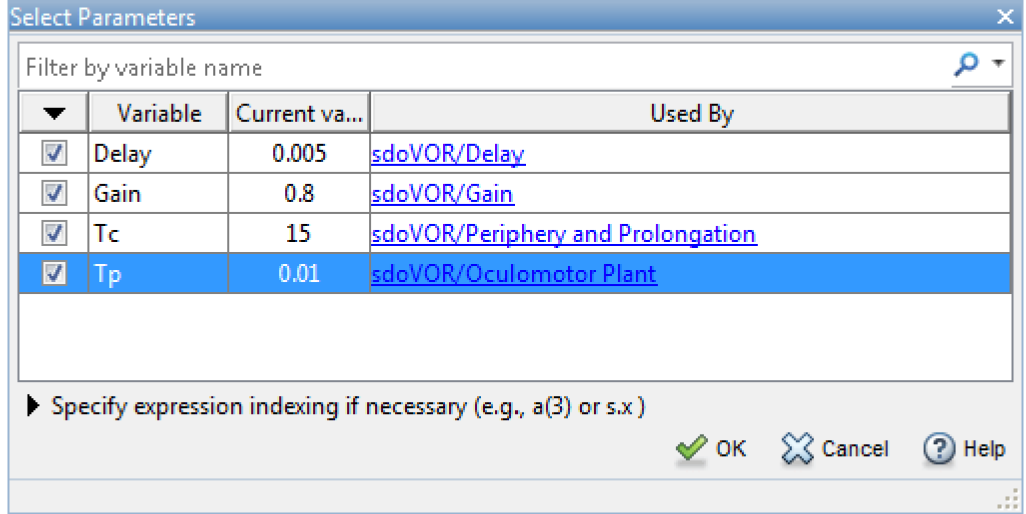


To view the eye movement data, navigate to the data browser on the left side of the UI, right-click the `SignalMatching` requirement, and select Plot & Simulate. The bottom plot shows the stimulation, consisting of a series of pulses. The top plot shows eye movement data, which resembles but does not exactly match the stimulation. It also shows that the model simulated output does not match the eye movement data, because model parameters need to be estimated.



Explore the Design Space

The model attempts to capture the phenomena which cause the difference between head movements and eye movements. Here we will explore the design space formed by the model parameters. To specify the parameters to explore in Sensitivity Analysis UI, click **Select Parameters** and create a new parameter set. Select all model parameters: `Delay`, `Gain`, `Tc` and `Tp`.



Explore the design space by generating parameter values. Click **Generate Values** and select random values. For repeatability of the example, reset the random number generator.

```
rng('default')
```

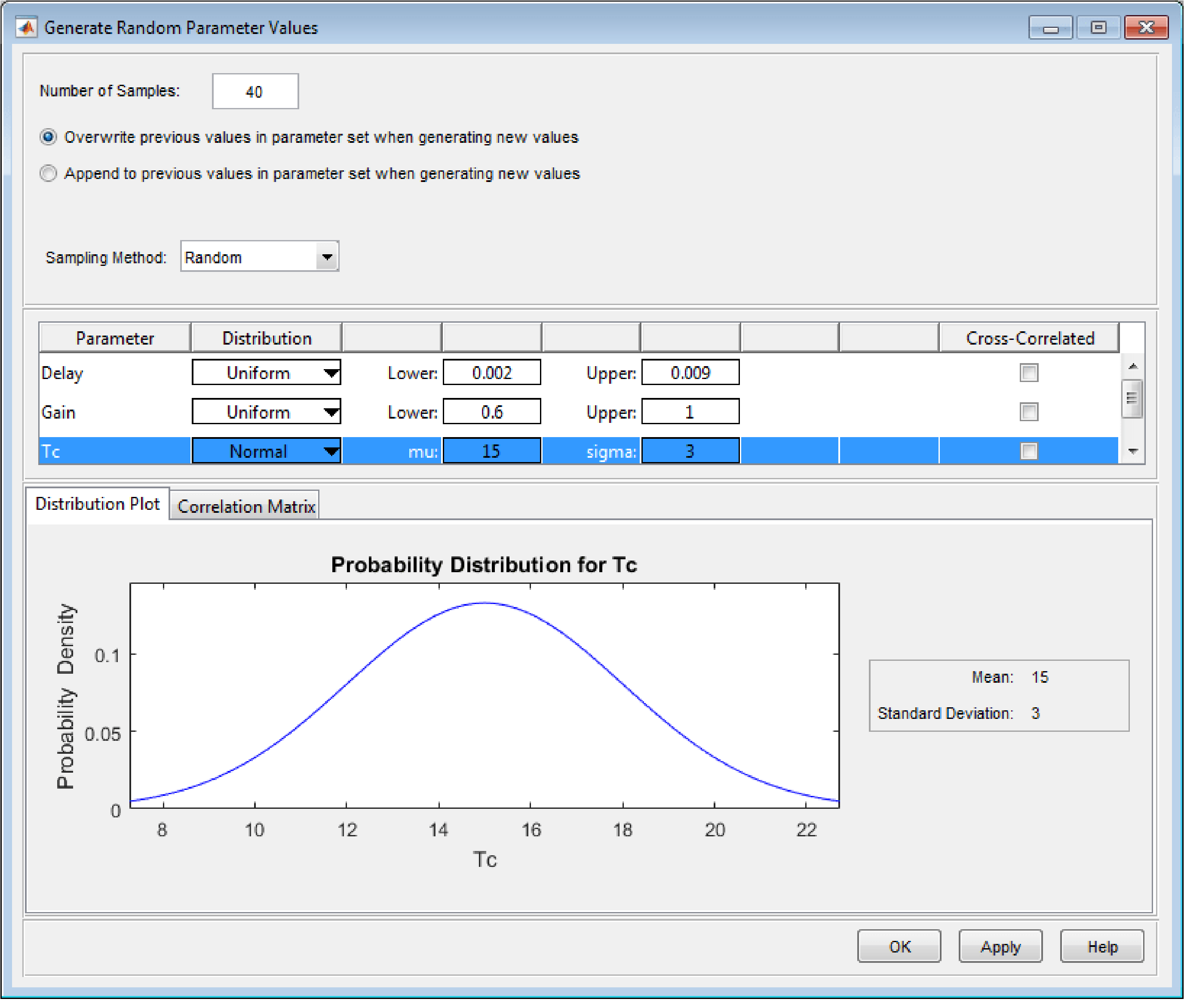
Since there are 4 parameters, we will generate 40 samples.

The `Delay` parameter models the fact that there is some delay in communicating the signals from the inner ear to the brain and eyes. This delay is due to the time needed for chemical neurotransmitters to traverse the synaptic clefts between nerve cells. Based on the number of synapses in the vestibulo-ocular reflex, this delay is expected to be around 5 ms. We will model it with a uniform distribution with a lower bound of 2 ms and an upper bound of 9 ms.

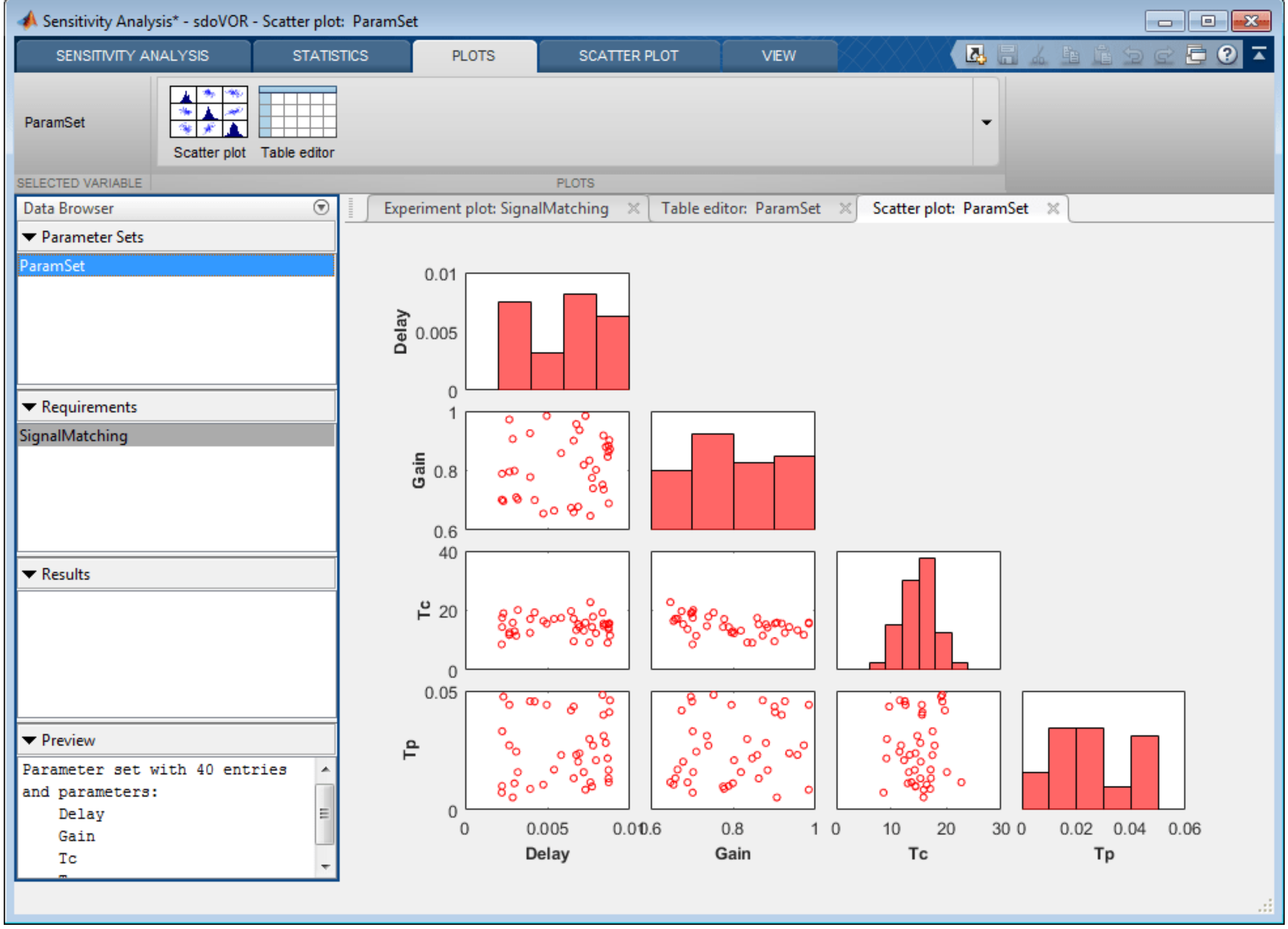
The `Gain` parameter models the fact that in the dark, the eyes do not move quite as much as the head. We will model it with a uniform distribution with a lower bound of 0.6 and an upper bound of 1.

The `Tc` parameter models the dynamics associated with the semicircular canals, as well as some additional neural processing. The canals are high-pass filters, because after a subject has been put into rotational motion, the neurally active membranes in the canals slowly relax back to resting position, so the canals stop sensing motion. Thus, after the stimulation undergoes transition edges, eye movements tend to depart from the stimulation over time. Based on mechanical characteristics of the canals, combined with additional neural processing which prolongs this time constant to improve the accuracy of the VOR, we will model `Tc` with a normal (i.e., bell curve) distribution with a mean of 15 seconds and a standard deviation of 3 seconds.

Finally, the `Tp` parameter models the dynamics of the oculomotor plant, i.e. the eye and the muscles and tissues attached to it. The plant can be modeled by two poles, however it is believed that the pole with the larger time constant is cancelled by precompensation in the brain, to enable the eye to make quick movements. Thus in the plot, when the stimulation undergoes transition edges, the eye movements follow with only a little delay. We will model `Tp` with a uniform distribution with a lower bound of 0.005 seconds and an upper bound of 0.05 seconds.



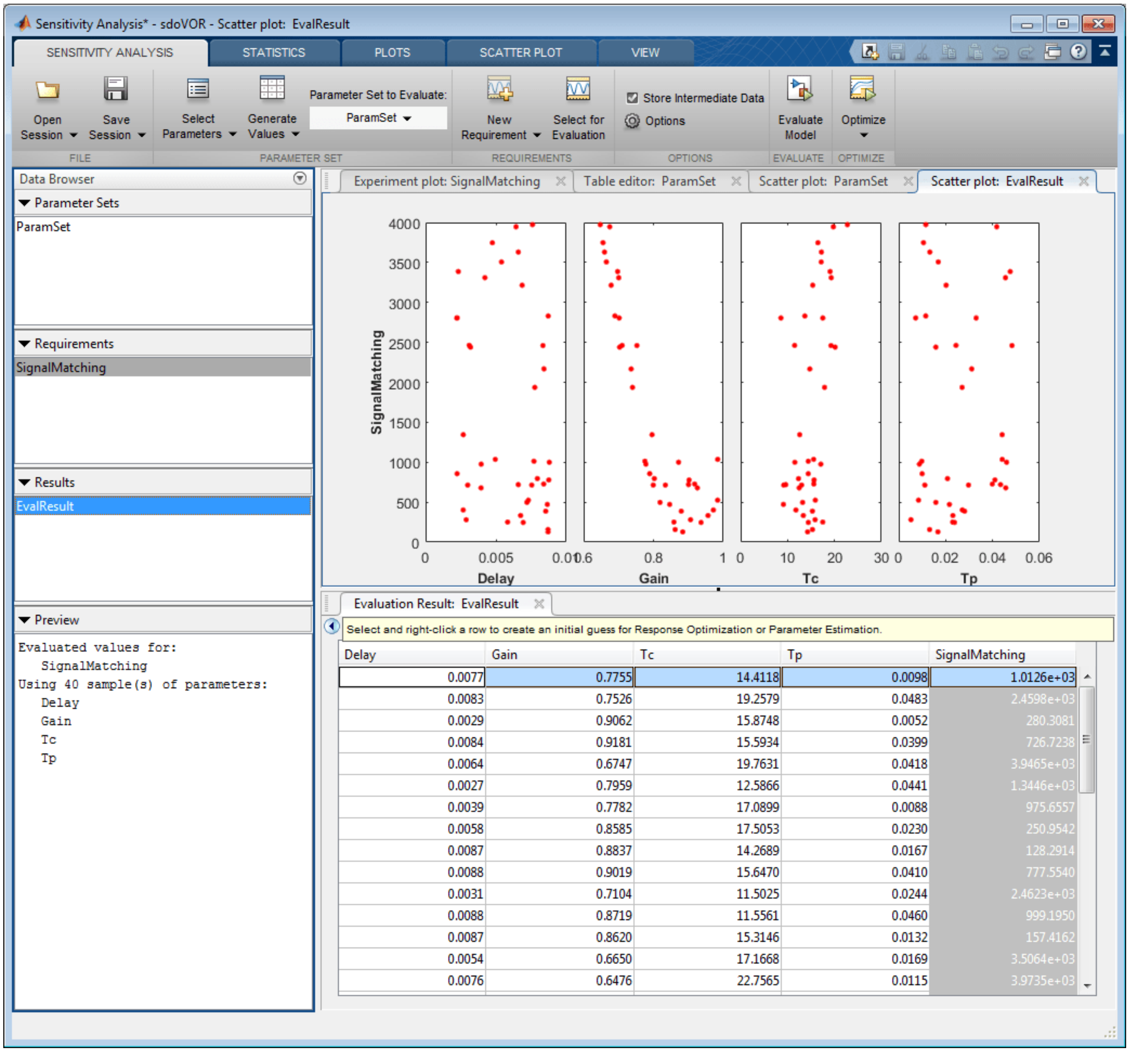
When the sample values are generated, they appear in a table in the Sensitivity Analysis UI. To plot them, select `ParamSet` in the data browser, click the **Plots** tab, and make a scatter plot. The sampling above used default options, and these are reflected in the scatter plot. For parameters modeled by a uniform distribution, the histograms appear approximately uniform. However, parameter `Tc` was modeled by a normal distribution, and its histogram has a bell curve profile. If Statistics and Machine Learning Toolbox™ is available, many other distributions may be used, and sampling can be done using Sobol or Halton low-discrepancy sequences. The off-diagonal plots show scatter plots between pairs of different variables. Since we did not specify cross-correlations between parameters, the scatter plots appear uncorrelated. However, if parameters were believed to be correlated, this can be specified using Correlation Matrix tab in the dialog for generating random parameter values.



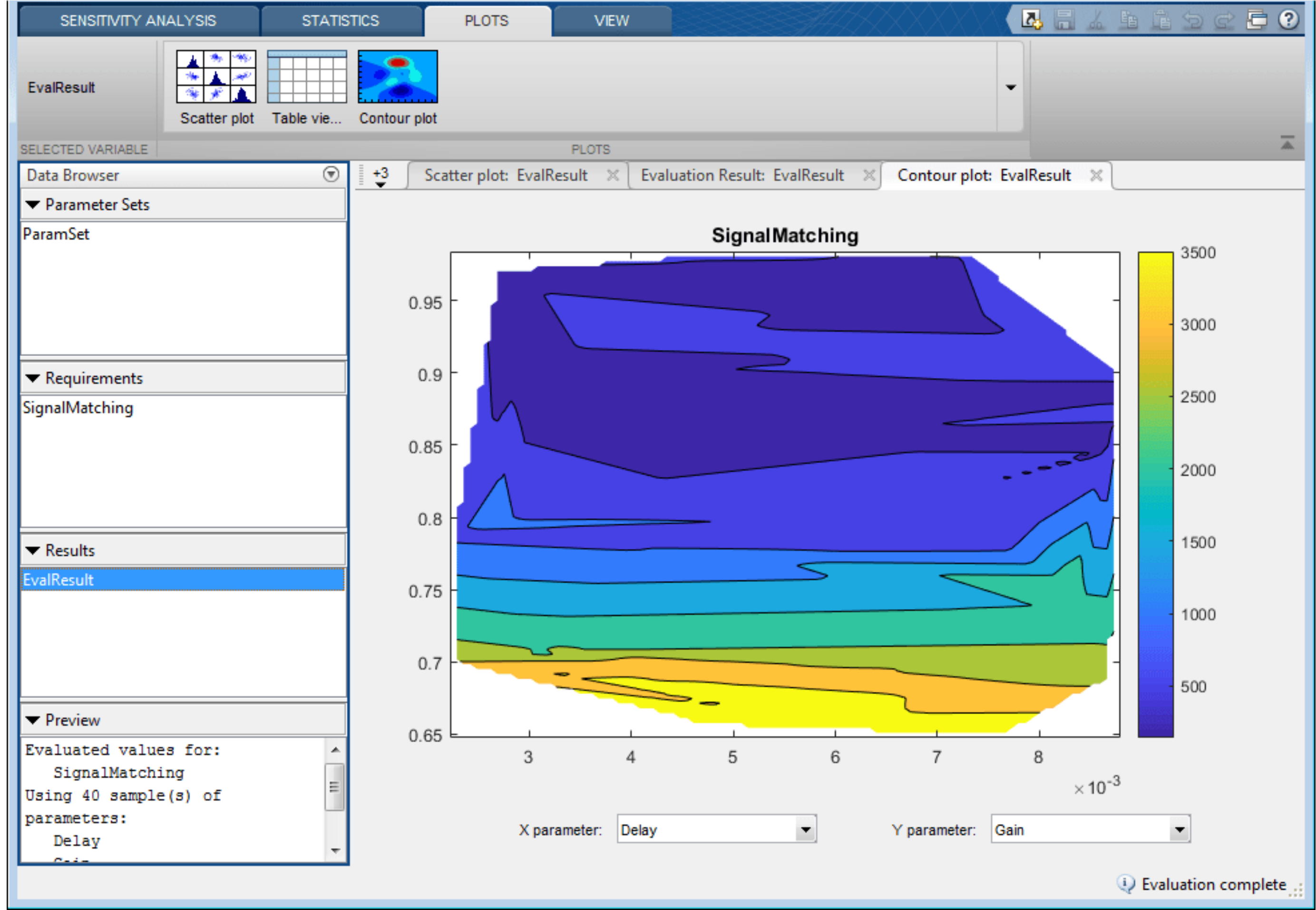
Evaluate the Model

Now that we have generated values for the parameter set and specified a requirement (`SignalMatching`), we can evaluate the model. In the **Sensitivity Analysis** tab, click **Evaluate Model**.

The model is run once for each set of parameter values, and the results scatter plot is updated as new computations become available. Evaluation could also be sped up using parallel computing. After evaluation is complete, all results are also displayed in a table.

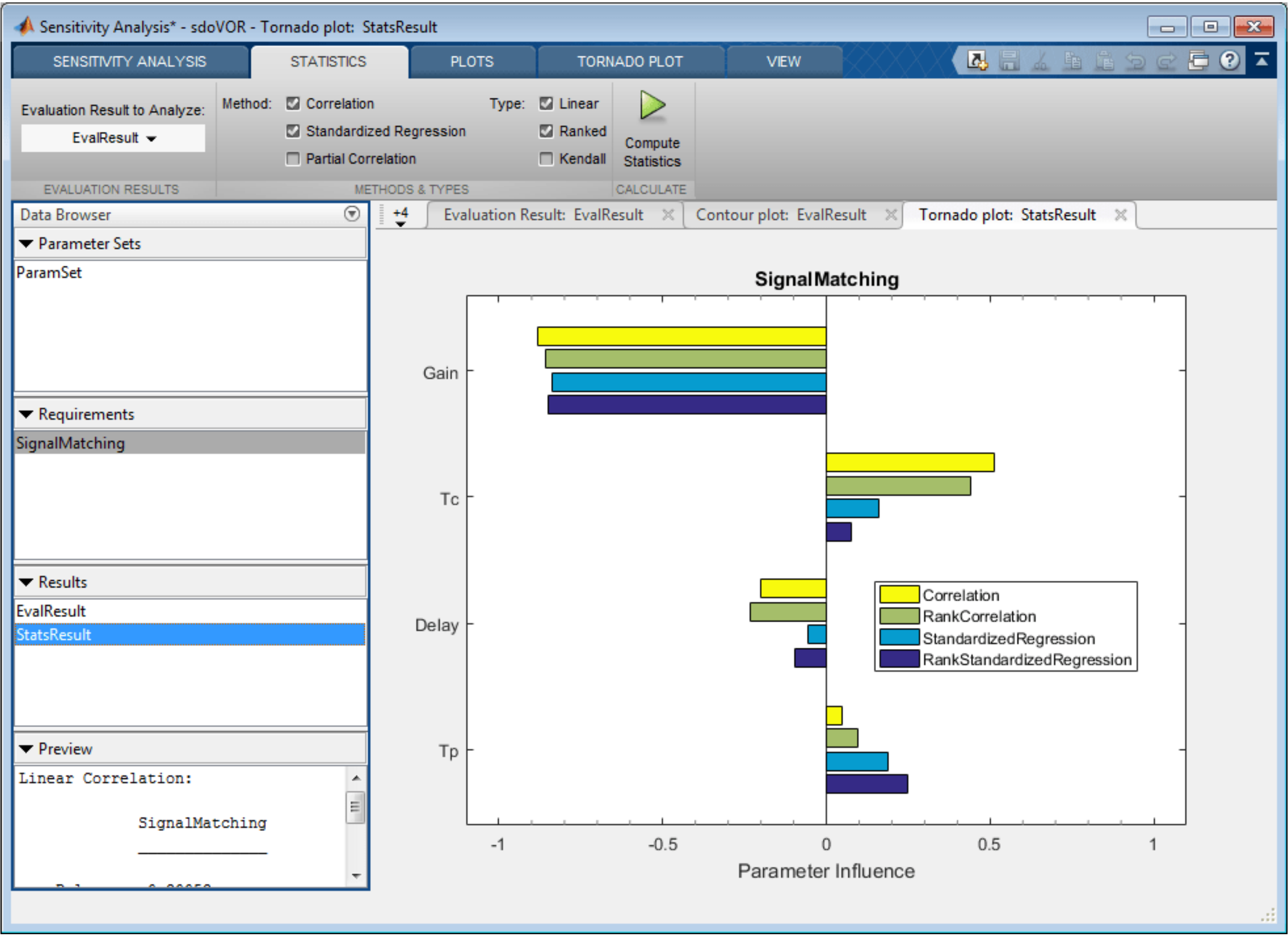


From the scatter plot of evaluation results, the `SignalMatching` requirement seems to vary systematically as a function of `Gain` and `Tc`, but not `Delay` or `Tp`. Something similar can be seen in a contour plot. Select the `EvalResults` variable in the data browser, click the **Plots** tab, and make a contour plot. The requirement does not vary systematically from left to right as a function of `Delay`, but it does vertically as a function of `Gain`.



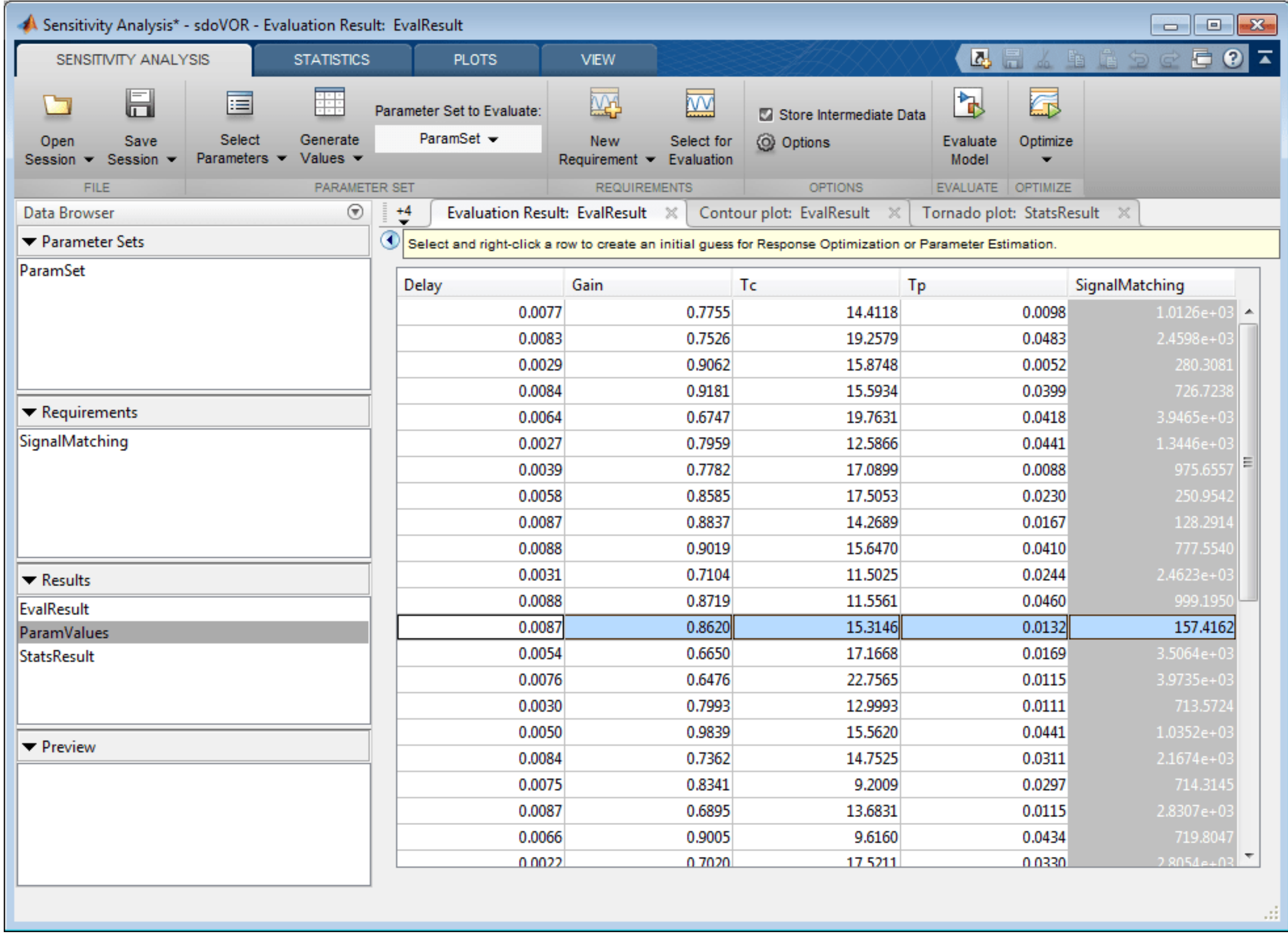
Statistical Analysis

We can use statistical analysis to quantify how much each parameter influences the requirement. Click the **Statistics** tab and select both correlation and standardized regression; and both linear and ranked analysis types. If Statistics and Machine Learning Toolbox is available, partial correlation and Kendall correlation can also be selected. Click **Compute Statistics** to carry out the calculations and show a tornado plot. The tornado plot displays results from top to bottom in order of which parameter most influences the requirement. The statistical values range from -1 to 1, where the magnitude indicates how much the parameter influences the requirement, and the sign indicates whether an increase in the parameter value corresponds to an increase or decrease in the requirement value. By most measures, this `SignalMatching` requirement is more sensitive to `Gain` and `Tc`, and less sensitive to `Delay` and `Tp`.

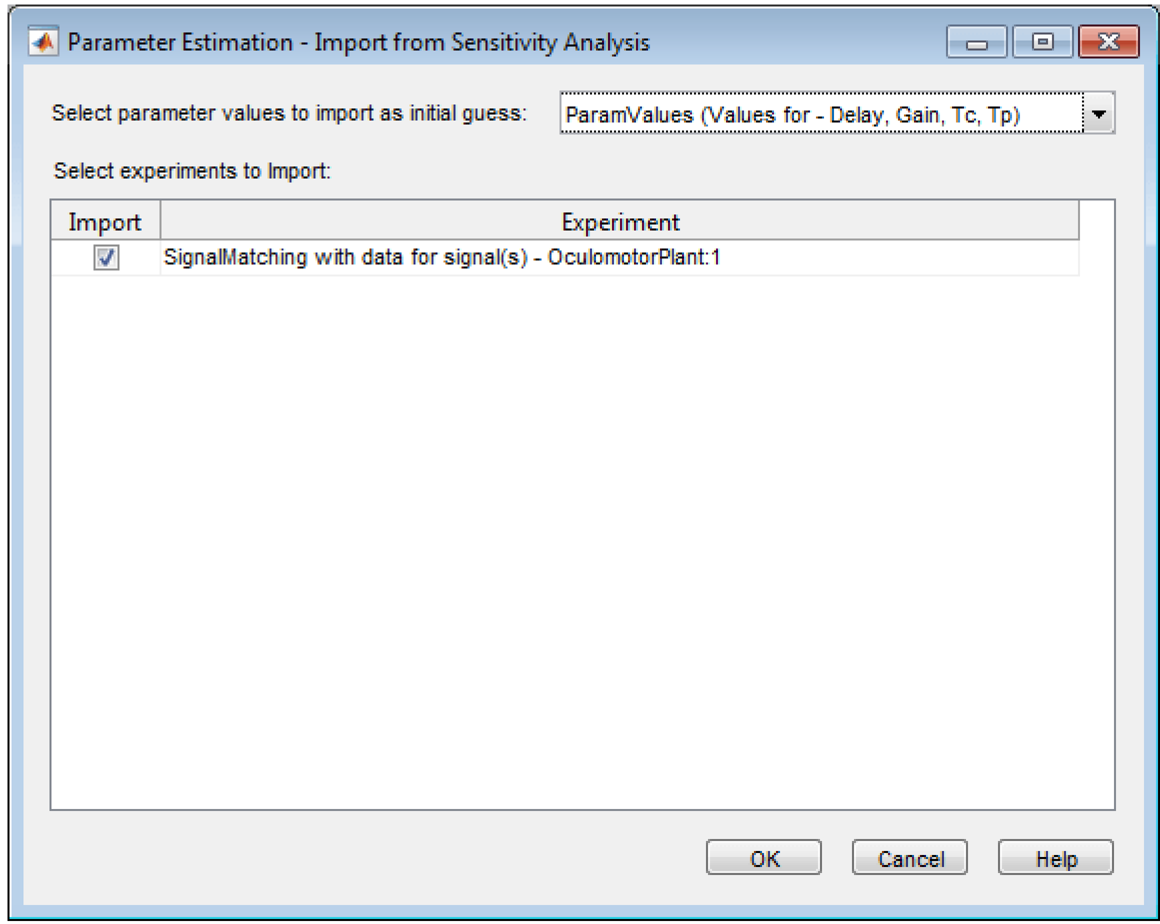


Select Parameters for Estimation

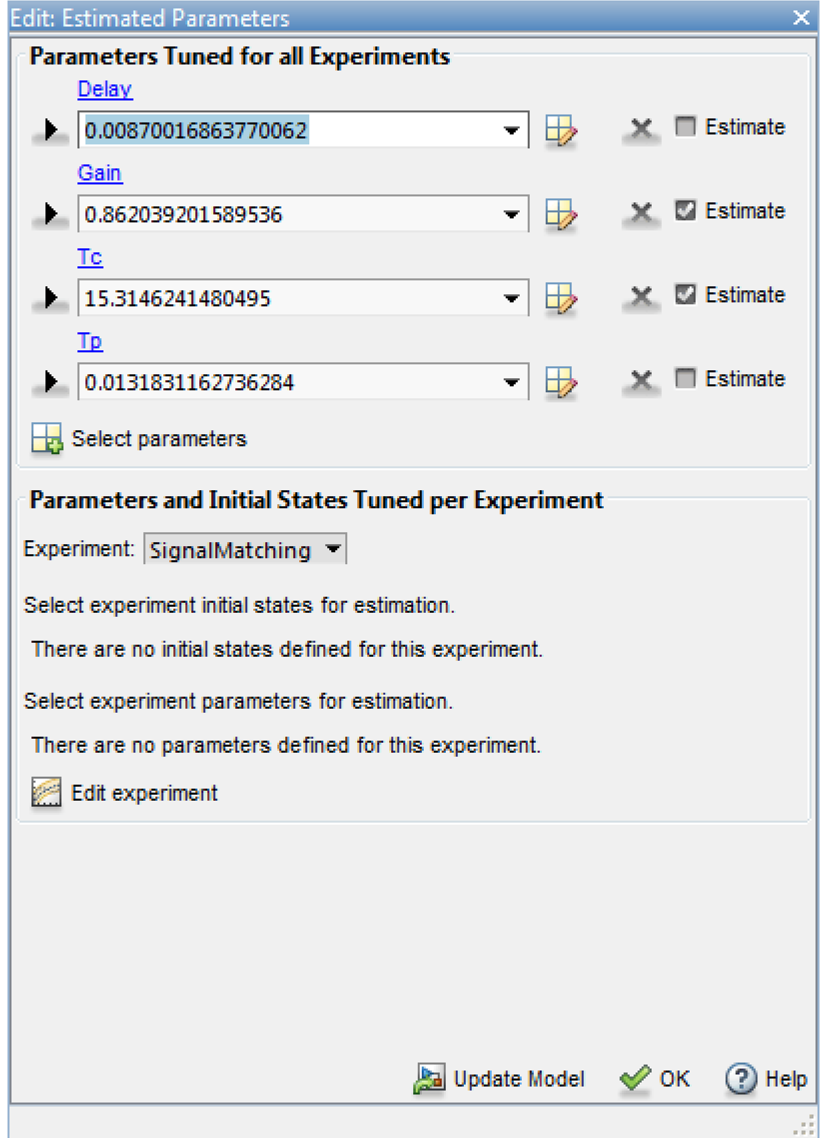
For parameter estimation, we need to specify starting values for the parameters. Click the evaluation results table and click the `SignalMatching` column header to sort results. Select the row of parameter values that minimizes the `SignalMatching` requirement. Right-click on the row and extract these parameter values. A new variable, `ParamValues`, is shown in the data browser.



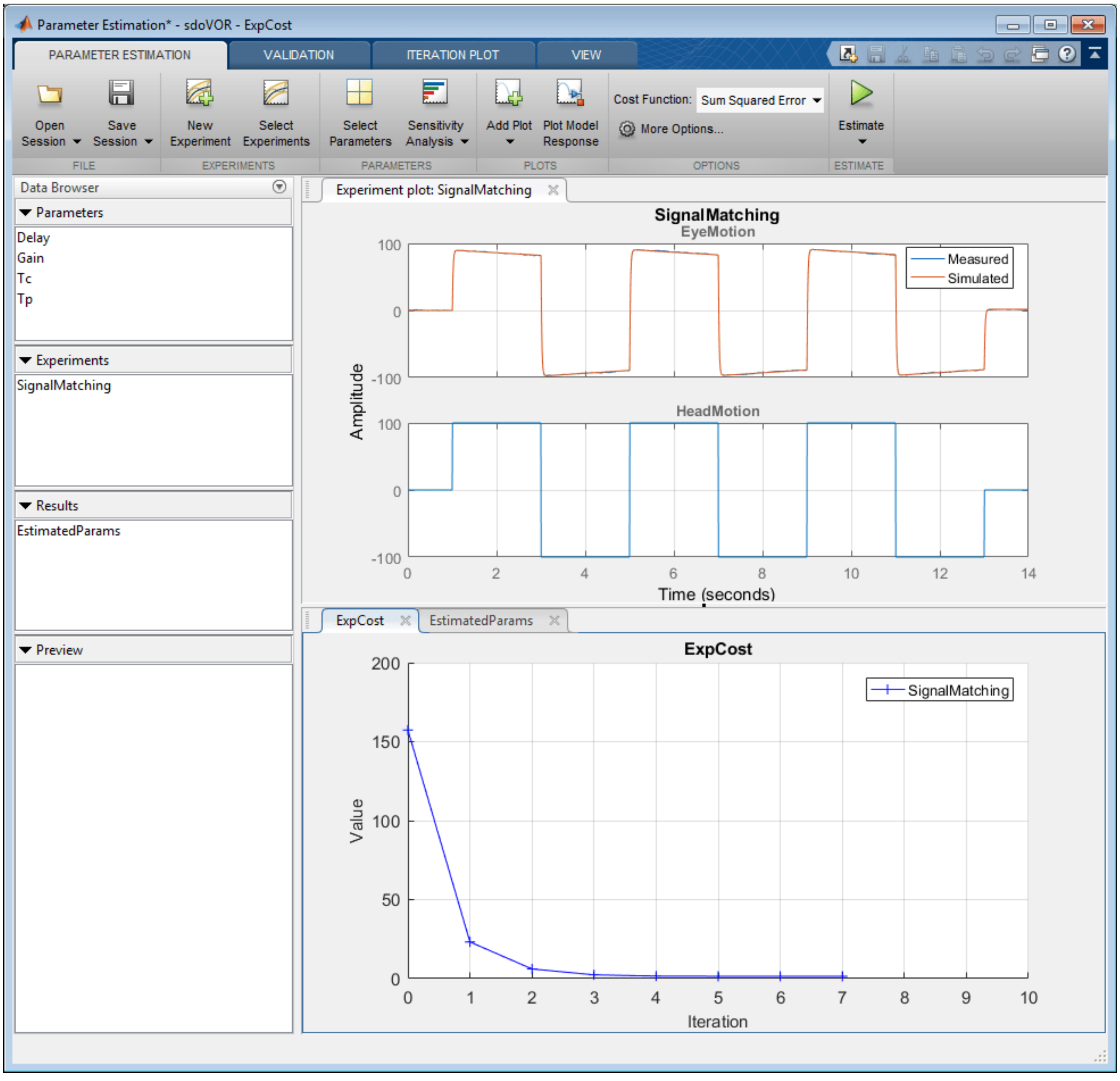
To transition from sensitivity analysis to parameter estimation, navigate to the **Sensitivity Analysis** tab, click **Optimize**, and open a parameter estimation session. In the dialog that appears, specify that you want to use the parameter values in `ParamValues`, and the `SignalMatching` requirement.



Since we found above that parameters `Gain` and `Tc` have the most influence on the value of `SignalMatching`, we would like to estimate only these two parameters, since the time for estimation increases with the number of parameters being estimated. In Parameter Estimation UI, click **Select Parameters** and select only `Gain` and `Tc` for estimation.



Since the experiment definition has been imported from `SignalMatching` and the parameter values have been imported from `ParamValues`, we have everything needed for estimation. Click **Estimate** to carry out parameter estimation for `Gain` and `Tc`. Because we are only estimating the two most influential parameters, estimation converges quickly and the model output closely matches the data. As was the case with model evaluations in sensitivity analysis, parallel computing could be used to speed up estimation.



In summary, Sensitivity Analysis UI was used to explore the parameter design space and determine that two parameters, `Gain` and `Tc`, were substantially more influential than the others. A start point for estimation was also determined. This start point and the requirement of obtaining a good fit to experimental data were imported into Parameter Estimation UI. Estimation completed quickly because only two parameters needed to be estimated, and the model output fit the data with very little residual error.

Close the model.

```
bdclose('sdoVOR')
```

See Also

Related Examples

- “Identify Key Parameters for Estimation (Code)” on page 4-169
- “Use Parallel Computing for Sensitivity Analysis” on page 4-104
- “Use Fast Restart Mode During Sensitivity Analysis” on page 4-109
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67
- “Validate Sensitivity Analysis” on page 4-96

Explore Design Reliability Using Parameter Sampling (GUI)

This example shows how to use the **Sensitivity Analyzer** to explore the behavior of a PI controller for a DC motor. The controller is susceptible to variations caused by component tolerances, and the impact on controller reliability is explored.

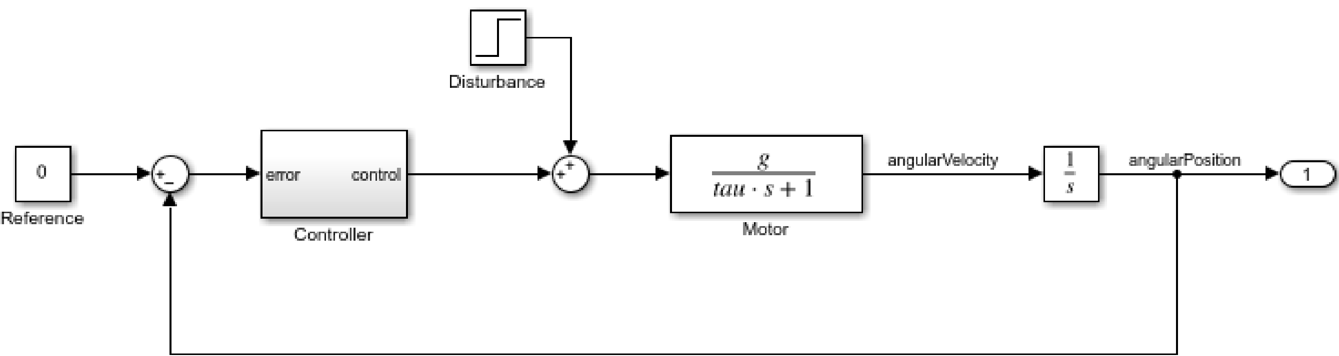
You explore the controller reliability by characterizing the components using probability distributions. You use the distributions to generate random samples and perform Monte-Carlo evaluation of the controller design at these sample points. You evaluate the impact of the component tolerances on the controller behavior, and use statistical analysis to determine which components have the most influence on whether the controller meets its requirements. This analysis guides the selection of component tolerances.

This example requires Statistics and Machine Learning Toolbox™.

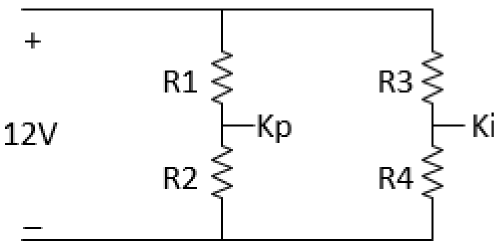
Implementation of Controller for DC Motor

The controller enables the DC motor's angular position to match a desired reference value. The load on the motor is subject to disturbances, and the controller needs to reject these disturbances. The Simulink® model can be used to probe how well the controller rejects a step disturbance at 1 second.

```
open_system('sdoMotorPosition');
```



The gains of the PI controller, `Kp` and `Ki`, are set using resistors in the circuit below:



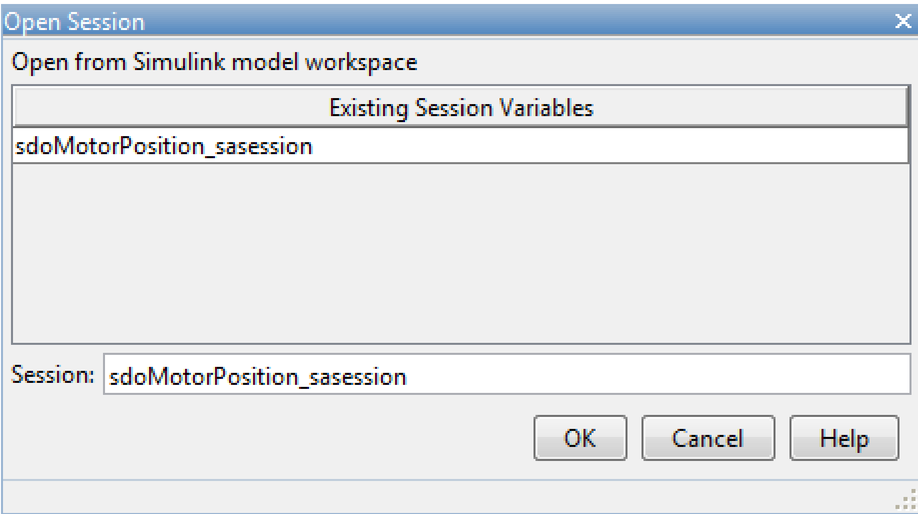
The resistances `R1` through `R4` are 47 kOhm, 180 kOhm, 10 kOhm and 10 kOhm respectively. These were chosen to set `Kp` and `Ki` to values that enable the controller to meet the requirements for

disturbance rejection. However, in practice the actual resistor values will differ from the nominal ones, within a tolerance. This raises concern about whether the actual controller will still satisfy the requirements. To explore the effect of different resistance values, use the **Sensitivity Analyzer**. In the Simulink model from the **Apps** tab, click **Sensitivity Analyzer** under **Control Systems** to open the app.

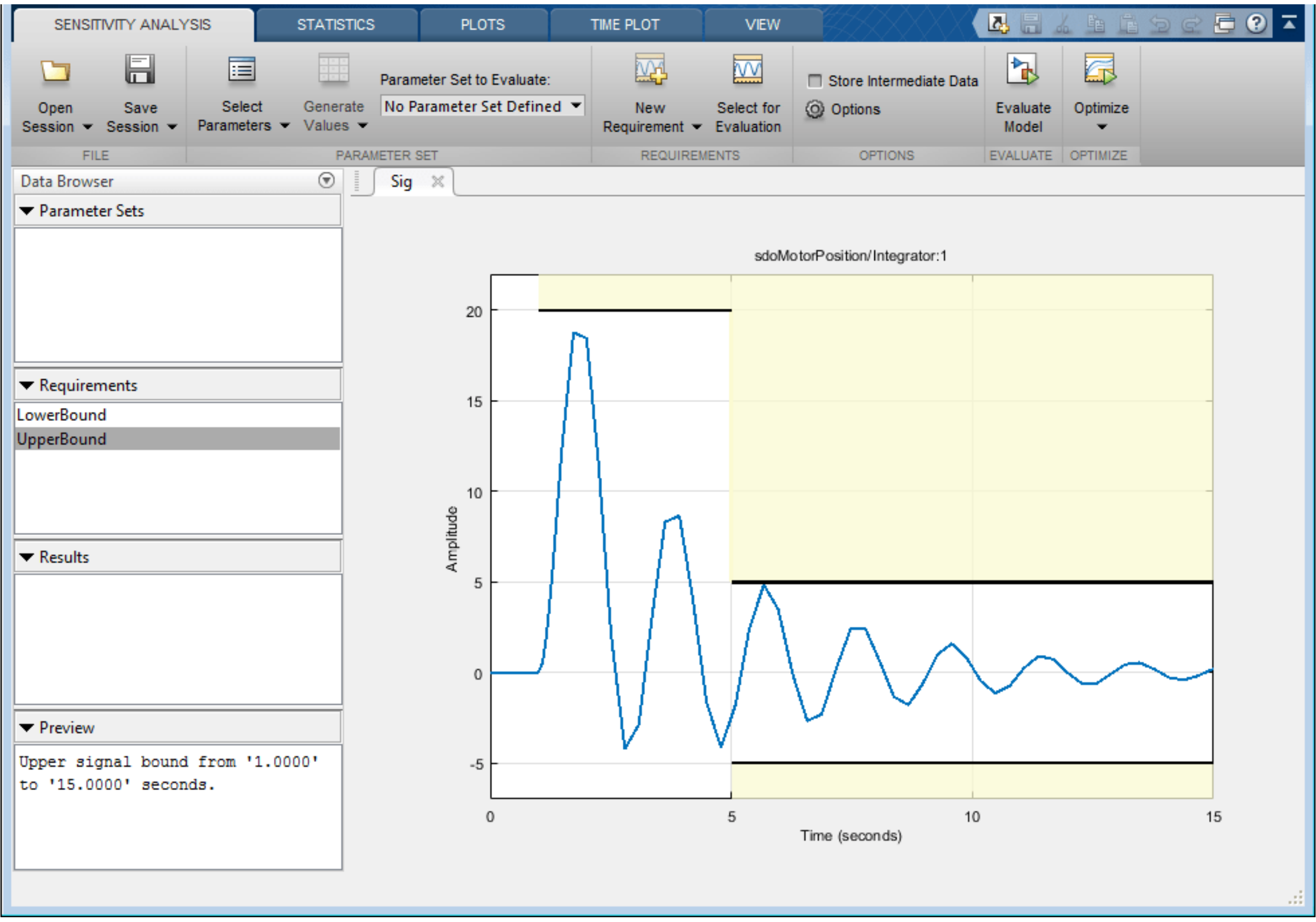
Design Requirements

The controller needs to maintain the motor at a reference position in the presence of disturbances. If a step disturbance occurs, the motor needs to deviate no more than 20 degrees, and needs to settle back to within 5 degrees of the reference position by 4 seconds after the disturbance.

Load previously specified design requirements for disturbance rejection. In the app, click **Open Session** and select **Open from model workspace** in the drop-down menu.

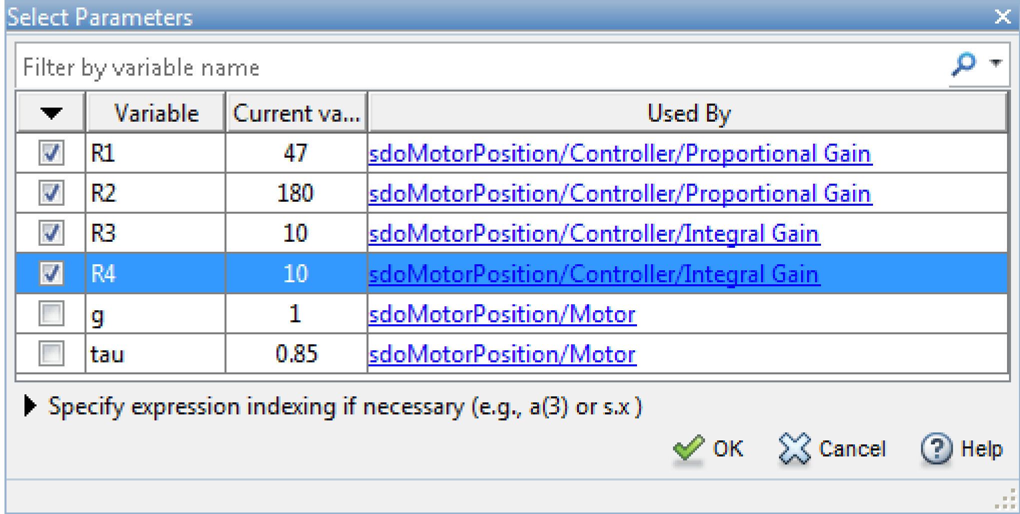


You can plot the requirements and verify that they are met when the resistances have the nominal values. In the **Requirements** area in the data browser, right-click on the `LowerBound` requirement, and select **Plot and Simulate**. Do the same for the `UpperBound` requirement.



Parameter Sampling

The motor position satisfies the disturbance rejection requirements, when the resistances are at their nominal values. However, in practice the actual resistor values will differ from the nominal ones, and we need to determine whether the controller will still meet the requirements. Click **Select Parameters** and make a new parameter set. This creates `ParamSet` in the **Parameter Sets** area of the app. Specify that R1, R2, R3, and R4 are in the parameter set, and click **OK**.



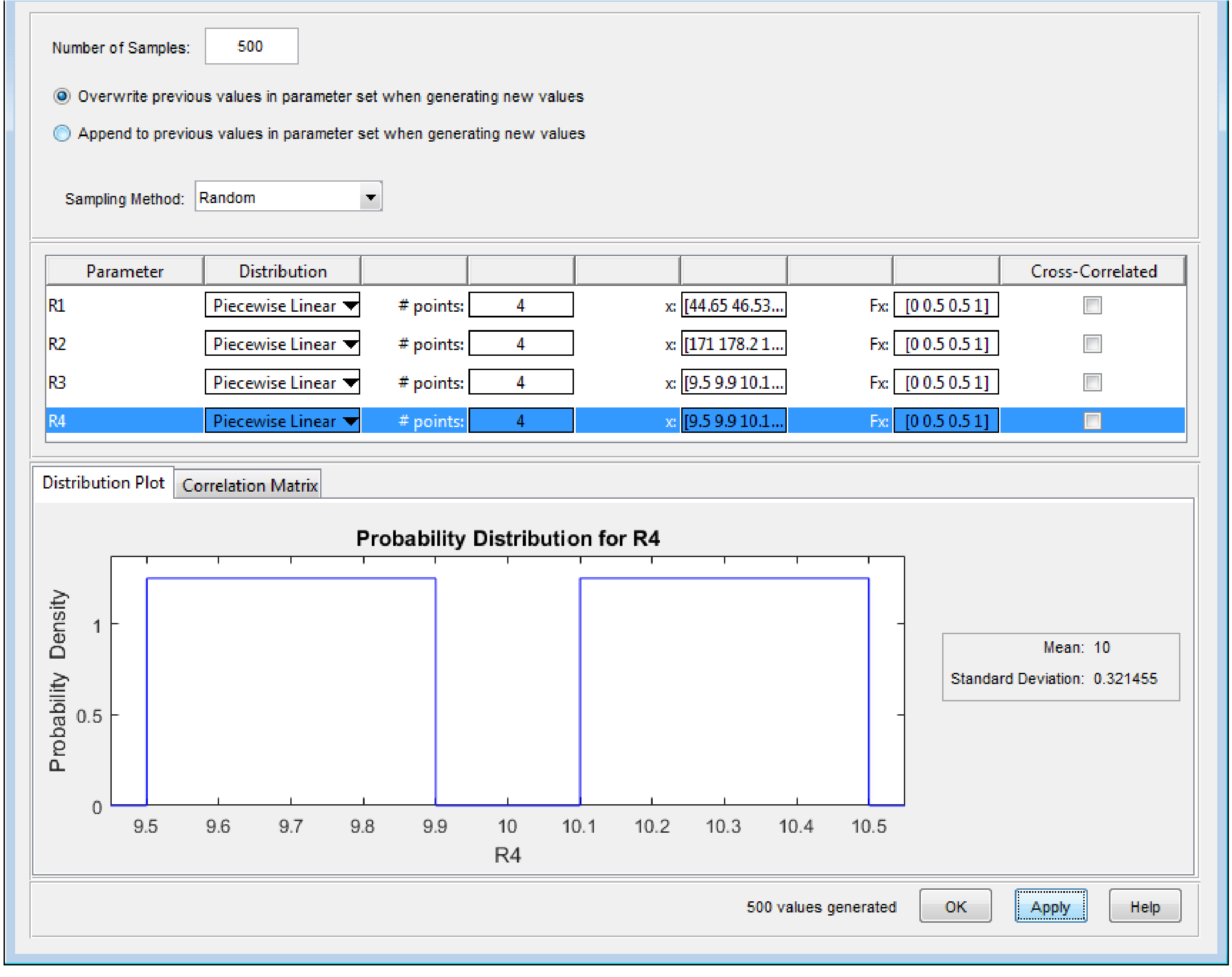
Click **Generate Values** and generate random values. For repeatable results, reset the state of the random number generator in MATLAB®.

```
rng('default')
```

In the Generate Random Parameters dialog box, specify 500 samples to generate.

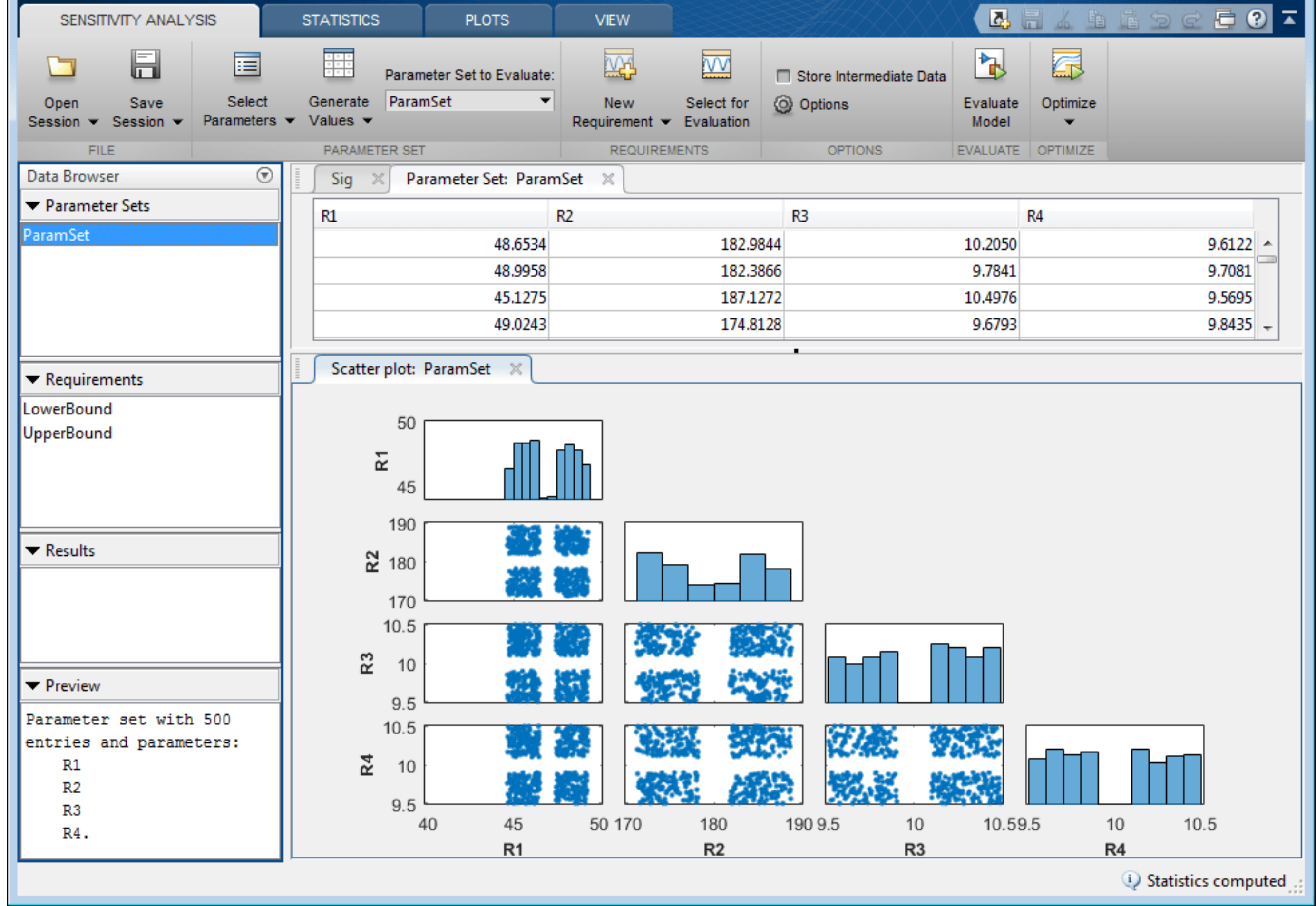
Specify the probability distribution for each parameter. Standard precision resistors match their nominal component value within a tolerance of 5%. This could be modeled using a uniform probability distribution. However, because resistors that measure within 1% of the nominal value are separated out and sold as higher-priced precision resistors, the 5% resistors can be more accurately modeled by a probability distribution with a well that excludes values within 1% of nominal. This can be modeled using a piecewise linear probability distribution if Statistics and Machine Learning Toolbox™ is available.

Specify the distribution of R1 as piecewise linear with 4 points. Specify the x values as [0.95 0.99 1.01 1.05] times 47 (the nominal value of the resistor). Specify the Fx values as [0 0.5 0.5 1]; these are the values of the cumulative distribution function corresponding to each x value. Similarly, set the distributions of R2, R3 and R4 to piecewise linear with 4 points, the x values as [0.95 0.99 1.01 1.05] times the nominal values (180, 10, and 10, respectively), and the Fx values as [0 0.5 0.5 1].



Click **OK** to generate parameter values. The generated values are stored in the `ParamSet` variable in the **Parameter Set** area of the app. (Note that due to the random number generator, the specific values in the table below may differ from what you get when running the example.)

To plot the parameter set click `ParamSet` in the **Parameter Sets** area of the app browser. In the **Plots** tab, select **Scatter Plot** in the plot gallery. The plot shows the histogram of the generated parameters on the diagonal and pair-wise parameter scatter plots off the diagonal. Each marker on the plot represents one row of the `ParamSet` table, with each row being simultaneously displayed on all the scatter plots. You can use the **View** tab to arrange the layout of the table and plot so they are both visible.

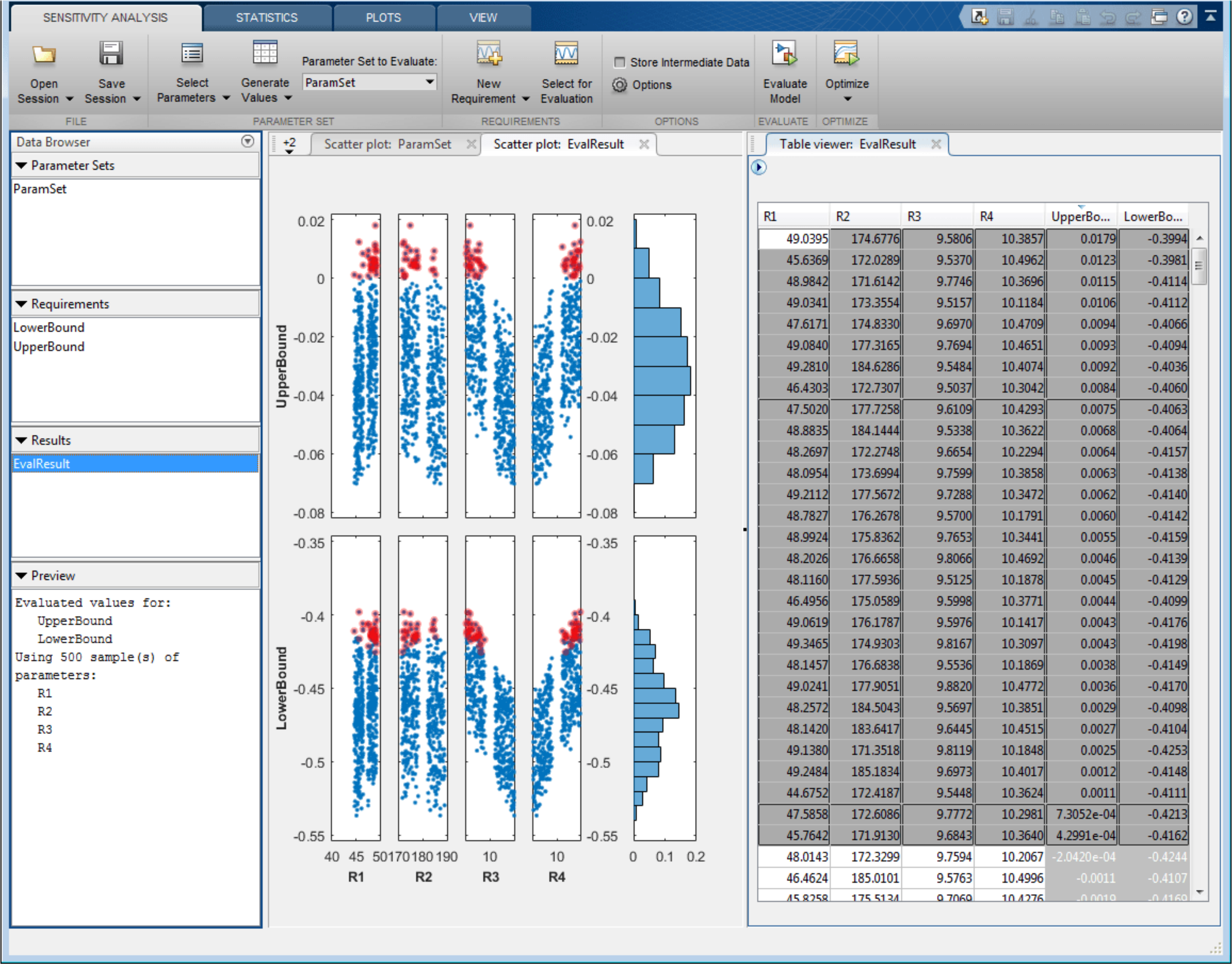


Evaluate Requirements with 5% Components

Evaluate the requirements for each row of parameter values in the table to see if the requirements are satisfied. In the **Sensitivity Analysis** tab, click **Select for Evaluation**. By default, all requirements are selected to be evaluated. Click **Evaluate Model** to evaluate the `UpperBound` and `LowerBound` requirements for each row of parameter values in `ParamSet`. Note you can speed up evaluation by using parallel computing if you have the Parallel Computing Toolbox™, or by using fast restart. For more information, see "Use Parallel Computing for Sensitivity Analysis" on page 4-104 and "Use Fast Restart Mode During Sensitivity Analysis" on page 4-109.

A results scatter plot showing each requirement vs. each parameter is updated during model evaluation. At the end of evaluation a table with the evaluation results is shown. Each row in the evaluation result table contains values for `R1`, `R2`, `R3`, `R4` and the resulting requirement values `UpperBound` and `LowerBound`. The evaluation results are stored in the `EvalResult` variable in the **Results** area of the app. You can use the **View** tab to arrange the layout of the table and plot so they are both visible.

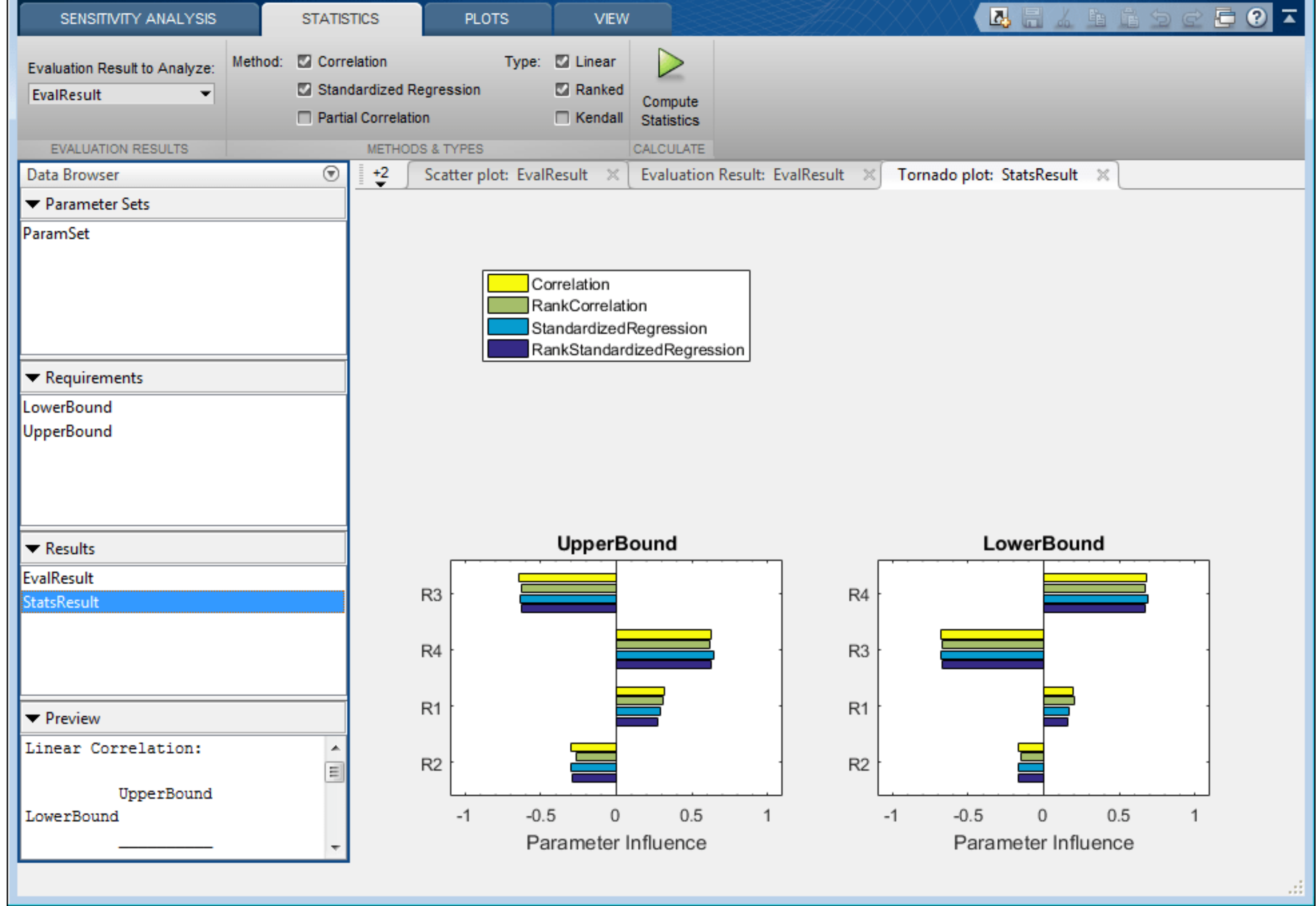
You can sort the evaluation results table by clicking on the column headers in the table. The `LowerBound` requirement is still met, as indicated by the fact that all evaluation results for the signal bound requirement are negative. That is not the case for the `UpperBound` requirement, which has several positive values. By selecting the rows of the table with these positive values, you can also see the corresponding points highlighted in the scatter plot.



Analyze the Evaluation Results

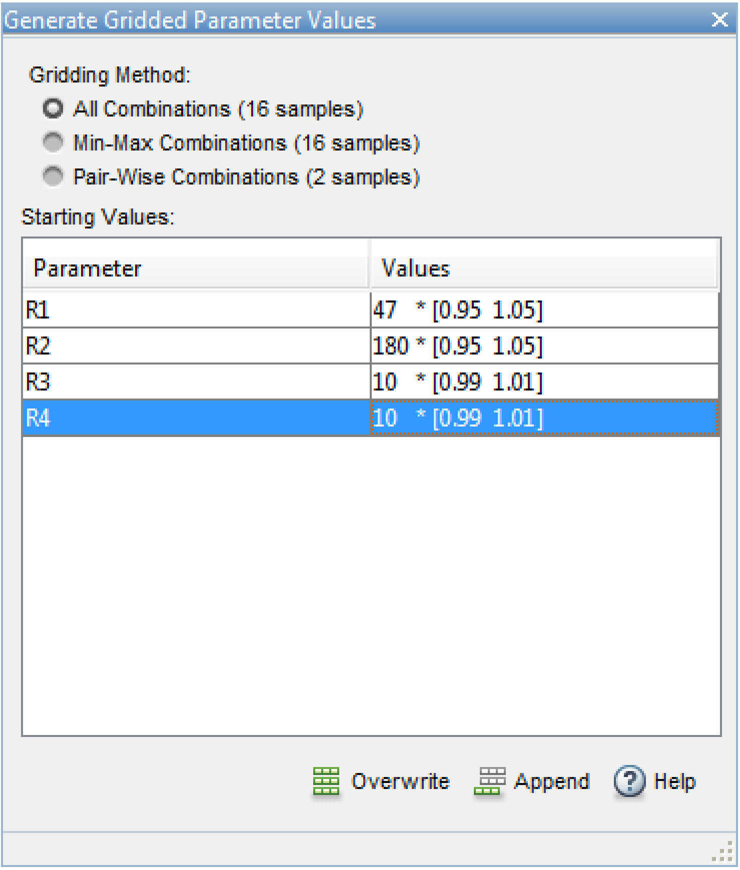
Using 5% tolerance components resulted in violation of the `UpperBound` requirement. Precision components with 1% tolerance would satisfy the design requirements, but they are more costly, so it is desirable to use only as many as necessary. You can use statistical analysis to identify the components that most influence the design requirements.

In the **Statistics** tab, select a variety of analyses to be done, including **Correlation** and **Standardized Regression** methods, and **Linear** and **Ranked** types of processing. Click **Compute Statistics**. The analysis result is stored in `StatsResult` in the **Results** area of the app, and a tornado plot shows the analysis results. For each requirement, the tornado plot shows the most influential parameters at the top, and the others in decreasing order of the magnitude of their influence on the requirement. For the `UpperBound` requirement, R3 and R4 have the most influence, so we will try replacing these by higher precision 1% components.

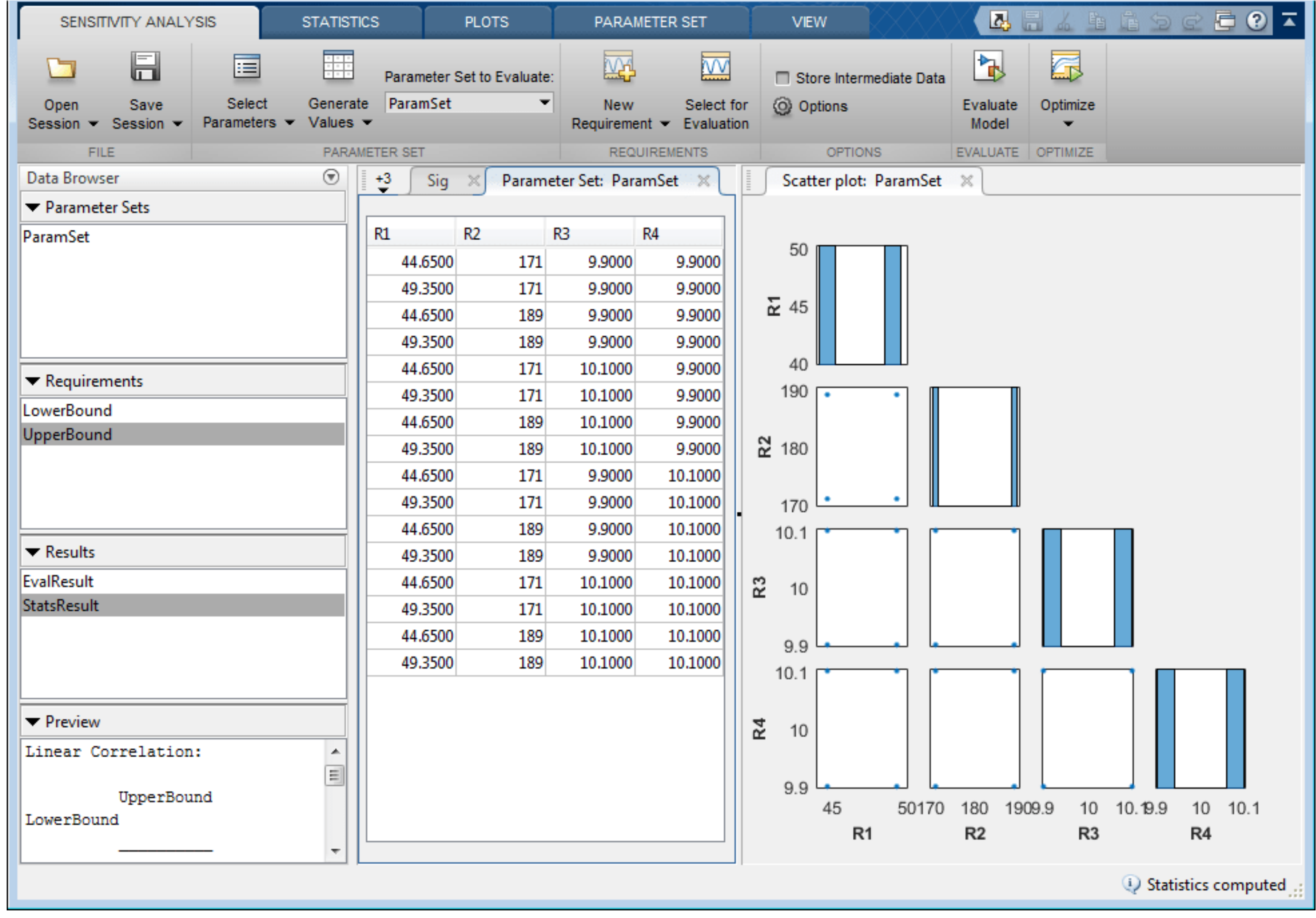


Evaluate Requirements with Mixed Components

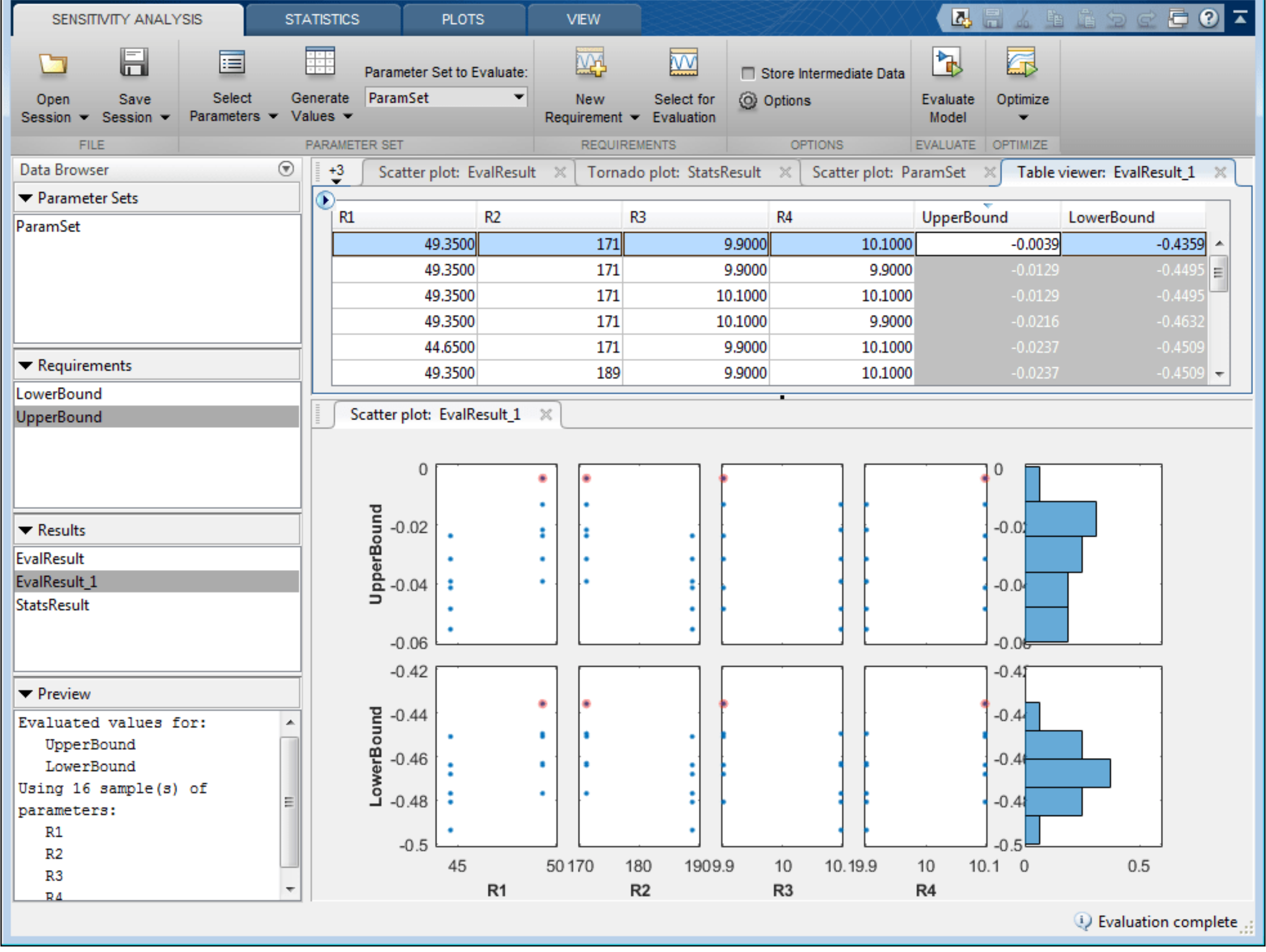
Explore the use of 1% component tolerances only for resistors R3 and R4. In the **Sensitivity Analysis** tab, click **Generate Values** and generate gridded values. For R1 and R2, specify that the nominal value is to be perturbed by plus-and-minus 5%. For R3 and R4, specify that the nominal value is to be perturbed by plus-and-minus 1%.



Click **Overwrite** to generate the new parameter values. To plot the parameter set click `ParamSet` in the **Parameter Sets** area of the app browser. In the **Plots** tab, select **Scatter Plot** in the plot gallery.



In the **Sensitivity Analysis** tab, click **Evaluate Model**. The requirements are evaluated for each row in the table of parameter values, and results are stored in `EvalResults_1` shown in the **Results** area of the app. The evaluation results scatter plot and the evaluation results table show that both requirements are met for all combinations of component values.



The **Sensitivity Analyzer** was used to explore the effect of standard precision components on the design requirements of a PI controller. With standard precision components, some requirements were found to be violated. Statistical analysis was used to identify which parameters most influence the requirements. The analysis resulted in replacement of only two of the four components with most costly high-precision components.

Close the model.

```
bdclose('sdoMotorPosition')
```

See Also

Related Examples

- “Specify Parameters for Design Exploration” on page 4-4
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67

- "Validate Sensitivity Analysis" on page 4-96
- "Interact with Plots in the Sensitivity Analyzer" on page 4-79

Design Exploration Using Parameter Sampling (Code)

This example shows how to sample and explore a design space. You explore the design of a Continuously Stirred Tank Reactor to minimize product concentration variation and production cost. The design includes feed stock uncertainty.

You explore the CSTR design by characterizing design parameters using probability distributions. You use the distributions to generate random samples in the design space and perform Monte-Carlo evaluation of the design at these sample points. You then create plots to visualize the design space and select the best design. You can then use the best design as an initial guess for optimization of the design.

You can also use the sampled design space and Monte-Carlo evaluation output to analyze the influence of design parameters on the design; see “Identify Key Parameters for Estimation (Code)” on page 4-169.

Continuously Stirred Tank Reactor (CSTR) Model

Continuously Stirred Tank Reactors (CSTRs) are common in the process industry. The Simulink® model, `sdoCSTR`, models a jacketed diabatic (i.e., non-adiabatic) tank reactor described in [1]. The CSTR is assumed to be perfectly mixed, with a single first-order exothermic and irreversible reaction, $A \rightarrow B$. A, the reactant, is converted to B, the product.

In this example, you use the following two-state CSTR model, which uses basic accounting and energy conservation principles:

$$\frac{dC_A}{dt} = \frac{F}{A*h}(C_{feed} - C_A) - r*C_A$$

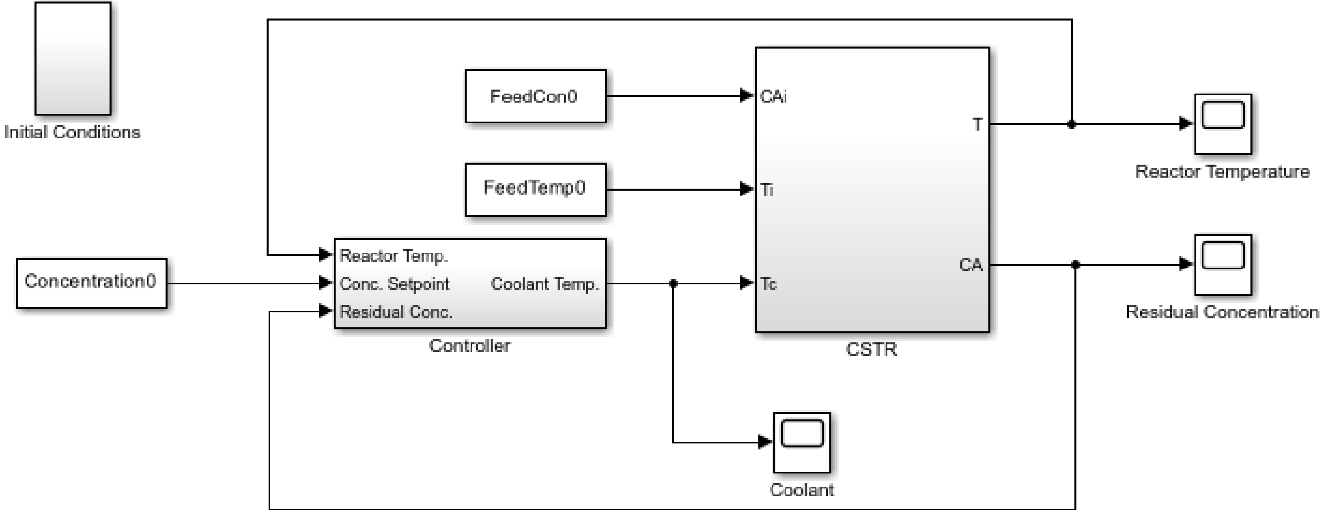
$$\frac{dT}{dt} = \frac{F}{A*h}(T_{feed} - T) - \frac{H}{c_p\rho}r - \frac{U}{c_p*\rho*h}(T - T_{cool})$$

$$r = k_0 * e^{\frac{-E}{R*T}}$$

- C_A, and C_{feed} - Concentrations of A in the CSTR and in the feed [kgmol/m^3]
- T, T_{feed}, and T_{cool} - CSTR, feed, and coolant temperatures [K]
- F and ρ - Volumetric flow rate [m^3/h] and the density of the material in the CSTR [1/m^3]
- h and A - Height [m] and heated cross-sectional area [m^2] of the CSTR.
- k_0 - Pre-exponential non-thermal factor for reaction $A \rightarrow B$ [1/h]
- E and H - Activation energy and heat of reaction for $A \rightarrow B$ [kcal/kgmol]
- R - Boltzmann's gas constant [kcal/(kgmol * K)]
- c_p and U - Heat capacity [kcal/K] and heat transfer coefficients [kcal/(m^2 * K * h)]

Open the Simulink model.

```
open_system('sdoCSTR');
```



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CSTR Design Problem

Assume that the CSTR is cylindrical, with the coolant applied to the base of the cylinder. Tune the CSTR cross-sectional area, A, and CSTR height, h, to meet the following design goals:

- Minimize the variation in residual concentration, C_A. Variations in the residual concentration negatively affect the quality of the CSTR product. Minimizing the variations also improves CSTR profit.

- Minimize the mean coolant temperature T_{cool}. Heating or cooling the jacket coolant temperature is expensive. Minimizing the mean coolant temperature improves CSTR profit.

The design must allow for variations in the quality of supply feed concentration, C_{feed}, and feed temperature, T_{feed}. The CSTR is fed with feed from different suppliers. The quality of the feed differs from supplier to supplier and also varies within each supply batch.

Specify Design Variables

Select the following model parameters as design variables:

- Cylinder cross-sectional area A

- Cylinder height h

```
p = sdo.getParameterFromModel('sdoCSTR',{'A','h'});
```

Limit the cross-sectional area to a range of [0.2 2] m^2.

```
p(1).Minimum = 0.2;
p(1).Maximum = 2;
```

Limit the height to a range of [0.5 3] m.

```
p(2).Minimum = 0.5;
p(2).Maximum = 3;
```

Sample the Design Space

Create a parameter space for the design variables. The parameter space characterizes the allowable parameter values and combinations of parameter values.

```
pSpace = sdo.ParameterSpace(p);
```

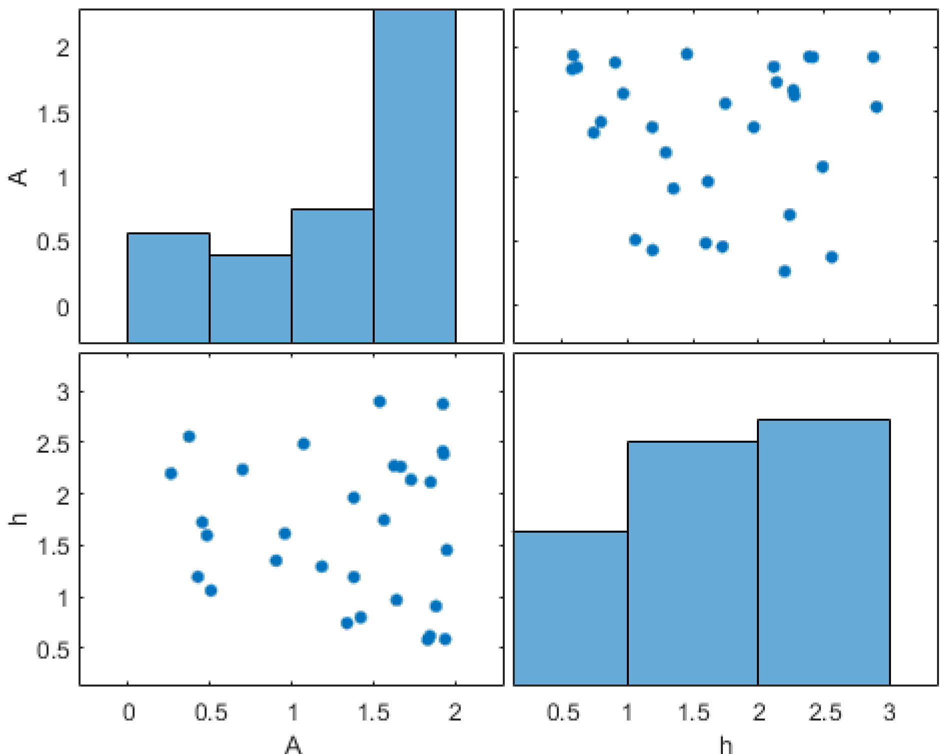
The parameter space uses default uniform distributions for the design variables. The distribution lower and upper bounds are set to the design variable minimum and maximum value respectively.

Use the `sdo.sample` function to generate samples from the parameter space. You use the samples to evaluate the model and explore the design space.

```
rng default; % For reproducibility
pSmpl = sdo.sample(pSpace,30);
```

Use the `sdo.scatterPlot` command to visualize the sampled parameter space. The scatter plot shows the parameter distributions on the diagonal subplots and pairwise parameter combinations on the off diagonal subplots.

```
figure, sdo.scatterPlot(pSmpl)
```



Specify Uncertain Variables

Select the feed concentration and feed temperature as uncertain variables. You evaluate the design using different values of feed temperature and concentration.

```
pUnc = sdo.getParameterFromModel('sdoCSTR',{'FeedCon0','FeedTemp0'});
```

Create a parameter space for the uncertain variables. Use normal distributions for both variables. Specify the mean as the current parameter value. Specify a variance of 5% of the mean for the feed concentration and 1% of the mean for the temperature.

```
uSpace = sdo.ParameterSpace(pUnc);
uSpace = setDistribution(uSpace,'FeedCon0',makedist('normal',pUnc(1).Value,0.05*pUnc(1).Value));
uSpace = setDistribution(uSpace,'FeedTemp0',makedist('normal',pUnc(2).Value,0.01*pUnc(2).Value))
```

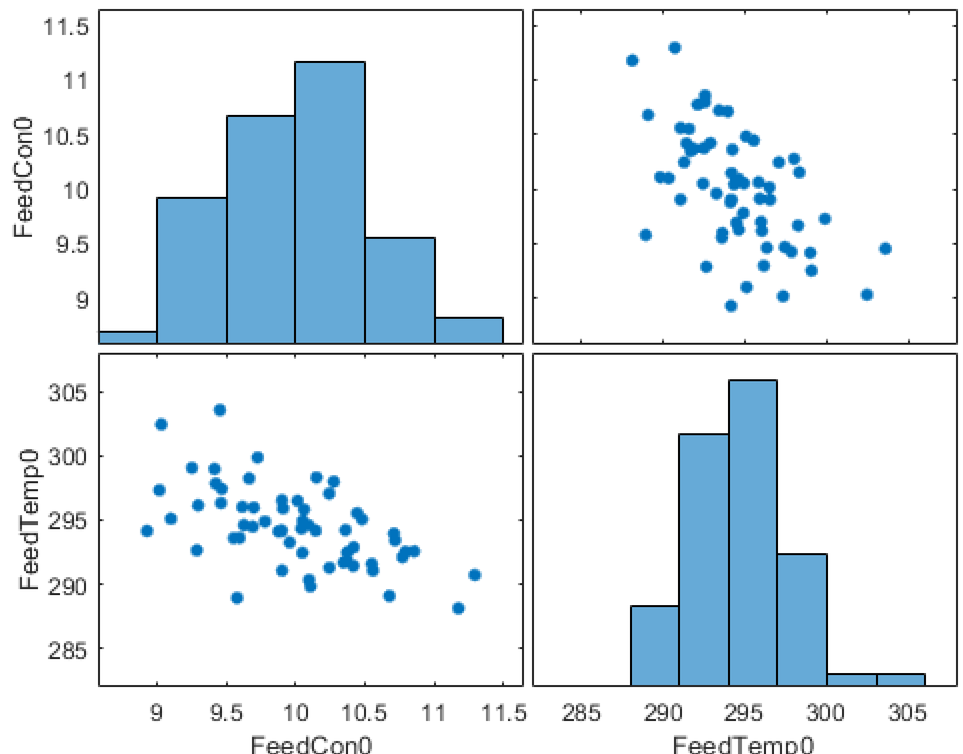
The feed concentration is inversely correlated with the feed temperature. Add this information to the parameter space.

```
uSpace.RankCorrelation = [1 -0.6; -0.6 1];
```

The rank correlation matrix has a row and column for each parameter with the (i,j) entry specifying the correlation between the i and j parameters.

Sample the parameter space. The scatter plot shows the correlation between concentration and temperature.

```
uSmpl = sdo.sample(uSpace,60);
sdo.scatterPlot(uSmpl)
```



Ideally you want to evaluate the design for every combination of points in the design and uncertain spaces, which implies 30*60 = 1800 simulations. Each simulation takes around 0.5 sec. You can use parallel computing to speed up the evaluation. For this example you instead only use the samples that have maximum & minimum concentration and temperature values, reducing the evaluation time to around 1 min.

```
[~,iminC] = min(uSmpl.FeedCon0);
[~,imaxC] = max(uSmpl.FeedCon0);
[~,iminT] = min(uSmpl.FeedTemp0);
[~,imaxT] = max(uSmpl.FeedTemp0);
uSmpl = uSmpl(unique([iminC,imaxC,iminT,imaxT]) ,:)
```

```
uSmpl =

  4x2 table

    FeedCon0    FeedTemp0
    ________    _________

     9.4555      303.58  
     11.175      288.13  
     11.293      290.73  
     8.9308      294.16  
```

Create Evaluation Function

Create a function that evaluates the design for a given sample point in the design space. The design is evaluated on how well it minimizes the variation in residual concentration and mean coolant temperature.

Specify Design Requirements

Evaluating a point in the design space requires logging model signals. Logged signals are used to evaluate the design requirements.

Log the following signals:

- CSTR concentration, available at the second output port of the `sdoCSTR/CSTR` block

```
Conc = Simulink.SimulationData.SignalLoggingInfo;
Conc.BlockPath               = 'sdoCSTR/CSTR';
Conc.OutputPortIndex         = 2;
Conc.LoggingInfo.NameMode    = 1;
Conc.LoggingInfo.LoggingName = 'Concentration';
```

- Coolant temperature, available at the first output of the `sdoCSTR/Controller` block

```
Coolant = Simulink.SimulationData.SignalLoggingInfo;
Coolant.BlockPath               = 'sdoCSTR/Controller';
Coolant.OutputPortIndex         = 1;
Coolant.LoggingInfo.NameMode    = 1;
Coolant.LoggingInfo.LoggingName = 'Coolant';
```

Create and configure a simulation test object to log the required signals.

```
simulator = sdo.SimulationTest('sdoCSTR');
simulator.LoggingInfo.Signals = [Conc,Coolant];
```

Evaluation Function

Use an anonymous function with one argument that calls the `sdoCSTR_design` function.

```
evalDesign = @(p) sdoCSTR_design(p,simulator,pUnc,uSmpl);
```

The `evalDesign` function:

- Has one input argument that specifies the CSTR dimensions
- Returns the optimization objective value

The `sdoCSTR_design` function uses a `for` loop that iterates through the sample values specified for the feed concentration and temperature. Within the loop, the function:

- Simulates the model using the current design point, feed concentration, and feed temperature values
- Calculates the residual concentration variation and coolant temperature costs

To view the objective function, type `edit sdoCSTR_design`.

```
type sdoCSTR_design
```

```
function design = sdoCSTR_design(p,simulator,pUnc,smplUnc)
%SDOCSTR_DESIGN
%
% The sdoCSTR_design function is used to evaluate a CSTR  design.
%
% The |p| input argument is the vector of CSTR dimensions.
%
% The |simulator| input argument is a sdo.SimulinkTest object used to
% simulate the |sdoCSTR| model and log simulation signals.
%
% The |pUnc| input argument is a vector of parameters to specify the CSTR
% input feed concentration and feed temperature. The |smplUnc| argument is
% a table of different feed concentration and temperature values.
%
% The |design| return argument contains information about the design
% evaluation that can be used by the |sdo.optimize| function to optimize
% the design.
%
% see also sdo.optimize, sdoExampleCostFunction
%

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%% Model Simulations and Evaluations
%
% For each value in |smplUnc|, configure and simulate the model. Use
% the logged concentration and coolant signals to compute the design cost.
%
costConc    = 0;
costCoolant = 0;
```

```
for ct=1:size(smplUnc,1)
    %Set the feed concentration and temperature values
    pUnc(1).Value = smplUnc{ct,1};
    pUnc(2).Value = smplUnc{ct,2};

    %Simulate model
    simulator.Parameters = [p; pUnc];
    simulator = sim(simulator);
    logName   = get_param('sdoCSTR','SignalLoggingName');
    simLog    = get(simulator.LoggedData,logName);

    %Compute Concentration cost based on the standard deviation of the
    %concentration from a nominal value.
    Sig = find(simLog,'Concentration');
    costConc = costConc+10*std(Sig.Values-2);

    %Compute coolant cost based on the mean deviation from room
    %temperature.
    Sig = find(simLog,'Coolant');
    costCoolant = costCoolant+abs(mean(Sig.Values - 294))/30;
end

%% Return Total Cost
%
% Compute the total cost as a sum of the concentration and coolant costs.
%
design.F = costConc + costCoolant;

%%
% Add the individual cost terms to the return argument. These are not used
% by the optimizer, but included for convenience.
design.costConc    = costConc;
design.costCoolant = costCoolant;
end
```

Evaluate

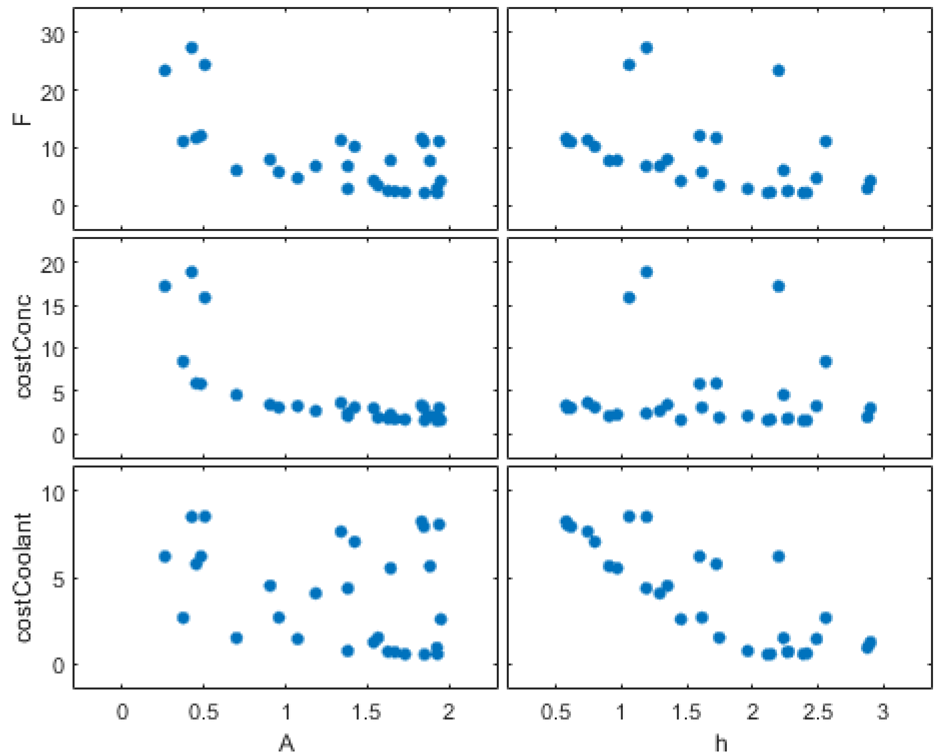
Use the `sdo.evaluate` command to evaluate the model at the sample design points.

```
y = sdo.evaluate(evalDesign,p,pSmpl);
```

```
Model evaluated at 30 samples.
```

View the results of the evaluation using a scatter plot. The scatter plot shows pairwise plots for each design variable (A,h) and design cost. The plot includes the total cost, `F`, as well as coolant and concentration costs, `costCoolant` and `costConc` respectively.

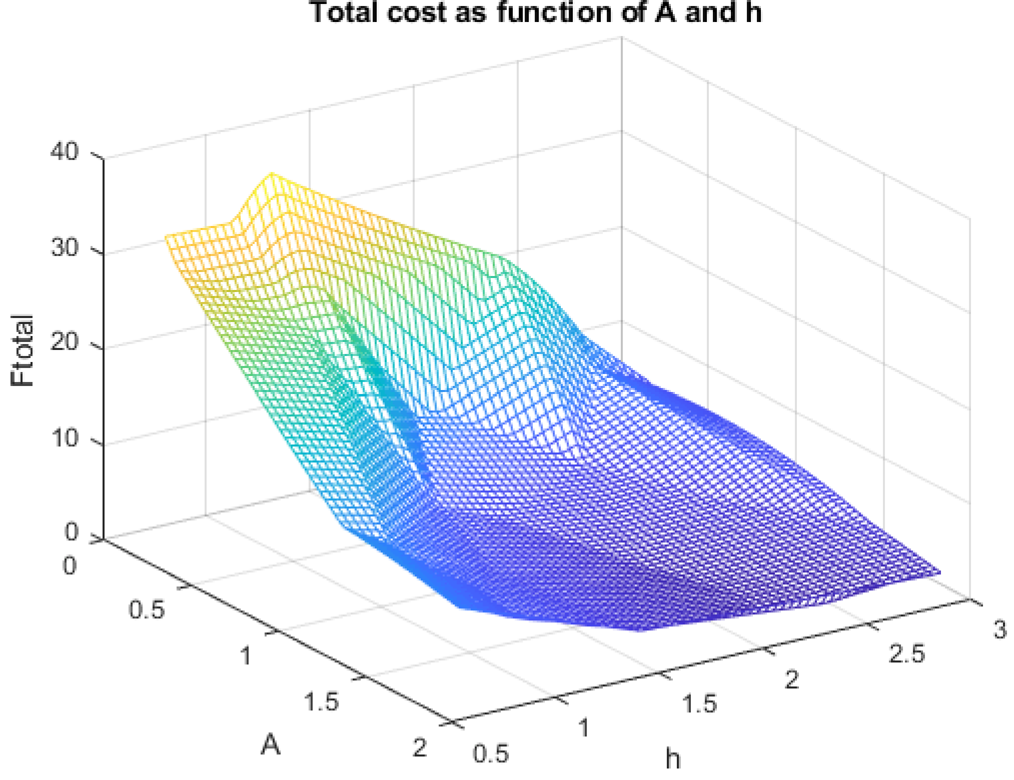
```
sdo.scatterPlot(pSmpl,y);
```



The plot shows that larger cross-sectional areas result in lower total costs. However it is difficult to tell how the height influences the total cost.

Create a mesh plot showing the total cost as a function of A and h.

```
Ftotal = scatteredInterpolant(pSmpl.A,pSmpl.h,y.F);
xR = linspace(min(pSmpl.A),max(pSmpl.A),60);
yR = linspace(min(pSmpl.h),max(pSmpl.h),60);
[xx,yy] = meshgrid(xR,yR);
zz = Ftotal(xx,yy);
mesh(xx,yy,zz)
view(56,30)
title('Total cost as function of A and h')
zlabel('Ftotal')
xlabel(p(1).Name), ylabel(p(2).Name);
```



The plot shows that high values of A and h result in lower costs. The best design in the sampled space corresponds to the design with the lowest cost value.

```
[~,idx] = min(y.F);
pBest = [y(idx,:), pSmpl(idx,:)]
```

```
pBest =

  1x5 table

      F       costConc    costCoolant      A          h   
    _____    ________    ___________    ______    ______

    2.106     1.5505       0.55552      1.9271    2.3867
```

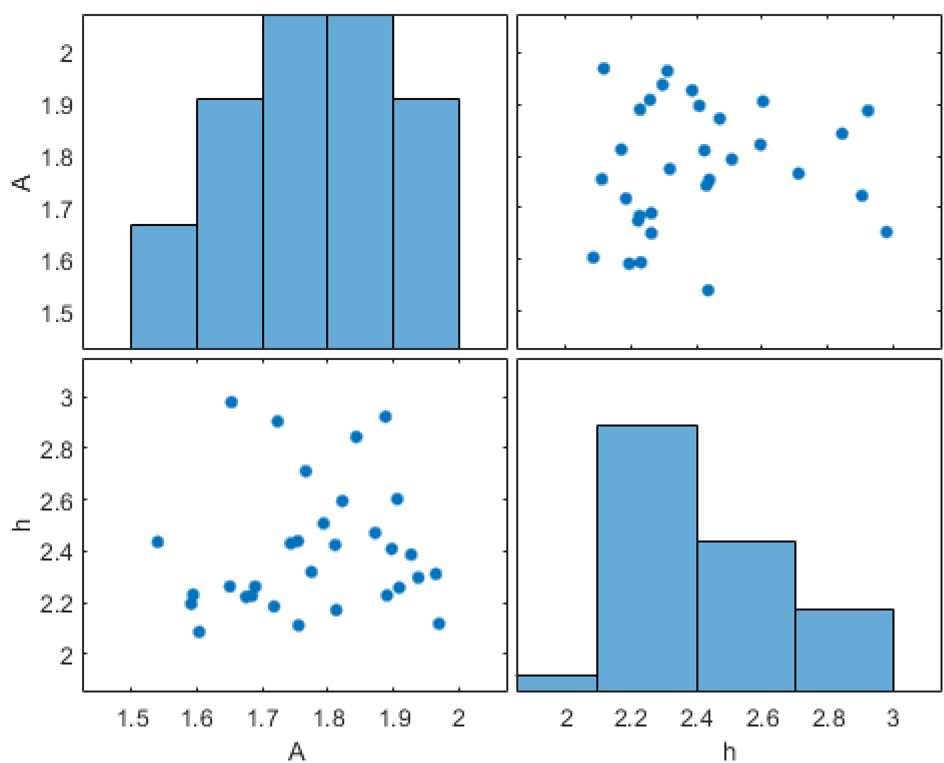
Refine the Design Space

The total cost surface plot shows that low cost designs are designs with A in the range [1.5 2] and h in the range [2 3]. Modify the parameter space distributions for A and h and resample the design space to focus on this region.

```
pSpace = setDistribution(pSpace,'A',makedist('uniform',1.5,2));
pSpace = setDistribution(pSpace,'h',makedist('uniform',2,3));
pSmpl = sdo.sample(pSpace,30);
```

Add the `pBest` found earlier to the new samples so that it is part of the refined design space.

```
pSmpl = [pSmpl;pBest(:,4:5)];
sdo.scatterPlot(pSmpl)
```



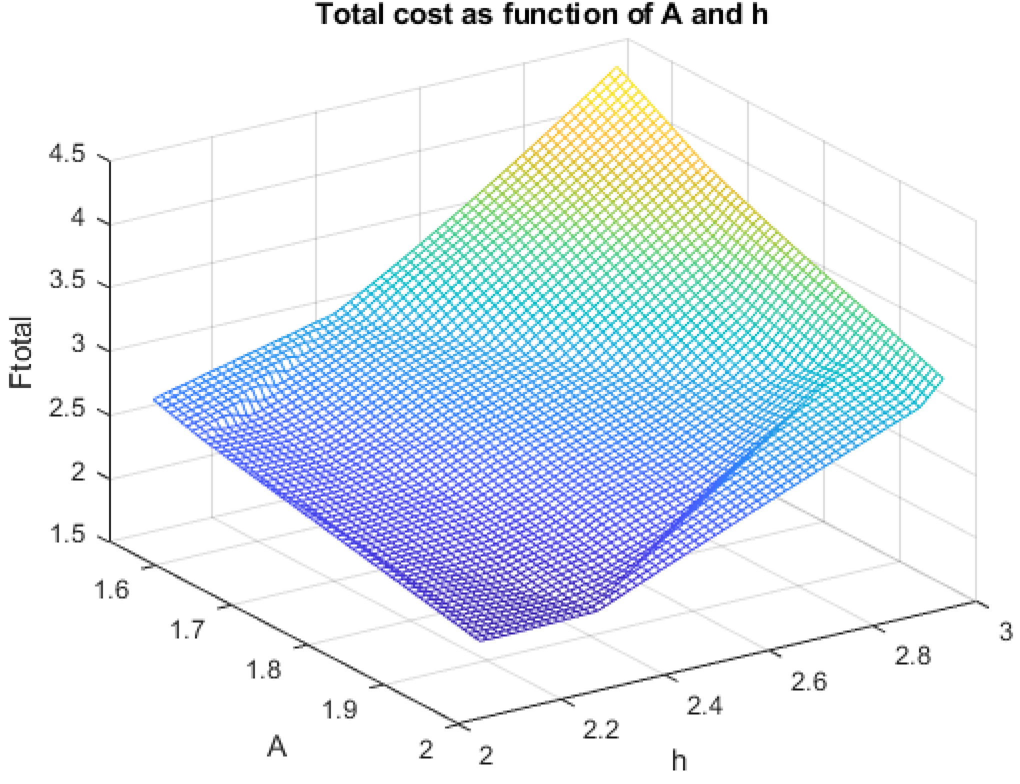
Evaluate Using Refined Design Space

```
y = sdo.evaluate(evalDesign,p,pSmpl);
```

```
Model evaluated at 31 samples.
```

Create a mesh plot for this section of the design space. The surface indicates that better designs are near the A = 1.9, h = 2.1 point.

```
Ftotal = scatteredInterpolant(pSmpl.A,pSmpl.h,y.F);
xR = linspace(min(pSmpl.A),max(pSmpl.A),60);
yR = linspace(min(pSmpl.h),max(pSmpl.h),60);
[xx,yy] = meshgrid(xR,yR);
zz = Ftotal(xx,yy);
mesh(xx,yy,zz)
view(56,30)
title('Total cost as function of A and h')
zlabel('Ftotal')
xlabel(p(1).Name), ylabel(p(2).Name);
```



Find the best design from the new design space and compare with the best design point found earlier.

```
[~,idx] = min(y.F);
pBest = [pBest; [y(idx,:), pSmpl(idx,:)]]
```

```
pBest =

  2x5 table

      F        costConc    costCoolant      A         h   
    ______    ________    ___________    ______    ______

     2.106     1.5505       0.55552      1.9271    2.3867
    1.9754     1.4824       0.49295      1.9695    2.1174
```

The best design in the refined design space is better than the design found earlier. This indicates that there may be better designs in the same region and warrants refining the design space further. Alternatively you can use the best design point as an initial guess for optimization.

Related Examples

To learn how to explore the CSTR design space using the **Sensitivity Analyzer**, see "Design Exploration Using Parameter Sampling (GUI)" on page 4-112.

To learn how to optimize the CSTR design using the `sdo.optimize` command, see "Design Optimization with Uncertain Variables (Code)" on page 3-159.

To learn how to analyze the influence of design parameters on the design using the `sdo.analyze` command, see “Identify Key Parameters for Estimation (Code)” on page 4-169

References

[1] Bequette, B.W. *Process Dynamics: Modeling, Analysis and Simulation.* 1st ed. Upper Saddle River, NJ: Prentice Hall, 1998.

Close the model

```
bdclose('sdoCSTR')
```

See Also

More About

- “Design Exploration Using Parameter Sampling (GUI)” on page 4-112
- “Use Parallel Computing for Sensitivity Analysis” on page 4-104
- “Use Fast Restart Mode During Sensitivity Analysis” on page 4-109
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67
- “Validate Sensitivity Analysis” on page 4-96

Identify Key Parameters for Estimation (Code)

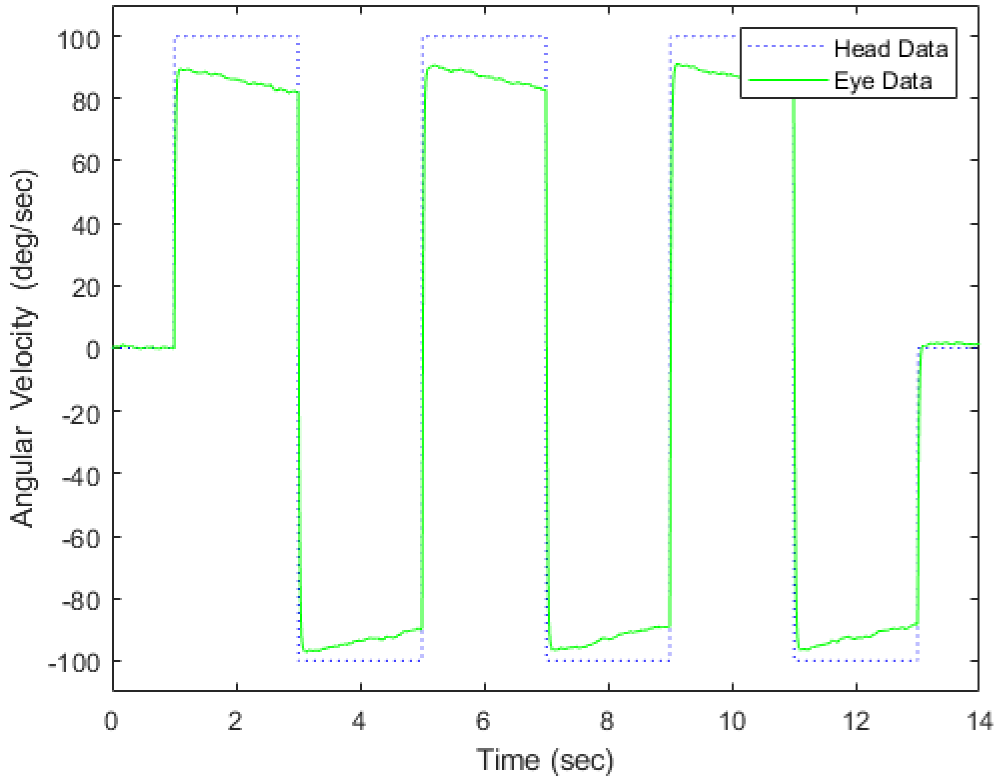
This example shows how to use sensitivity analysis to narrow down the number of parameters that you need to estimate to fit a model. This example uses a model of the vestibulo-ocular reflex, which generates compensatory eye movements.

Model Description

The vestibulo-ocular reflex (VOR) enables the eyes to move at the same speed and in the opposite direction as the head, so that vision is not blurred when the head moves during normal activity. For example, if the head turns in one direction, the eyes turn in the opposite direction, with the same speed. This happens even in the dark. In fact, the VOR is most easily characterized by measurements in the dark, to ensure that eye movements are predominantly driven by the VOR.

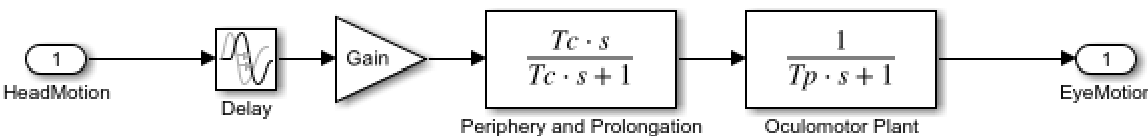
The file `sdoVOR_Data.mat` contains uniformly sampled data of stimulation and eye movements. If the VOR were perfectly compensatory, then a plot of eye movement data, when flipped vertically, would overlay exactly on top of a plot of head motion data. Such a system would be described by a gain of 1 and a phase of 180 degrees. However, when we plot the data in the file `sdoVOR_Data.mat`, the eye movements are close, but not perfectly compensatory.

```
load sdoVOR_Data.mat;   % Column vectors:   Time  HeadData  EyeData
figure
plot(Time, HeadData, ':b',    Time, EyeData, '-g')
xlabel('Time (sec)')
ylabel('Angular  Velocity  (deg/sec)')
ylim([-110  110])
legend('Head Data', 'Eye Data')
```



The eye movement data does not perfectly overlay the head motion data, and this can be modeled by several factors. Head rotation is sensed by organs in the inner ears, known as semicircular canals. These detect head motion and transmit signals about head motion to the brain, which sends motor commands to the eye muscles, so that eye movements compensate for head motion. We would like to use this eye movement data to estimate the parameters in the models for these various stages. The model we will use is shown below. There are four parameters in the model: `Delay`, `Gain`, `Tc`, and `Tp`.

```
model_name = 'sdoVOR';
open_system(model_name)
```



The Delay parameter models the fact that there is some delay in communicating the signals from the inner ear to the brain and the eyes. This delay is due to the time needed for chemical neurotransmitters to traverse the synaptic clefts between nerve cells. Based on the number of synapses involved in the vestibulo-ocular reflex, this delay is expected to be around 5 ms. For estimation purposes, we will assume it is between 2 and 9 ms.

```
Delay = sdo.getParameterFromModel(model_name, 'Delay');
Delay.Value = 0.005;   % seconds
Delay.Minimum = 0.002;
Delay.Maximum = 0.009;
```

The Gain parameter models the fact that the eyes do not move quite as much as the head does. We will use 0.8 as our initial guess, and assume it is between 0.6 and 1.

```
Gain = sdo.getParameterFromModel(model_name, 'Gain');
Gain.Value = 0.8;
Gain.Minimum = 0.6;
Gain.Maximum = 1;
```

The Tc parameter models the dynamics associated with the semicircular canals, as well as some additional neural processing. The canals are high-pass filters, because after a subject has been put into rotational motion, the neurally active membranes in the canals slowly relax back to resting position, so the canals stop sensing motion. Thus in the plot above, after the stimulation undergoes transition edges, the eye movements tend to depart from the stimulation over time. Based on mechanical characteristics of the canals, combined with additional neural processing which prolongs this time constant to improve the accuracy of the VOR, we will estimate the Tc parameter to be 15 seconds, and assume it is between 10 and 30 seconds.

```
Tc = sdo.getParameterFromModel(model_name, 'Tc');
Tc.Value = 15;
Tc.Minimum = 10;
Tc.Maximum = 30;
```

Finally, the Tp parameter models the dynamics of the oculomotor plant, i.e. the eye and the muscles and tissues attached to it. The plant can be modeled by two poles, however it is believed that the pole with the larger time constant is cancelled by precompensation in the brain, to enable the eye to make quick movements. Thus in the plot, when the stimulation undergoes transition edges, the eye movements follow with only a little delay. For the Tp parameter, we will use 0.01 seconds as our initial guess, and assume it is between 0.005 and 0.05 seconds.

```
Tp = sdo.getParameterFromModel(model_name, 'Tp');
Tp.Value = 0.01;
Tp.Minimum = 0.005;
Tp.Maximum = 0.05;
```

Collect these parameters into a vector.

```
v = [Delay Gain Tc Tp];
```

Compare Measured Data to Initial Simulated Output

Create an Experiment object. Specify `HeadData` as input.

```
Exp = sdo.Experiment(model_name);
Exp.InputData = timeseries(HeadData, Time);
```

Associate eye movement data with model output.

```
EyeMotion = Simulink.SimulationData.Signal;
EyeMotion.Name = 'EyeMotion';
EyeMotion.BlockPath = [model_name  '/Oculomotor Plant'];
EyeMotion.PortType = 'outport';
EyeMotion.PortIndex = 1;
EyeMotion.Values = timeseries(EyeData, Time);
```

Add `EyeMotion` to the experiment.

```
Exp.OutputData = EyeMotion;
```

Use the data's timing characteristics in the model.

```
stop_time = Time(end);
set_param(gcs, 'StopTime', num2str(stop_time));
dt = Time(2) - Time(1);
set_param(gcs, 'FixedStep', num2str(dt))
```

Create a simulation scenario using the experiment, and obtain the simulated output.

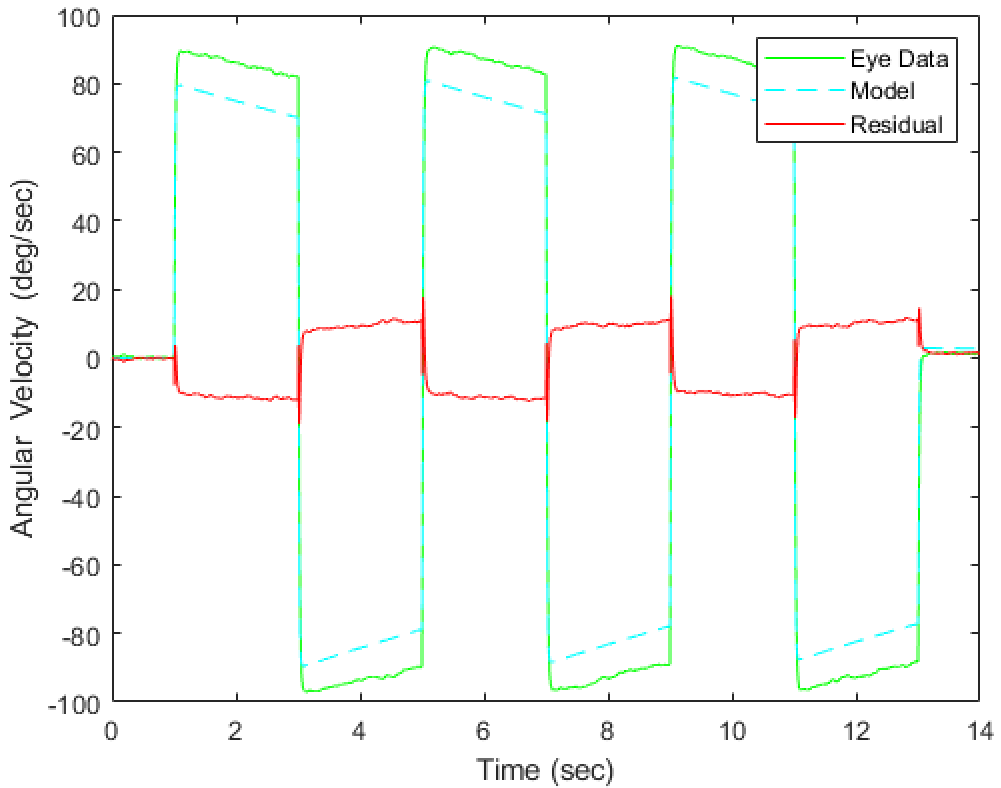
```
Exp = setEstimatedValues(Exp, v);   % use vector of parameters/states
Simulator = createSimulator(Exp);
Simulator = sim(Simulator);
```

Search for the model_residual signal in the logged simulation data.

```
SimLog = find(Simulator.LoggedData,  ...
    get_param(model_name, 'SignalLoggingName') );
EyeSignal = find(SimLog, 'EyeMotion');
```

The model output does not match the data very well, as shown by the residual, which we can compute by calling the objective function.

```
estFcn = @(v) sdoVOR_Objective(v, Simulator, Exp, 'Residuals');
Model_Error = estFcn(v);
plot(Time, EyeData, '-g',  ...
    EyeSignal.Values.Time, EyeSignal.Values.Data, '--c',  ...
    Time, Model_Error.F, '-r');
xlabel('Time (sec)');
ylabel('Angular  Velocity  (deg/sec)');
legend('Eye Data', 'Model', 'Residual');
```



The objective function used above is defined in the file "sdoVOR_Objective.m".

```
type sdoVOR_Objective.m
```

```
function vals = sdoVOR_Objective(v, Simulator, Exp, Method)
% Compare model output with data
%
%    Inputs:
%       v - vector of parameters and/or states
%       Simulator - used to simulate the model
%       Exp - Experiment object
%       Method - 'SSE' for scalar output, 'Residuals' for vector of residuals

% Copyright 2014-2015 The MathWorks, Inc.

% Requirement setup
req = sdo.requirements.SignalTracking;
req.Type = '==';
req.Method = Method;

% If Residuals requested, keep on same scale as signals, for plotting
switch Method
    case 'Residuals'
        req.Normalize = 'off';
end

% Simulate the model
```

```
Exp = setEstimatedValues(Exp, v);   % use vector of parameters/states
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);

% Compare model output with data
SimLog = find(Simulator.LoggedData,  ...
    get_param(Exp.ModelName, 'SignalLoggingName') );
OutputModel = find(SimLog, 'EyeMotion');
Model_Error = evalRequirement(req, OutputModel.Values, Exp.OutputData.Values);
vals.F = Model_Error;
```

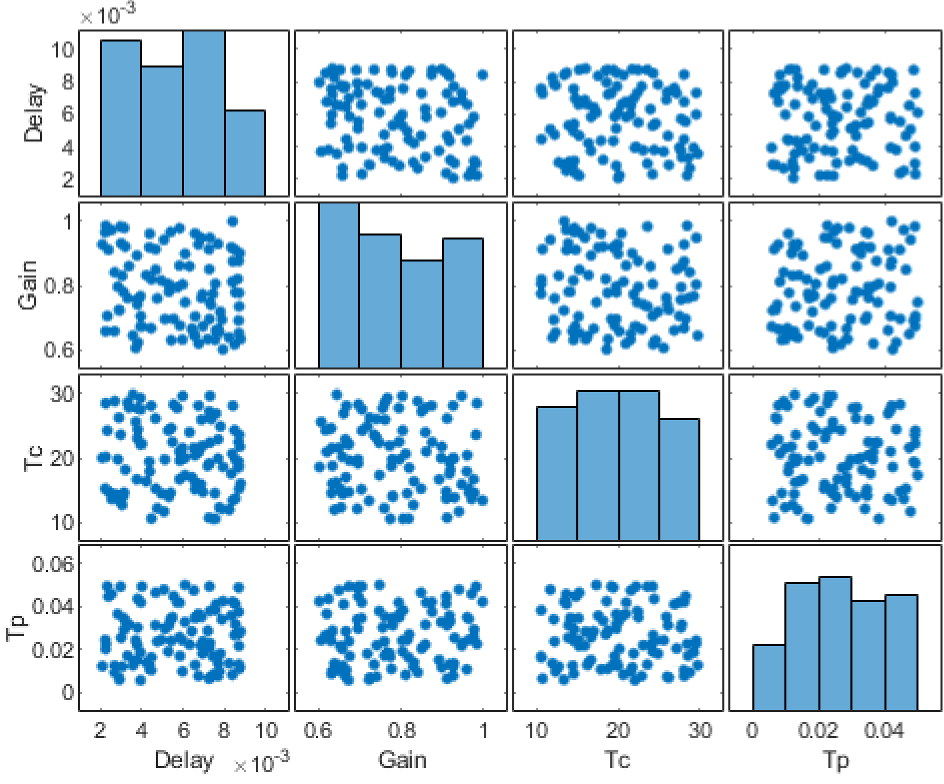
Sensitivity Analysis

Create an object to sample the parameter space.

```
ps = sdo.ParameterSpace([Delay ; Gain ; Tc ; Tp]);
```

Generate 100 samples from the parameter space.

```
rng default;   % for reproducibility
x  = sdo.sample(ps, 100);
sdo.scatterPlot(x);
```



The sampling above used default options, and these are reflected in the plots above. Parameter values were selected at random from distributions that were uniform over the range of each parameter. Consequently, the histogram plots along the diagonal appear approximately uniform. If Statistics and Machine Learning Toolbox™ is available, many other distributions may be used, and sampling can be done using Sobol or Halton low-discrepancy sequences.

The off-diagonal plots above show scatter plots between pairs of different variables. Since we did not specify a RankCorrelation matrix in ps, the scatter plots do not indicate correlations. However, if parameters were believed to be correlated, this can be specified using the RankCorrelation property of `ps`.

For sensitivity analysis, it is simpler to use a scalar objective, so we will specify the sum of squared errors, "SSE":

```
estFcn = @(v) sdoVOR_Objective(v, Simulator, Exp, 'SSE');
y = sdo.evaluate(estFcn, ps, x);
```

```
Model evaluated at 100 samples.
```

Evaluation could also be sped up using parallel computing.

Obtain the standardized regression coefficients.

```
opts = sdo.AnalyzeOptions;
opts.Method = 'StandardizedRegression';
sensitivities = sdo.analyze(x, y, opts);
```

Other types of analysis include correlation and, if Statistics and Machine Learning Toolbox is available, partial correlation.

We can view the analysis results.

```
disp(sensitivities)
```

```
                 F     
             _________

    Delay      0.01303
    Gain      -0.90873
    Tc       -0.044395
    Tp         0.19919
```

For standardized regression, parameters that highly influence the model output have sensitivity magnitudes close to 1. On the other hand, less influential parameters have smaller sensitivity magnitudes. We see that this objective function is sensitive to changes in the Gain and Tp parameters, but much less sensitive to changes in the Delay and Tc parameters.

You can validate sensitivity analysis results by resampling and reevaluating the objective function for the samples. You can also use engineering intuition for a quick analysis. For example, in this model, the time constant `Tc` ranges from 10 to 30 seconds. Even the minimum value of 10 seconds is large compared to the 2-second duration for which the head motion stimulation is held at constant velocity. Therefore, `Tc` is not expected to affect the output greatly. However, even when this kind of intuition is not readily available in other models, sensitivity analysis can help highlight which parameters are influential.

Based on the results of sensitivity analysis, designate the `Delay` and `Tc` parameters as fixed when optimizing. This reduction in the number of free parameters speeds up optimization.

```
Delay.Free = false;
Tc.Free = false;
```

Optimization

We can use the minimum from sensitivity analysis as the initial guess for optimization.

```
[fval, idx_min] = min(y.F);
Delay.Value = x.Delay(idx_min);
Gain.Value = x.Gain(idx_min);
Tc.Value = x.Tc(idx_min);
Tp.Value = x.Tp(idx_min);
%
v = [Delay Gain Tc Tp];
opts = sdo.OptimizeOptions;
opts.Method = 'fmincon';
```

As was the case with model evaluations in sensitivity analysis, parallel computing could be used to speed up the optimization.

```
vOpt = sdo.optimize(estFcn, v, opts);
disp(vOpt)
```

```
 Optimization started 01-Sep-2022 14:36:09

                                  max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      5      13.4798            0
    1     18      12.2052            0        0.129          305
    2     30      11.1441            0       0.0648          790
    3     41      10.0493            0       0.0843          290
    4     46      9.23607            0       0.0758          286
    5     51      8.76122            0       0.0183         10.1
    6     56      8.75862            0      0.00184        0.476
    7     57      8.75862            0     8.41e-05        0.476
Local minimum possible. Constraints satisfied.

fmincon stopped because the size of the current step is less than
the value of the step size tolerance and constraints are
satisfied to within the value of the constraint tolerance.

(1,1) =

       Name: 'Delay'
      Value: 0.0038
    Minimum: 0.0020
    Maximum: 0.0090
       Free: 0
      Scale: 0.0078
       Info: [1x1 struct]


(1,2) =

       Name: 'Gain'
      Value: 0.9012
    Minimum: 0.6000
    Maximum: 1
       Free: 1
      Scale: 1
```

```
       Info: [1x1 struct]


(1,3) =

       Name: 'Tc'
      Value: 16.6833
    Minimum: 10
    Maximum: 30
       Free: 0
      Scale: 16
       Info: [1x1 struct]


(1,4) =

       Name: 'Tp'
      Value: 0.0157
    Minimum: 0.0050
    Maximum: 0.0500
       Free: 1
      Scale: 0.0156
       Info: [1x1 struct]


1x4 param.Continuous
```

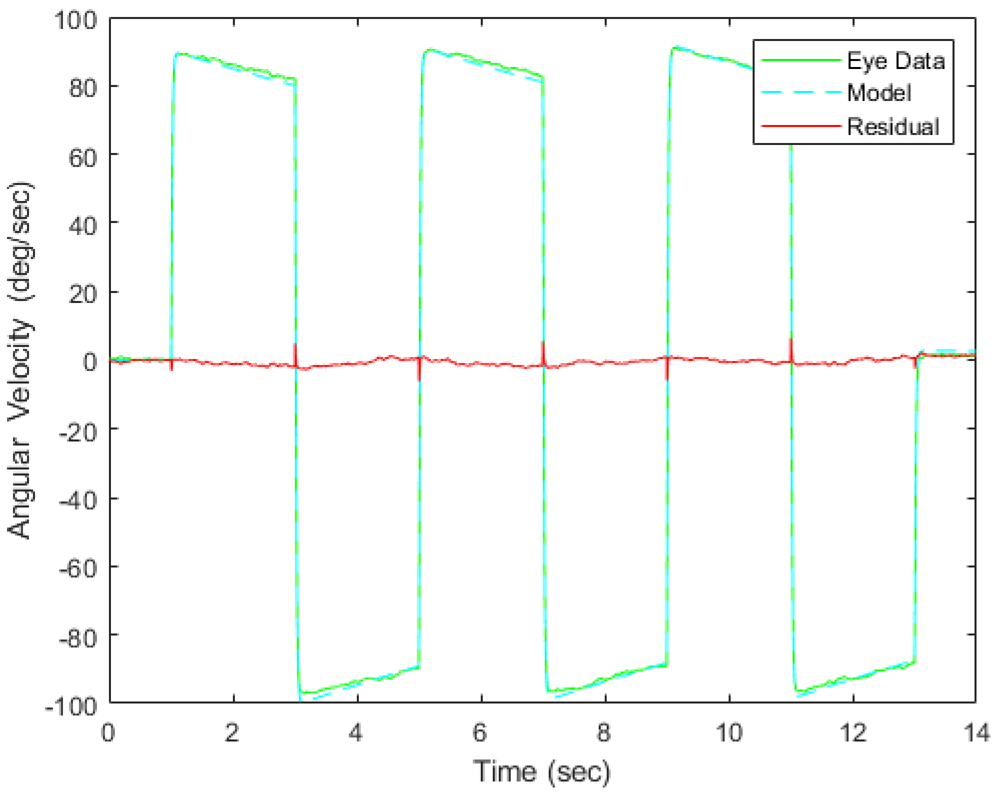
Visualizing Result of Optimization

Obtain the model response after estimation. Search for the model_residual signal in the logged simulation data.

```
Exp = setEstimatedValues(Exp, vOpt);
Simulator = createSimulator(Exp,Simulator);
Simulator = sim(Simulator);
SimLog = find(Simulator.LoggedData,  ...
    get_param(model_name, 'SignalLoggingName') );
EyeSignal = find(SimLog, 'EyeMotion');
```

Comparing the measured eye data with the optimized model response shows that the residuals are much smaller.

```
estFcn = @(v) sdoVOR_Objective(v, Simulator, Exp, 'Residuals');
Model_Error = estFcn(vOpt);
plot(Time, EyeData, '-g',  ...
    EyeSignal.Values.Time, EyeSignal.Values.Data, '--c',  ...
    Time, Model_Error.F, '-r');
xlabel('Time (sec)');
ylabel('Angular  Velocity  (deg/sec)');
legend('Eye Data', 'Model', 'Residual');
```



Close the model.

```
bdclose(model_name)
```

See Also

Related Examples

- “Identify Key Parameters for Estimation (GUI)” on page 4-131
- “Use Parallel Computing for Sensitivity Analysis” on page 4-104
- “Use Fast Restart Mode During Sensitivity Analysis” on page 4-109
- “Generate Parameter Samples for Sensitivity Analysis” on page 4-8
- “Analyze Relation Between Parameters and Design Requirements” on page 4-67
- “Validate Sensitivity Analysis” on page 4-96

Generate MATLAB Code for Sensitivity Analysis Statistics to Identify Key Parameters (GUI)

This example shows how to automatically generate a MATLAB function to solve a Sensitivity Analysis statistics problem. You use the **Sensitivity Analyzer** to define a sensitivity statistics problem for a model of the body's vestibulo-ocular reflex, and generate MATLAB® code to solve this statistics problem.

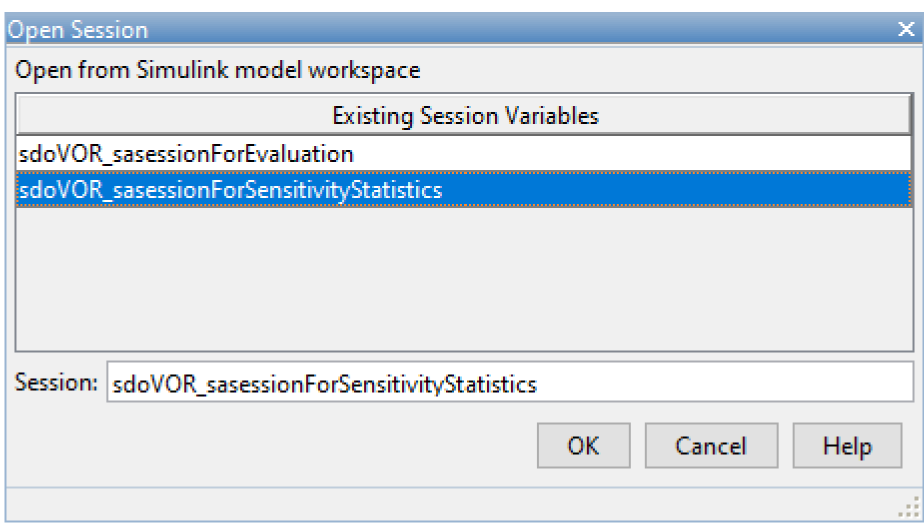
Vestibulo-Ocular Reflex Sensitivity Statistics Problem

The "Identify Key Parameters for Estimation (GUI)" on page 4-131 example shows how to use the **Sensitivity Analyzer** to compute sensitivity statistics for different parameter values in a model of the body's vestibulo-ocular reflex. In this example, we load a preconfigured **Sensitivity Analyzer** session based on that example.

Open the **Sensitivity Analyzer** for the sdoVOR model:

```
ssatool('sdoVOR')
```

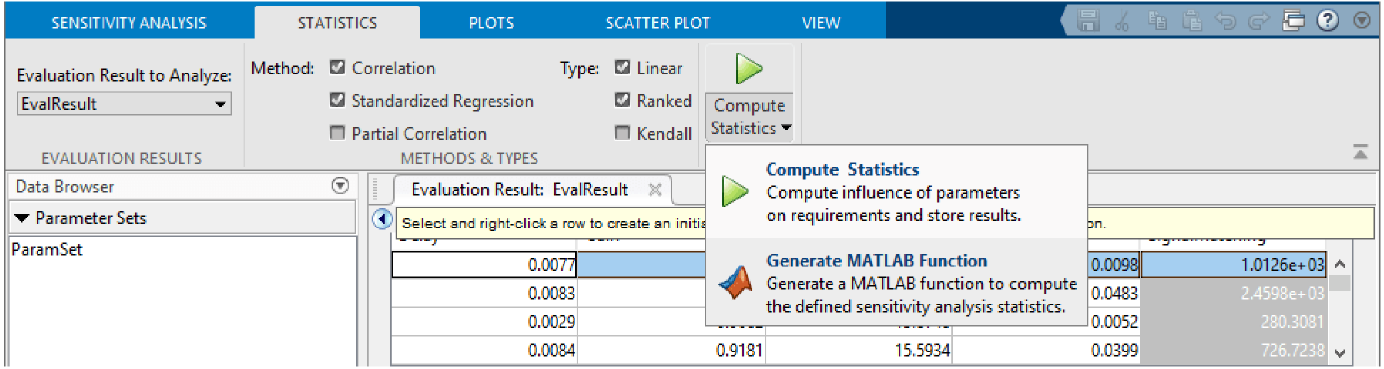
In the **Sensitivity Analyzer**, click **Open Session** and `Open from model workspace`. Open session `sdoVOR_sasessionForSensitivityStatistics`.



This opens a preconfigured session in the **Sensitivity Analyzer**.

Generate MATLAB Code

From the **Compute Statistics** list, select `Generate MATLAB Function`.



The generated code is added to the MATLAB editor as an unsaved MATLAB function.

Editor - Untitled2*

```
function sensitivity = sensitivityStatistics(x,y)
%SENSITIVITYSTATISTICS
%
% Compute sensitivity analysis statistics for the  model.
%
% The function returns sensitivity analysis statistics, sensitivity,
% indicating which parameters, x, have the most influence on the
% requirements, y.
%
% The input argument, x, defines the parameters.  If omitted, the
% parameters specified in the function body are used.
%
% Modify the function to change the analysis techniques.
%
% Auto-generated by SSATOOL on 09-Jul-2019 16:26:25.
%

%% Specify Analysis Variables
%
% Specify parameters and requirements.
if (nargin < 1)  ||  isempty(x)
    x = getData('x');
end

if (nargin < 2)  ||  isempty(y)
    y = getData('y');
end


%% Statistics Options
%
% Specify options for statistical analysis
opts = sdo.AnalyzeOptions;
opts.Method = getData('opts_Method');
opts.MethodOptions = {'Linear', 'Ranked'};

%% Compute Statistics
%
% Call sdo.analyze with the parameters and requirements, to determine which
% parameters most influence the requirements.
sensitivity = sdo.analyze(x,y,opts);
```

Untitled2*

Examine the generated code. Significant portions are:

- **Statistics Analysis Variables** - Specify the inputs and outputs, to determine which inputs have the most influence on outputs.
- **Statistics Options** - Specify the types of analyses to be computed.
- **Compute Statistics** - Solve the sensitivity statistics problem using the sdo.analyze command.

Select **Save** from the MATLAB editor to save the generated function.

Run Generated Code

Run the generated function.

```
Command Window

>> sensitivity = sensitivityStatistics

sensitivity =

  struct with fields:

                   Correlation: [4×1 table]
               RankCorrelation: [4×1 table]
        StandardizedRegression: [4×1 table]
    RankStandardizedRegression: [4×1 table]

>> sensitivity.Correlation

ans =

  4×1 table

             SignalMatching
             ______________

    Delay       -0.20052
    Gain        -0.88175
    Tc           0.51264
    Tp          0.046374

fx >>
```

The computation shows the result of analyzing which inputs have the most influence on the output. For example, the `Correlation` field shows that the `Gain` parameter has the largest magnitude correlation with the output, and in a negative direction, meaning that when Gain increases, the output decreases.

Modify the Generated Code

You can:

- Modify the specified input and output variables.
- Modify the options to change the types of analyses computed.

See Also

More About

- "Generate MATLAB Code for Sensitivity Analysis for Design Space Exploration and Evaluation (GUI)" on page 4-183

Generate MATLAB Code for Sensitivity Analysis for Design Space Exploration and Evaluation (GUI)

This example shows how to automatically generate a MATLAB® function to solve a Sensitivity Analysis evaluation problem. You use the **Sensitivity Analyzer** to define an evaluation problem for a model of the body's vestibulo-ocular reflex, and generate MATLAB code to solve this evaluation problem.

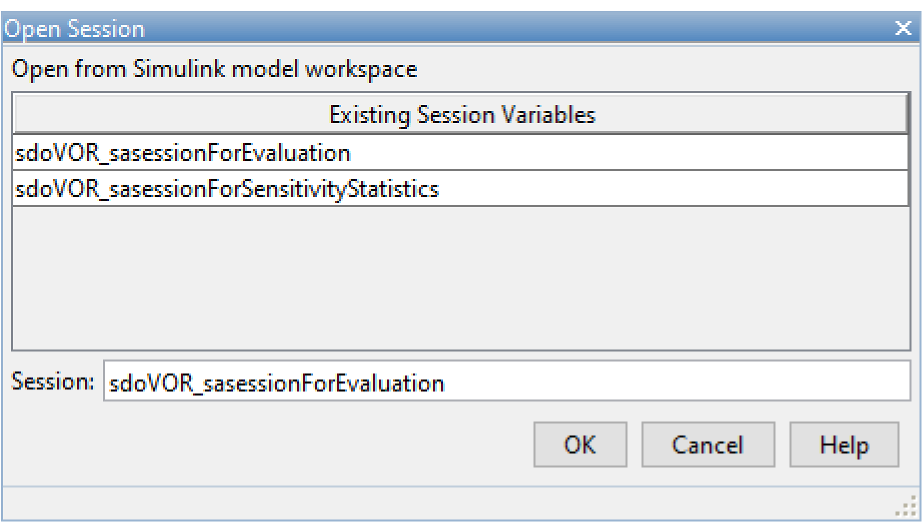
Vestibulo-Ocular Reflex Evaluation Problem

The “Identify Key Parameters for Estimation (GUI)” on page 4-131 example shows how to use the **Sensitivity Analyzer** to evaluate a cost function for different parameter values in a model of the body's vestibulo-ocular reflex. In this example we load a pre-configured **Sensitivity Analyzer** session based on that example.

Open the **Sensitivity Analyzer** for the sdoVOR model:

```
ssatool('sdoVOR')
```

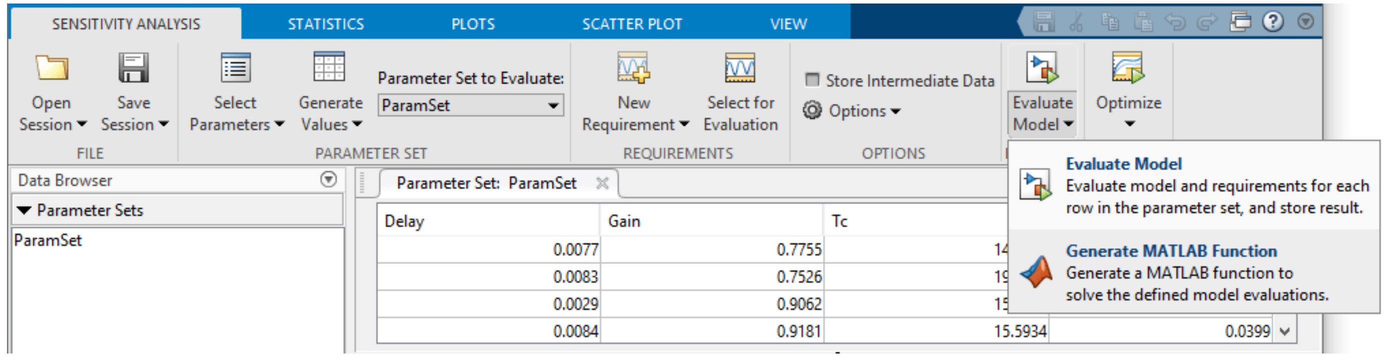
In the **Sensitivity Analyzer**, click **Open Session** and `Open from model workspace`. Open session `sdoVOR_sasessionForEvaluation`.



This opens a preconfigured session in the **Sensitivity Analyzer**.

Generate MATLAB Code

From the **Evaluate Model** list, select `Generate MATLAB Function`.



The generated code is added to the MATLAB editor as an unsaved MATLAB function.

```
function [EvalResult, Info] = sensitivityEvaluationSdoVOR(p)
%SENSITIVITYEVALUATIONSDOVOR
%
% Solve a design exploration problem for the sdoVOR model.
%
% The function returns model results, EvalResult,
% and model evaluation information, Info.
%
% The input argument, p, defines the model parameters to vary,
% if omitted the parameters specified in the function body are varied.
%
% Modify the function to include or exclude new design requirements, or
% to change the evaluation options.
%
% Auto-generated by SDOTOOL on 09-Jul-2019 13:37:12.
%

%% Open the model.
open_system('sdoVOR')

%% Specify Design Variables
%
% Specify model parameters as design variables to vary.
if nargin < 1 || isempty(p)
    p = sdo.getParameterFromModel('sdoVOR',{'Delay','Gain','Tc','Tp'});
    p(1).Value = 0.0055;
    p(1).Minimum = 0.002;
    p(1).Maximum = 0.0089999999999999;
    p(2).Minimum = 0.6;
```

Examine the generated code. Significant code portions are:

- **Specify Design Variables** - Definition of the model parameters being varied.
- **Define the Experiments (Signal Matching Requirements)** - Definition of the measured and expected signal data to use for signal matching requirements. In this case the signal matching requirement is the only requirement. In other cases, there may be other requirements such as signal bounds.
- **Create the Objective Function** - Creation of an anonymous function that calls the subfunction `sdoVOR_evalFcn`, which evaluates the model using each experiment and compares simulation and measured experiment outputs. This anonymous function is called by `sdo.evaluate` at each iteration of the evaluation problem to evaluate the model at all combinations of parameters.
- **Evaluate the Model** - Solve the evaluation problem using the `sdo.evaluate` command.

Select **Save** from the MATLAB editor to save the generated function.

Run Generated Code

Run the generated function.

```
>> [EvalResult, Info] = sensitivityEvaluationSdoVOR

EvalResult =

  40×1 table

    SignalMatching
    ______________

        1012.6
        2459.8
        280.31
        726.72
        3946.5
        1344.6
        975.66
        250.95
        128.29
        777.55
        2462.3
         999.2
```

The first output argument, `EvalResult`, contains the result of evaluating the model at each combination of parameter values. The second output argument, `Info`, contains information about each evaluation.

Modify the Generated Code

You can:

- Modify the generated `sensitivityEvaluationSdoVOR` function to include or exclude new experiments or other requirements, or change evaluation options.
- Call the generated `sensitivityEvaluationSdoVOR` function with a different set of parameter values to evaluate.

For details on how to write an objective/constraint function to use with the `sdo.evaluate` command, type `help sdoExampleCostFunction` at the MATLAB command prompt.

Close the model.

See Also

More About

- "Generate MATLAB Code for Sensitivity Analysis Statistics to Identify Key Parameters (GUI)" on page 4-179

Optimization-Based Control Design

- “Time-Domain Design Requirements in Simulink” on page 5-2
- “Frequency-Domain Design Requirements in Simulink” on page 5-9
- “Time- and Frequency-Domain Requirements in Control System Designer App” on page 5-22
- “Time-Domain Simulations in Control System Designer App” on page 5-25
- “Design Optimization-Based Controllers for LTI Systems” on page 5-26
- “Optimize LTI System to Meet Frequency-Domain Requirements” on page 5-27
- “Design Linear Controllers for Simulink Models” on page 5-46
- “Enforcing Time and Frequency Requirements on a Single-Loop Controller Design” on page 5-48
- “Airframe Controller Tuning” on page 5-63
- “DC Motor Controller Tuning” on page 5-65
- “Hydraulic Piston Regulator Tuning” on page 5-67

Time-Domain Design Requirements in Simulink

Specify Piecewise-Linear Lower and Upper Bounds

To specify upper and lower bounds on a signal:

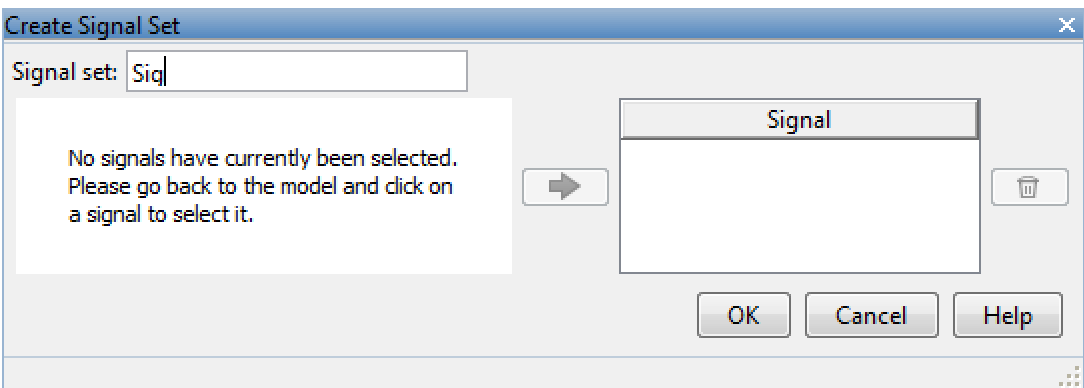
1. In the **Response Optimizer** , select **Signal Bound** in the **New** drop-down list. A window opens where you specify upper or lower bounds on a signal.
2. Specify a requirement name in the **Name** box.
3. Select the requirement type using the **Type** list.
4. Specify the edge start and end times and corresponding amplitude in the **Time (s)** and **Amplitude** columns.
5. Click [+] to specify additional bound edges.

   Select a row and click [delete] to delete a bound edge.
6. In the **Select Signals to Bound** area, select a logged signal to apply the requirement to.

   If you have already selected signals, as described in “Specify Signals to Log” on page 3-10, they appear in the list. Select the corresponding check-box.

   If you have not selected a signal to log:

   a. Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.
   b. In the Simulink model window, click the signal to which you want to add a requirement.



   The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

   c. Select the signal and click [arrow] to add it to the signal set.
   d. In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.
7. Click **OK**.

A variable with the specified requirement name appears in the **Data** area of the app. A graphical display of the requirement also appears in the **Response Optimizer** app window.

8. (Optional) In the graphical display, you can:

   - “Move Constraints Graphically” on page 3-14
   - “Position Constraints Exactly” on page 3-15

Alternatively, you can add a Check Custom Bounds block to your model to specify piecewise-linear bounds.

Specify Step Response Characteristics

To apply a step response requirement to a signal in your model, specify the step response characteristics as follows:

1. Select a step response requirement from the **Response Optimizer**.

   In the **New** drop-down menu of the app, in the **New Time Domain Requirement** section, select **Step Response Envelope**.

   A Create Requirement dialog box opens where you specify the step response requirements on a signal.
2. Specify a requirement name in the **Name** field of the dialog box.
3. Specify the step response characteristics:

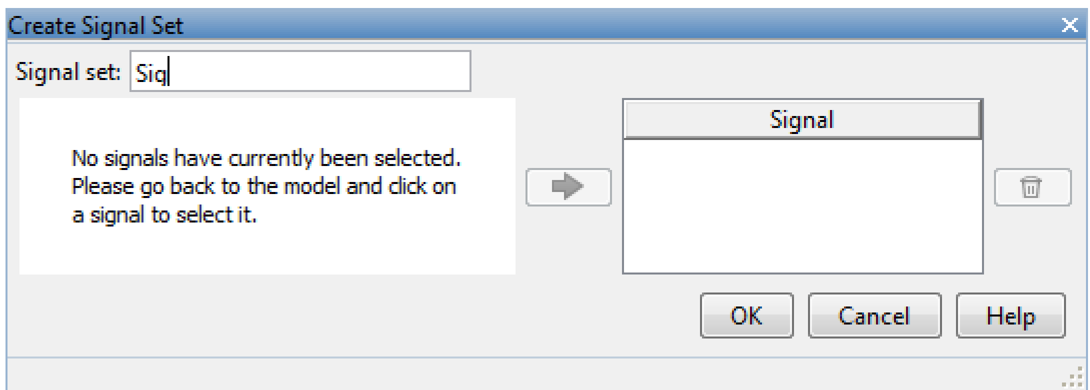
   - **Initial value** — Input level before the step occurs
   - **Step time** — Time at which the step takes place
   - **Final value** — Input level after the step occurs
   - **Rise time** — The time taken for the response signal to reach a specified percentage of the step range. The step range is the difference between the final and initial values.
   - **% Rise** — The percentage of the step range used with **Rise time** to define the overall rise time characteristics.
   - **Settling time** — Time taken until the response signal settles within a specified region around the final value. This settling region is defined as the final step value plus or minus the settling range, defined in **% Settling**.
   - **% Settling** — The percentage of the step range value that defines the settling range of settling time characteristic specified in **Settling time**.
   - **% Overshoot** — The amount by which the response signal can exceed the final value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
   - **% Undershoot** — The amount by which the response signal can undershoot the initial value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
4. Specify the signal to be bound.

   To apply this requirement to a model signal, in the **Select Signals to Bound** area, select a logged signal to which you will apply the requirement.

If you have already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, it appears in the list. Select the corresponding check-box.

If you have not selected a signal to log:

a. Click [+]. The Create Signal Set dialog box opens where you specify the logged signal.
b. In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c. Select the signal and click [⇨] to add it to the signal set.
d. In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

Alternatively, you can use the Check Step Response Characteristics block to specify step response bounds for a signal.

See Also

“Design Optimization to Meet Step Response Requirements (GUI)”

Track Reference Signals

Use reference tracking to force a model signal to match a desired signal. To track a reference signal:

1. In the **Response Optimizer**, select **Signal Tracking** in the **New** drop-down list. A window opens where you specify the reference signal to track.
2. Specify a requirement name in the **Name** box.
3. Define the reference signal by entering vectors, or variables from the workspace, in the **Time vector** and **Amplitude** fields.

   Click **Update reference signal data** to use the new amplitude and time vector as the reference signal.
4. Specify how the optimization solver minimizes the error between the reference and model signals using the **Tracking Method** list:

- SSE — Reduces the sum of squared errors
- SAE — Reduces the sum of absolute errors

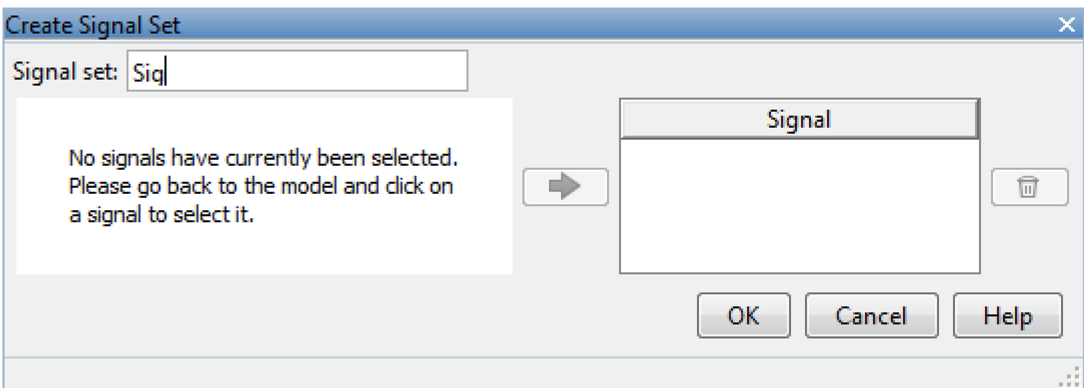
5 In the **Specify Signal to Track Reference Signal** area, select a logged signal to apply the requirement to.

If you already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, they appear in the list. Select the corresponding check-box.

If you have not selected a signal to log:

a Click [+]. A Create Signal Set dialog box opens where you specify the logged signal.

b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [→] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

e Select the check-box corresponding to the signal and click **OK**.

A variable with the specified requirement name appears in the **Data** area of the app. A graphical display of the signal bound also appears in the **Response Optimizer** app window.

Note When tracking a reference signal, the software ignores the maximally feasible solution option. For more information on this option, in the **Response Optimization** tab, click **Options** > **Optimization Options**, and click **Help**.

Alternatively, you can use the Check Against Reference block to specify a reference signal to track.

See Also

“Design Optimization to Track Reference Signal (GUI)”

Specify Custom Requirements

You can specify custom requirements, such as minimizing system energy. To specify custom requirements:

1. In the **Response Optimizer**, in **New** drop-down menu, select **Custom Requirement**. The Create Requirement dialog box opens where you specify the custom requirement.
2. Specify a requirement name in **Name**.
3. Specify the requirement type in the **Type** drop-down menu.
4. Specify the name of the function that contains the custom requirement in **Function**. The field must be specified as a function handle using `@`. The function must be on the MATLAB path. Click to review or edit the function.

   If the function does not exist, clicking opens a template MATLAB file. Use this file to implement the custom requirement. The default function name is `myCustomRequirement`.
5. (Optional) To prevent the solver from considering specific parameter combinations, select **Error if constraint is violated**. Use this option for parameter-only constraints.

   During an optimization iteration, the solver first evaluates requirements with this option selected.

   - If the constraint is violated, the solver skips evaluating any remaining requirements and proceeds to the next iteration.
   - If the constraint is *not* violated, the solver evaluates the remaining requirements for the current iteration. If any of the remaining requirements bound signals or systems, then the solver simulates the model.

   For more information, see “Skip Model Simulation Based on Parameter Constraint Violation (GUI)” on page 3-170.

   Note If you select this check box, then do not specify signals or systems to bound. If you *do* specify signals or systems, then this check box is ignored.

   ---
6. (Optional) Specify the signal or system, or both, to be bound.

   You can apply this requirement to model signals, or a linearization of your Simulink model (requires Simulink Control Design), or both.

   Click **Select Signals and Systems to Bound (Optional)** to view the signal and linearization I/O selection area.

   - To apply this requirement to a model signal:

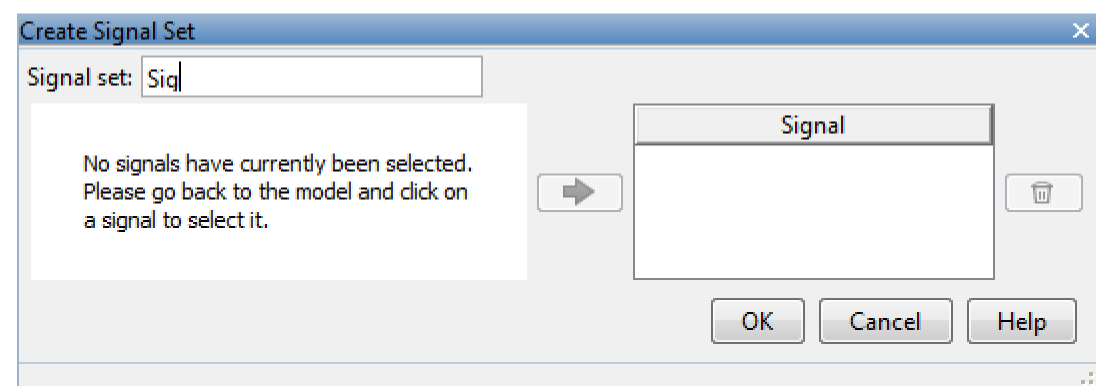
     In the **Signal** area, select a logged signal to which you will apply the requirement.

     If you have already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, it appears in the list. Select the corresponding check box.

     If you have not selected a signal to log:

     a. Click . A Create Signal Set dialog box opens where you specify the logged signal.

b In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [button] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

- To apply this requirement to a linear system:

  a Specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.

  b Select the linearization input/output set from the **Linearization I/O** area.

  If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

  If you have not created a linearization input/output set, click [button] to open the Create linearization I/O set dialog box. For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

  For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

7 Click **OK**.

A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**. A graphical display of the requirement also appears in the **Response Optimizer** app window.

See Also

- “Design Optimization to Meet a Custom Objective (GUI)” on page 3-110
- “Design Optimization to Meet a Custom Objective (Code)” on page 3-125

Edit Design Requirements

The Edit Design Requirement dialog box allows you to exactly position constraint segments and to edit other properties of these constraints. The dialog box has two main components:

- An upper panel to specify the constraint you are editing
- A lower panel to edit the constraint parameters

The upper panel of the Edit Design Requirement dialog box resembles the image in the following figure.

In the **Control System Designer** app in Control System Toolbox, you can edit design requirements from the analysis plots. The **Design requirement** drop-down list will contain all the requirements on that plot.

Edit Design Requirement Dialog Box Parameters

The particular parameters shown within the lower panel of the Edit Design Requirement dialog box depend on the type of constraint/requirement. In some cases, the lower panel contains a grid with one row for each segment and one column for each constraint parameter. The following table summarizes the various constraint parameters.

Edit Design Requirement Dialog Box Parameters

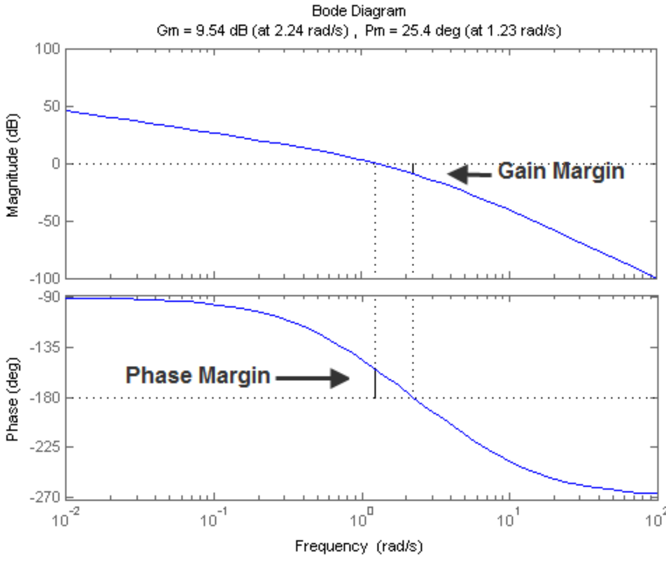
Parameter	Found in	Description
Time	Upper and lower time response bounds on step and impulse response plots	Defines the time range of a segment within a constraint/requirement.
Amplitude	Upper and lower time response bounds on step and impulse response plots	Defines the beginning and ending amplitude of a constraint segment.
Slope (1/s)	Upper and lower time response bounds	Defines the slope, in 1/s, of a constraint segment. It is an alternative method of specifying the magnitude values. Entering a new **Slope** value changes any previously defined magnitude values.
Final value	Step response bounds	Defines the input level after the step occurs.
Rise time	Step response bounds	Defines a constraint segment for a particular rise time.
% Rise	Step response bounds	The percentage of the step range used to describe the rise time.
Settling time	Step response bounds	Defines a constraint segment for a particular settling time.
% Settling	Step response bounds	The percentage of the step range that defines the settling region used to describe the settling time.
% Overshoot	Step response bounds	The percentage amount by which the signal can exceed the final value before settling.
% Undershoot	Step response bounds	Defines the constraint segments for a particular percent undershoot.

Frequency-Domain Design Requirements in Simulink

Specify Lower Bounds on Gain and Phase Margin

To specify lower bounds on the gain and phase margin of a linear system:

1. In the **Response Optimizer**, select **Gain and Phase Margin** in the **New** list. A window opens where you specify lower bounds on the gain and phase margin of your linear system.
2. Specify a requirement name in **Name**.
3. Specify bounds on the gain margin or phase margin, or both.



   - **Gain margin** — Amount of gain increase or decrease required to make the loop gain unity at the frequency where the phase angle is –180°.
   - **Phase margin** — Amount of phase increase or decrease required to make the phase angle –180° when the loop gain is 1.0

   To specify a lower bound on the gain margin or phase margin, or both, select the corresponding check box and enter the lower bound value.

4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

If you have not created a linearization input/output set, click to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

5 Click **OK**.

A variable with the specified requirement name appears in the **Data** area of the app. A graphical display of the requirement also appears in the **Response Optimizer** app window.

6 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Gain and Phase Margins block to specify bounds on the gain and phase margin. (Requires Simulink Control Design.)

Specify Piecewise-Linear Lower and Upper Bounds on Frequency Response

To specify upper or lower bounds on the magnitude of a system response:

1 In the **Response Optimizer**, select **Bode Magnitude** in the **New** list. A window opens where you specify the lower or upper bounds on the magnitude of the system response.

2 Specify a requirement name in the **Name** box.

3 Specify the requirement type using the **Type** list.

4 Specify the edge start and end frequencies and corresponding magnitude in the **Frequency** and **Magnitude** columns.

5 Insert or delete bound edges.

Click to specify additional bound edges.

Select a row and click to delete a bound edge.

6 In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

a Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.

b Select the linearization input/output set from the **Linearization I/O** area.

If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

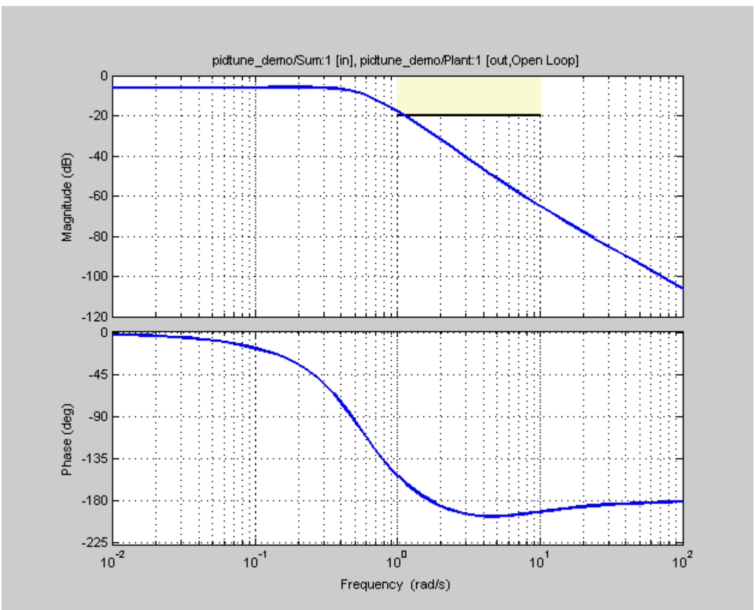
If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

7. Click **OK**.

   A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app window. A graphical display of the requirement also appears in the **Response Optimizer** app window.



8. (Optional) In the graphical display, you can:

   - “Move Constraints Graphically” on page 3-14
   - “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Bode Characteristics block to specify bounds on the magnitude of the system response. (Requires Simulink Control Design.)

Specify Bound on Closed-Loop Peak Gain

To specify an upper bound on the closed-loop peak response of a system:

1. In the **Response Optimizer**, select **Closed-Loop Peak Gain** in the **New** list. A window opens where you specify an upper bound on the closed-loop peak gain of the system.
2. Specify a requirement name in the **Name** box.
3. Specify the upper bound on the closed-loop peak gain in the **Closed-Loop peak gain** box.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

a Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.

b Select the linearization input/output set from the **Linearization I/O** area.

If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

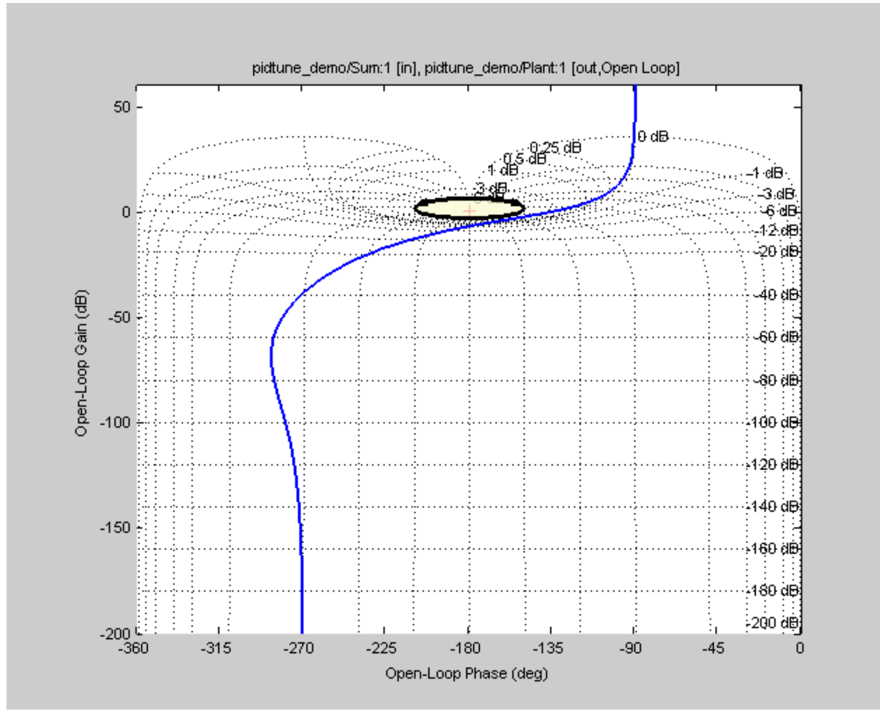
If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see "Create Linearization I/O Sets" on page 3-64.

For more information on linearization, see "What Is Linearization?" (Simulink Control Design).

5 Click **OK**.

A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app window. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6 (Optional) In the graphical display, you can:

- "Move Constraints Graphically" on page 3-14
- "Position Constraints Exactly" on page 3-15

Alternatively, you can use the Check Nichols Characteristics block to specify bounds on the magnitude of the system response. (Requires Simulink Control Design.)

Specify Lower Bound on Damping Ratio

To specify a lower bound on the damping ratio of the system:

1. In the **Response Optimizer**, select **Damping Ratio** in the **New** list. A window opens where you specify a lower bound on the damping ratio of the system.
2. Specify a requirement name in the **Name** box.
3. Specify the lower bound on the damping ratio in the **Damping ratio** box.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

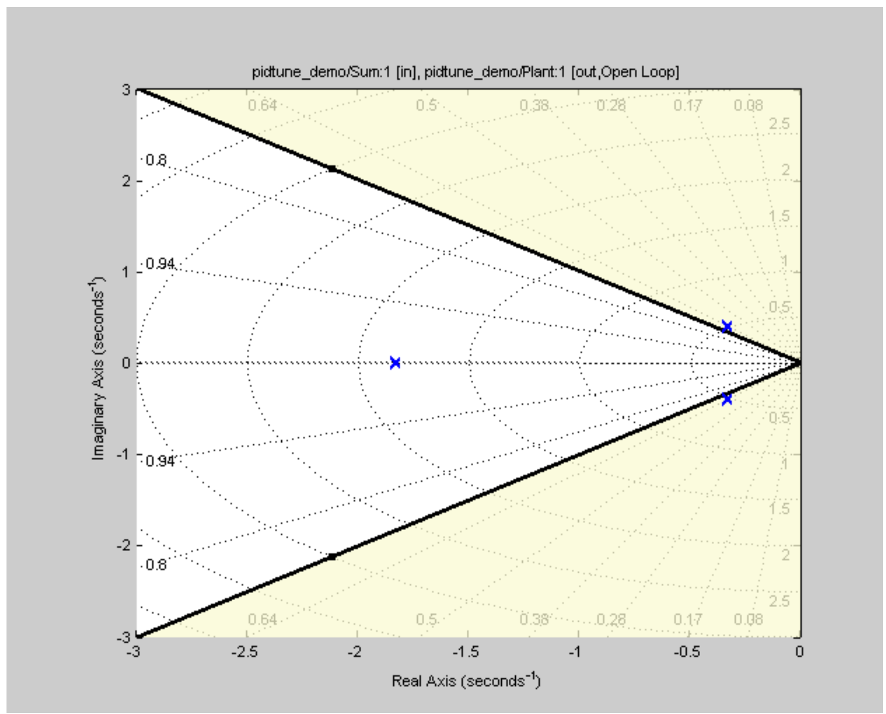
      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see "Create Linearization I/O Sets" on page 3-64.

   For more information on linearization, see "What Is Linearization?" (Simulink Control Design).
5. Click **OK**.

   A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Pole-Zero Characteristics block to specify a bound on the damping ratio. (Requires Simulink Control Design.)

Specify Upper and Lower Bounds on Natural Frequency

To specify a bound on the natural frequency of the system:

1. In the **Response Optimizer**, select **Natural Frequency** in the **New** list. A window opens where you specify a bound on the natural frequency of the system.
2. Specify a requirement name in the **Name** box.
3. Specify a lower or upper bound on the natural frequency in the **Natural frequency** box.
4. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

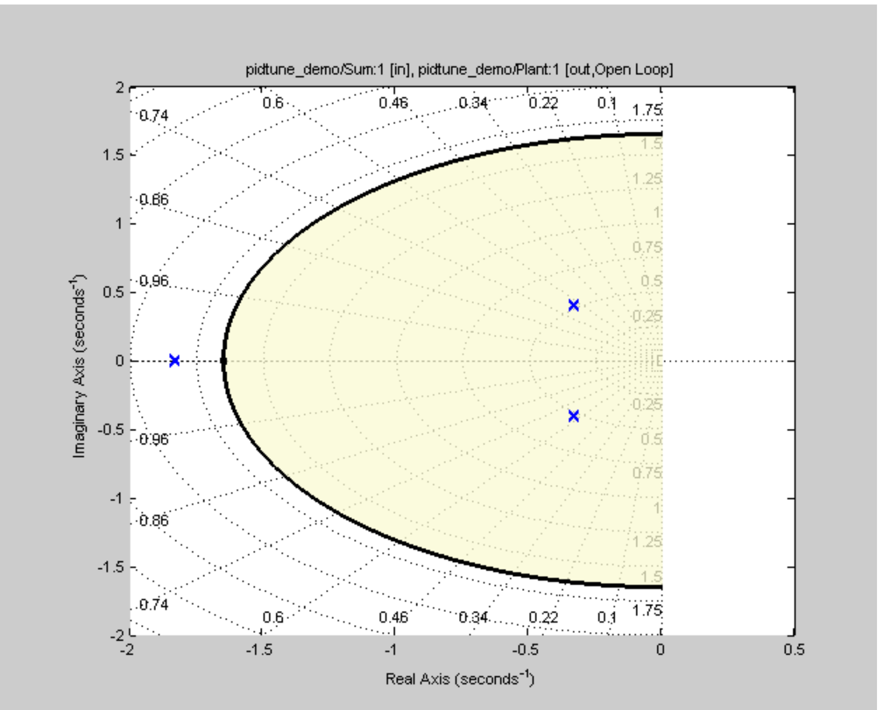
If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

For more information on using this dialog box, see "Create Linearization I/O Sets" on page 3-64.

For more information on linearization, see "What Is Linearization?" (Simulink Control Design).

5 Click **OK**.

A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6 (Optional) In the graphical display, you can:

- "Move Constraints Graphically" on page 3-14
- "Position Constraints Exactly" on page 3-15

Alternatively, you can use the Check Pole-Zero Characteristics block to specify a bound on the natural frequency. (Requires Simulink Control Design.)

Specify Upper Bound on Approximate Settling Time

To specify an upper bound on the approximate settling time of the system:

1 In the **Response Optimizer**, select **Settling Time** in the **New** list. A window opens where you specify an upper bound on the approximate settling time of the system.

2 Specify a requirement name in the **Name** box.

3 Specify the upper bound on the approximate settling time in the **Settling time** box.

4 In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

 Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

 a Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.

 b Select the linearization input/output set from the **Linearization I/O** area.

  If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

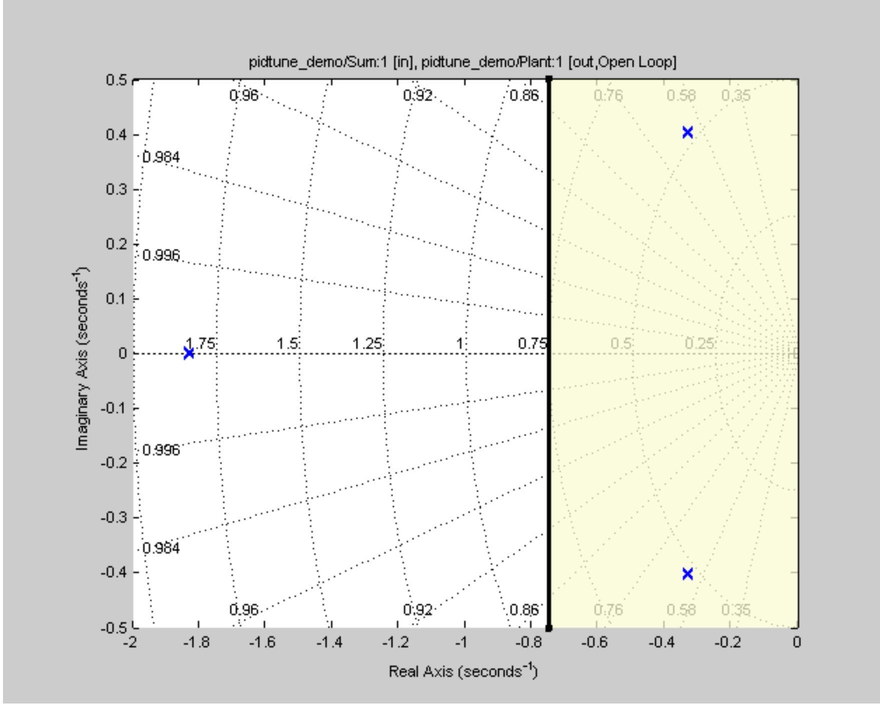
  If you have not created a linearization input/output set, click to open the Create linearization I/O set dialog box.

  For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

 For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

5 Click **OK**.

 A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



6 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Pole-Zero Characteristics block to specify the approximate settling time. (Requires Simulink Control Design.)

Specify Piecewise-Linear Upper and Lower Bounds on Singular Values

To specify piecewise-linear upper and lower bounds on the singular values of a system:

1. In the **Response Optimizer**, select **Singular Values** in the **New** list. A window opens where you specify the lower or upper bounds on the singular values of the system.
2. Specify a requirement name in the **Name** box.
3. Specify the requirement type using the **Type** list.
4. Specify the edge start and end frequencies and corresponding magnitude in the **Frequency** and **Magnitude** columns, respectively.
5. Insert or delete bound edges.

   Click to specify additional bound edges.

   Select a row and click to delete a bound edge.
6. In the **Select Systems to Bound** section, select the linear systems to which this requirement applies.

   Linear systems are defined by snapshot times at which the model is linearized and sets of linearization I/O points defining the system inputs and outputs.

   a. Specify the simulation time at which the model is linearized using the **Snapshot Times** box. For multiple simulation snapshot times, specify a vector.
   b. Select the linearization input/output set from the **Linearization I/O** area.

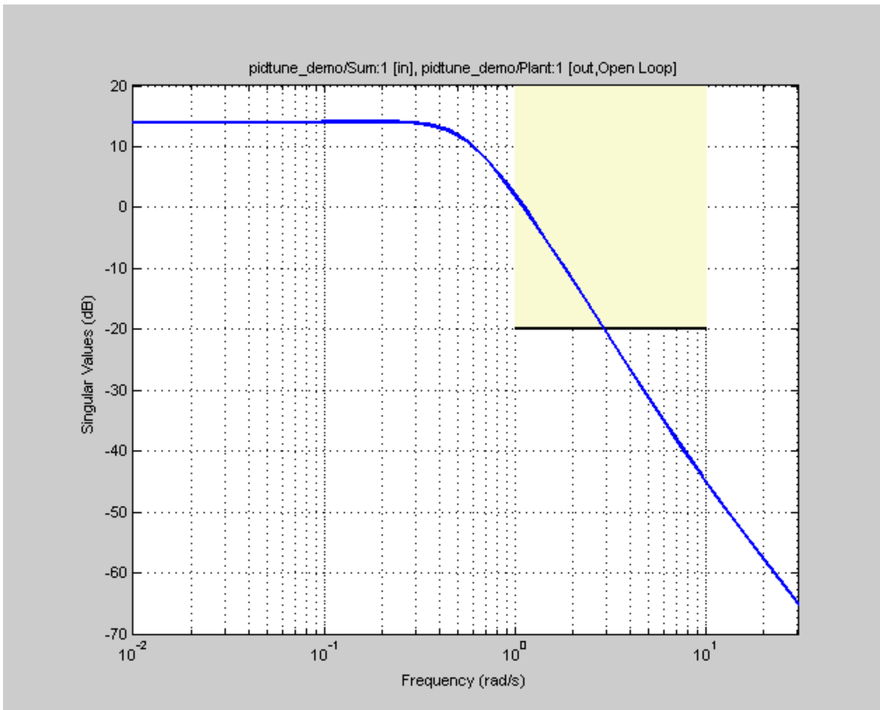
      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).
7. Click **OK**.

   A new variable with the specified name appears in the **Data** area of the **Response Optimizer** app. A graphical display of the requirement also appears in the **Response Optimizer** app window.



8 (Optional) In the graphical display, you can:

- “Move Constraints Graphically” on page 3-14
- “Position Constraints Exactly” on page 3-15

Alternatively, you can use the Check Singular Value Characteristics block to specify bounds on the singular value. (Requires Simulink Control Design).

Specify Step Response Characteristics

To apply a step response requirement to a linearization of your model (requires Simulink Control Design), specify the step response characteristics as follows:

1 Select a step response requirement from the **Response Optimizer**.

   In the **New** drop-down menu of the app, in the **New Frequency Domain Requirement** section, select **Step Response Envelope**.

   A Create Requirement dialog box opens where you specify the step response requirements.
2 Specify a requirement name in the **Name** field of the dialog box.
3 Specify the step response characteristics:

   - **Initial value** — Input level before the step occurs
   - **Step time** — Time at which the step takes place
   - **Final value** — Input level after the step occurs
   - **Rise time** — The time taken for the response signal to reach a specified percentage of the step range. The step range is the difference between the final and initial values.

- **% Rise** — The percentage of the step range used with **Rise time** to define the overall rise time characteristics.
- **Settling time** — Time taken until the response signal settles within a specified region around the final value. This settling region is defined as the final step value plus or minus the settling range, defined in **% Settling**.
- **% Settling** — The percentage of the step range value that defines the settling range of settling time characteristic specified in **Settling time**.
- **% Overshoot** — The amount by which the response signal can exceed the final value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.
- **% Undershoot** — The amount by which the response signal can undershoot the initial value. This amount is specified as a percentage of the step range. The step range is the difference between the final and initial values.

4 Specify the systems to be bound.

   To apply this requirement to a linearization of your Simulink model:

   a In the **Select Systems to Bound** area, specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.

   b Select the linearization input/output set from the **Linearization I/O** area.

      If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

      If you have not created a linearization input/output set, click [+] to open the Create linearization I/O set dialog box.

      For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

   For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

Alternatively, you can use the Check Step Response Characteristics block to specify step response bounds for a signal.

Specify Custom Requirements

You can specify custom requirements, such as minimizing system energy. To specify custom requirements:

1 In the **Response Optimizer**, in **New** drop-down menu, select **Custom Requirement**. The Create Requirement dialog box opens where you specify the custom requirement.
2 Specify a requirement name in **Name**.
3 Specify the requirement type in the **Type** drop-down menu.
4 Specify the name of the function that contains the custom requirement in **Function**. The field must be specified as a function handle using `@`. The function must be on the MATLAB path. Click [folder] to review or edit the function.

If the function does not exist, clicking [folder button] opens a template MATLAB file. Use this file to implement the custom requirement. The default function name is `myCustomRequirement`.

5. (Optional) To prevent the solver from considering specific parameter combinations, select **Error if constraint is violated**. Use this option for parameter-only constraints.

   During an optimization iteration, the solver first evaluates requirements with this option selected.

   - If the constraint is violated, the solver skips evaluating any remaining requirements and proceeds to the next iteration.
   - If the constraint is *not* violated, the solver evaluates the remaining requirements for the current iteration. If any of the remaining requirements bound signals or systems, then the solver simulates the model.

   For more information, see “Skip Model Simulation Based on Parameter Constraint Violation (GUI)” on page 3-170.

   Note If you select this check box, then do not specify signals or systems to bound. If you *do* specify signals or systems, then this check box is ignored.

   ---

6. (Optional) Specify the signal or system, or both, to be bound.

   You can apply this requirement to model signals, or a linearization of your Simulink model (requires Simulink Control Design), or both.

   Click **Select Signals and Systems to Bound (Optional)** to view the signal and linearization I/O selection area.

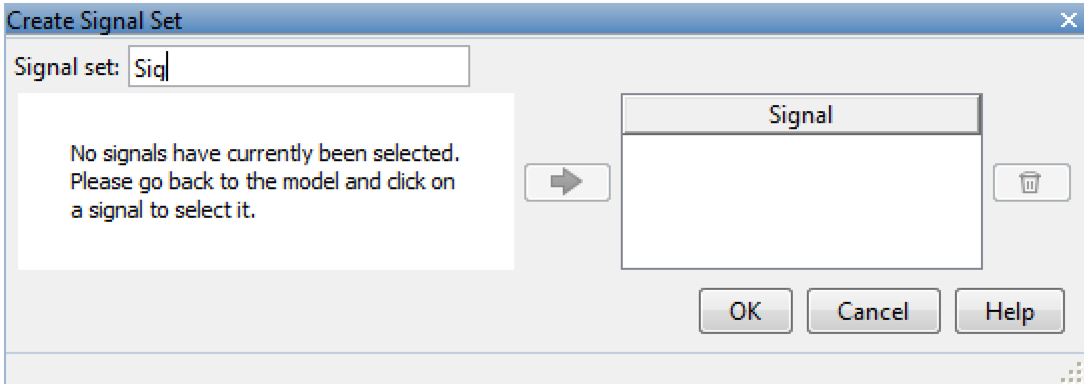
   - To apply this requirement to a model signal:

     In the **Signal** area, select a logged signal to which you will apply the requirement.

     If you have already selected a signal to log, as described in “Specify Signals to Log” on page 3-10, it appears in the list. Select the corresponding check box.

     If you have not selected a signal to log:

     a. Click [+ button]. A Create Signal Set dialog box opens where you specify the logged signal.
     b. In the Simulink model window, click the signal to which you want to add a requirement.



The Create Signal Set dialog box updates and displays the name of the block and the port number where the selected signal is located.

c Select the signal and click [arrow button] to add it to the signal set.

d In **Signal set** field, enter a name for the selected signal set.

   Click **OK**. A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**.

- To apply this requirement to a linear system:

  a Specify the simulation time at which the model is linearized in **Snapshot Times**. For multiple simulation snapshot times, specify a vector.

  b Select the linearization input/output set from the **Linearization I/O** area.

     If you have already created a linearization input/output set, it appears in the list. Select the corresponding check box.

     If you have not created a linearization input/output set, click [+ button] to open the Create linearization I/O set dialog box. For more information on using this dialog box, see “Create Linearization I/O Sets” on page 3-64.

  For more information on linearization, see “What Is Linearization?” (Simulink Control Design).

7 Click **OK**.

   A new variable, with the specified name, appears in the **Data** area of the **Response Optimizer**. A graphical display of the requirement also appears in the **Response Optimizer** app window.

See Also

- “Design Optimization to Meet a Custom Objective (GUI)” on page 3-110
- “Design Optimization to Meet a Custom Objective (Code)” on page 3-125

Time- and Frequency-Domain Requirements in Control System Designer App

Root Locus Diagrams

Settling Time

If you specify a settling time in the continuous-time root locus, a vertical line appears on the root locus plot at the pole locations associated with the value provided (using a first-order approximation). In the discrete-time case, the constraint is a curved line.

It is required that $\mathrm{Re}\{pole\} < -4.6/T_{settling}$ for continuous systems and $\log(\mathrm{abs}(pole))/T_{discrete} < -4.6/T_{settling}$ for discrete systems. This is an approximation of the settling time based on second-order dominant systems.

Percent Overshoot

Specifying percent overshoot in the continuous-time root locus causes two rays, starting at the root locus origin, to appear. These rays are the locus of poles associated with the percent value (using a second-order approximation). In the discrete-time case, the constraint appears as two curves originating at (1,0) and meeting on the real axis in the left-hand plane.

The percent overshoot *p.o* constraint can be expressed in terms of the damping ratio, as in this equation:

$$p.o. = 100e^{-\pi\zeta/\sqrt{1-\zeta^2}}$$

where ζ is the damping ratio.

Damping Ratio

Specifying a damping ratio in the continuous-time root locus causes two rays, starting at the root locus origin, to appear. These rays are the locus of poles associated with the damping ratio. In the discrete-time case, the constraint appears as curved lines originating at (1,0) and meeting on the real axis in the left-hand plane.

The damping ratio defines a requirement on $-\mathrm{Re}\{pole\}/\mathrm{abs}(pole)$ for continuous systems and on

$$r = \mathrm{abs}(pSys)$$
$$t = \mathrm{angle}(pSys)$$
$$c = -\log(r)/\sqrt{(\log(r))^2 + t^2}$$

for discrete systems.

Natural Frequency

If you specify a natural frequency, a semicircle centered around the root locus origin appears. The radius equals the natural frequency.

The natural frequency defines a requirement on *abs(pole)* for continuous systems and on

$r = \text{abs}(pSys)$

$t = \text{angle}(pSys)$

$c = \sqrt{(\log(r))^2 + t^2}/Ts_{model}$

for discrete systems.

Region Constraint

Specifies an exclusion region in the complex plane, causing a line to appear between the two specified points with a shaded region below the line. The poles must not lie in the shaded region.

Open-Loop and Prefilter Bode Diagrams

Gain and Phase Margins

Specify a minimum phase and or a minimum gain margin.

Upper Gain Limit

You can specify an upper gain limit, which appears as a straight line on the Bode magnitude curve. You must select frequency limits, the upper gain limit in decibels, and the slope in dB/decade.

Lower Gain Limit

Specify the lower gain limit in the same fashion as the upper gain limit.

Open-Loop Nichols Plots

Phase Margin

Specify a minimum phase amount.

While displayed graphically at only one location around a multiple of -180 degrees, this requirement applies to phase margin regardless of actual phase (i.e., it is interpreted for all multiples of -180).

Gain Margin

Specify a minimum gain margin.

While displayed graphically at only one location around a multiple of -180 degrees, this requirement applies to gain margin regardless of actual phase (i.e., it is interpreted for all multiples of -180).

Closed-Loop Peak Gain

Specify a peak closed-loop gain at a given location. The specified value can be positive or negative in dB. The constraint follows the curves of the Nichols plot grid, so it is recommended that you have the grid on when using this feature.

While displayed graphically at only one location around a multiple of -180 degrees, this requirement applies to gain margin regardless of actual phase (i.e., it is interpreted for all multiples of -180).

Gain-Phase Requirement

Specifies an exclusion region for the response on the Nichols plot. The response must not pass through the shaded region.

This only applies to the region (phase and gain) drawn.

Step/Impulse Response Plots

Upper Time Response Bound

You can specify an upper time response bound for step and impulse responses.

Lower Time Response Bound

You can specify a lower time response bound for step and impulse responses.

Step Response Bound

For a step response plot, you can also specify a step response bound design requirement.

To define a step response bound requirement, specify the following step response parameters:

- **Final value** — Final steady-state value
- **Rise time** — Time required to reach the specified percentage, **% Rise**, of the step range.
- **Settling time** — Time at which the response enters and stays within the settling percentage, **% Settling**, of the step range.
- **% Overshoot** — Maximum percentage overshoot above the **Final value**.
- **% Undershoot** — Maximum percentage undershoot below the **Initial value**.

In the **Control System Designer** app, step response plots always use an **Initial value** and a **Step time** of `0`.

See Also

Related Examples

- "Design Optimization-Based Controllers for LTI Systems" on page 5-26
- "Optimize LTI System to Meet Frequency-Domain Requirements" on page 5-27
- "Design Optimization-Based PID Controller for Linearized Simulink Model (GUI)"

Time-Domain Simulations in Control System Designer App

When performing optimization-based tuning in the **Control System Designer** app, Simulink Design Optimization software automatically sets the model simulation start and stop times; you cannot directly change them. By default, the simulation starts at 0 and continues until the app determines that the dynamics of the model have settled out. In addition, when the design requirements extend beyond this point, the simulation continues to the extent of the design requirements. Although you cannot directly adjust the start or stop time of the simulation, you can adjust the design requirements to extend further in time and thus force the simulation to continue to a certain point.

See Also

Related Examples

- “Optimize LTI System to Meet Frequency-Domain Requirements” on page 5-27

Design Optimization-Based Controllers for LTI Systems

This topic shows how to design optimization-based linear controllers for an LTI model.

To design an optimization-based linear controller:

1. Create and import a linear model into the **Control System Designer** app. You can create an LTI model at the MATLAB command line, as described in “Create an LTI Plant Model” on page 5-27.
2. Create a Control System Designer session, as described in “Open the Control System Designer App” on page 5-28.
3. In the **Tuning Methods** drop-down list, select `Optimization Based Tuning` to open the Response Optimization window. For more information, see “Open Optimization Based Tuning Method” on page 5-31 .
4. In the Response Optimization window, select the **Compensators** tab to select and configure the compensator elements you want to tune during the response optimization. For more information, see “Select Tunable Compensator Elements” on page 5-33.
5. In the **Design requirements** tab, select the design requirements you want the system to satisfy. For more information, see “Add Design Requirements” on page 5-34.
6. In the Response Optimization window, click **Start Optimization**. The optimization progress results are displayed in the **Optimization** tab. The **Compensators** pane contains the new, optimized compensator element values. For more information, see “Optimize the System Response” on page 5-42.

See Also

Related Examples

- “Optimize LTI System to Meet Frequency-Domain Requirements” on page 5-27

Optimize LTI System to Meet Frequency-Domain Requirements

This example shows how to use frequency-domain design requirements to optimize the response of an LTI system in the **Control System Designer** app.

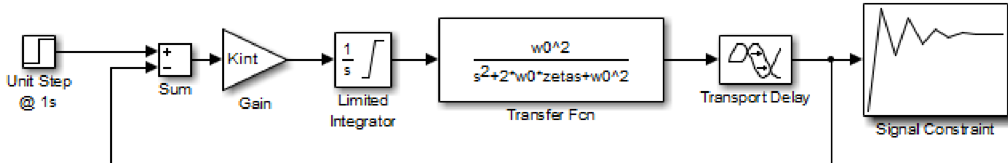
When used with Control System Toolbox software, you can place Simulink Design Optimization design requirements or constraints on plots in the **Control System Designer** app. You can include design requirements for response optimization in the frequency-domain and time-domain.

You can specify frequency-domain design requirements to optimize response signals for any model that you design in the **Control System Designer** app, such as:

- Command-line LTI models created with the Control System Toolbox commands
- Simulink models that have been linearized using Simulink Control Design software

Design Requirements

In this example, you use a linearized version of the Simulink model, `srotut1`.



You use optimization methods to design a compensator so that the closed-loop system meets the following design specifications when you excite the system with a unit step input:

- Maximum 30-second settling time
- Maximum 10% overshoot
- Maximum 10-second rise time
- Limit of ±0.7 on the actuator signal

Create an LTI Plant Model

In the `srotut1` model, the plant model is composed of a gain, a limited integrator, a transfer function, and a transport delay block.

Design the compensator for the open-loop transfer function of the linearized `srotut1` model. The linearized `srotut1` plant model is composed of the gain, an unlimited integrator, the transfer function, and a Padé approximation to the transport delay.

To create an open-loop transfer function based on the linearized `srotut1` model, enter the following commands.

```
w0 = 1;
zeta = 1;
Kint = 0.5;
Tdelay = 1;
[delayNum,delayDen] = pade(Tdelay,1);
integrator = tf(Kint,[1 0]);
```

```
transfer_fcn = tf(w0^2,[1 2*w0*zeta w0^2]);
delay_block = tf(delayNum,delayDen);
open_loopTF = integrator*transfer_fcn*delay_block;
```

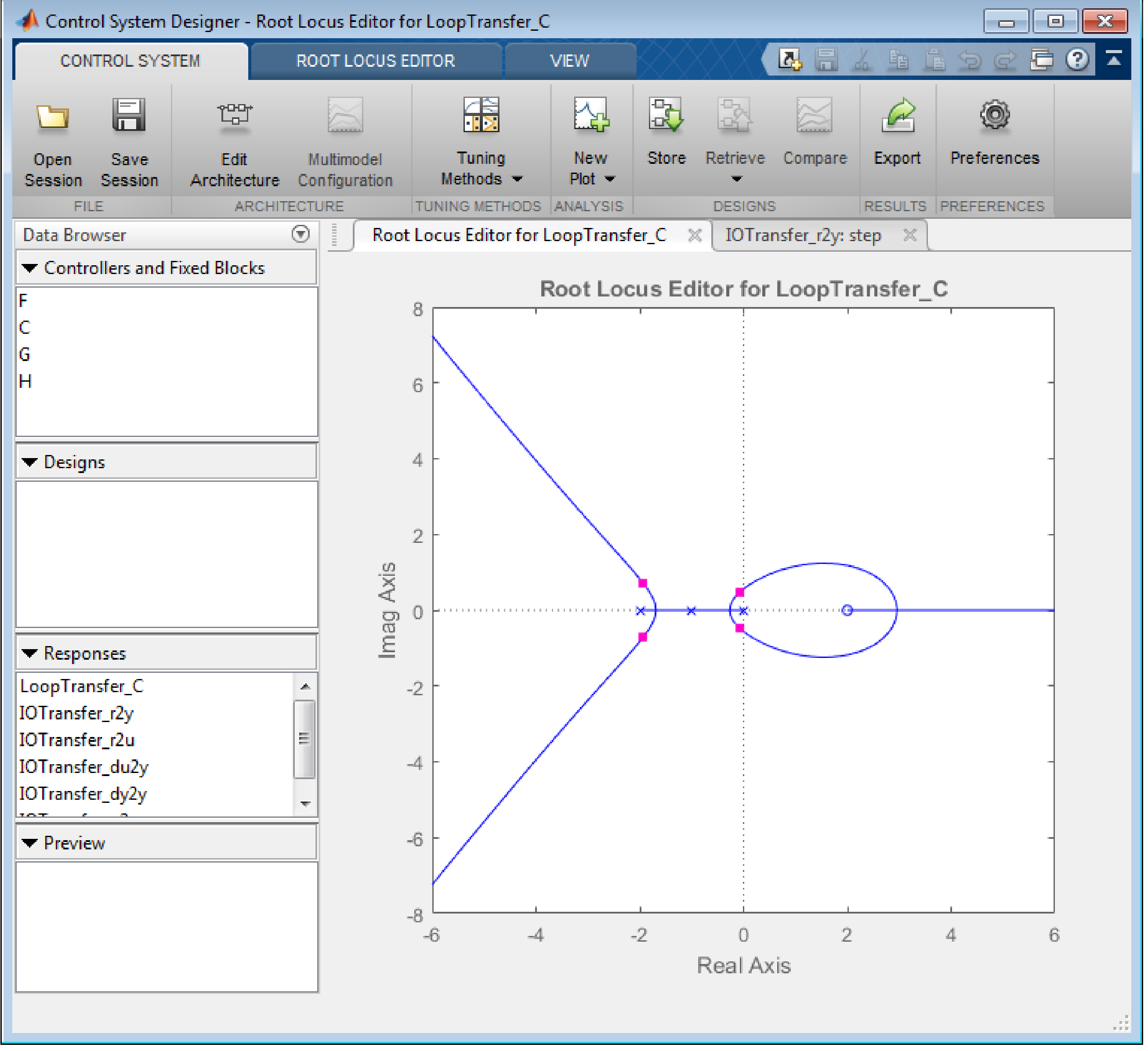
If the plant model is an array of models (Control System Toolbox), the controller is designed for a nominal model only. You can also analyze the control design for the remaining models in the array. For more information, see “Multimodel Control Design” (Control System Toolbox).

Tip You can directly linearize the Simulink model using Simulink Control Design software.

Open the Control System Designer App

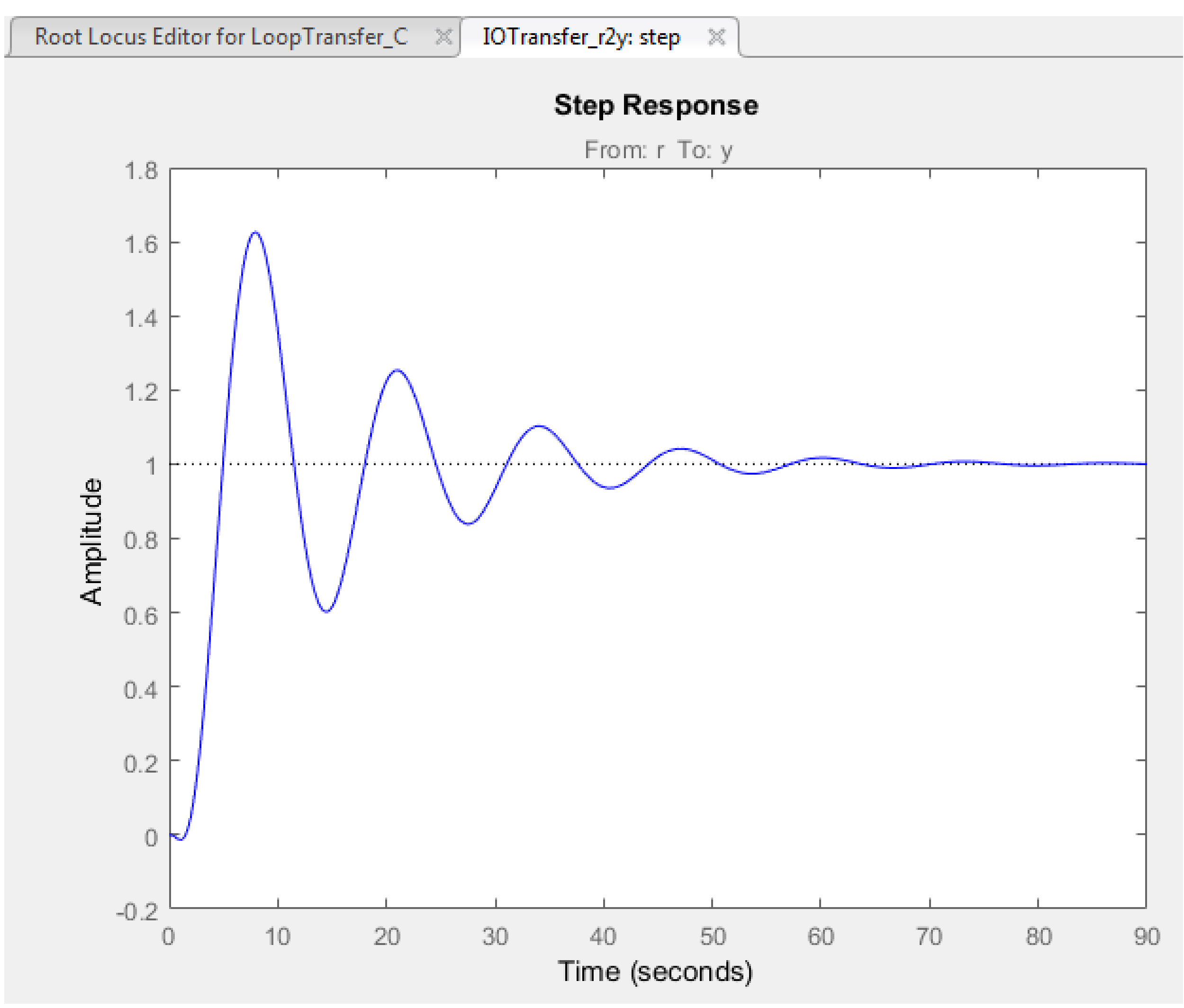
This example uses a root locus diagram to design the response of the open-loop transfer function, `open_loopTF`. To create a **Control System Designer** app session with a root locus plot for the open-loop transfer function, use the following command:

```
controlSystemDesigner('rlocus',open_loopTF)
```

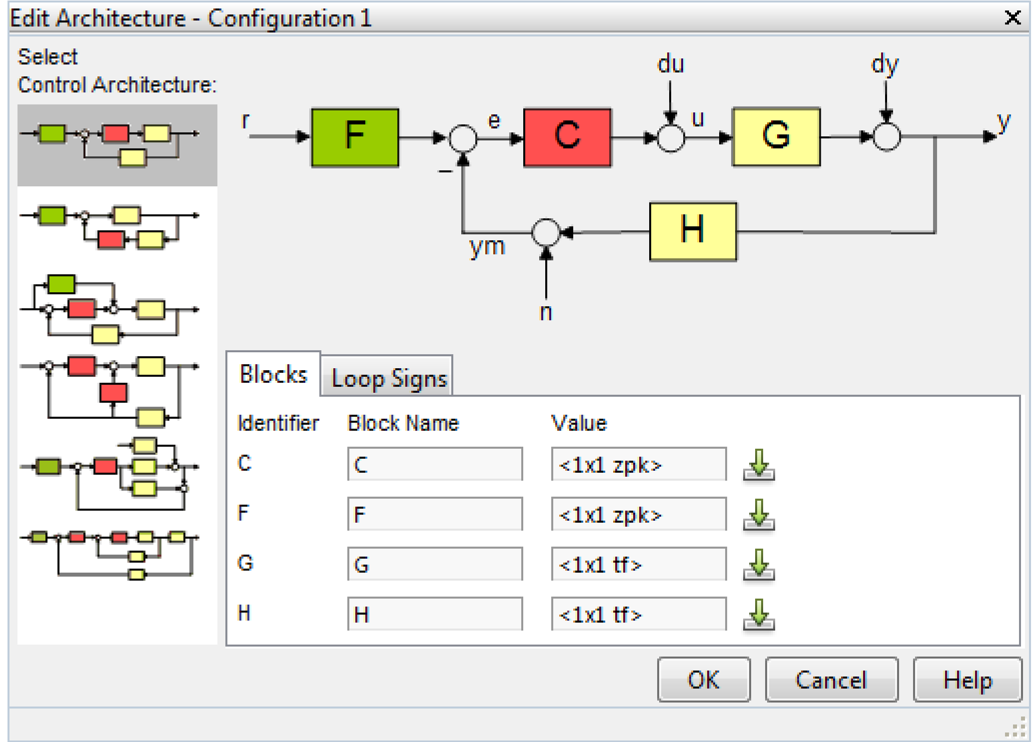


The **Control System Designer** app opens, and a **Root Locus Editor** is displayed. The app lets you design controllers for single-input, single-output (SISO) systems in MATLAB and Simulink. For more information, see the “Classical Control Design” (Control System Toolbox) category.

The app also displays the step response plot of the system. The plot shows the response of the closed-loop system from `r` (input to the prefilter, *F*) to `y` (output of the plant model, *G*).



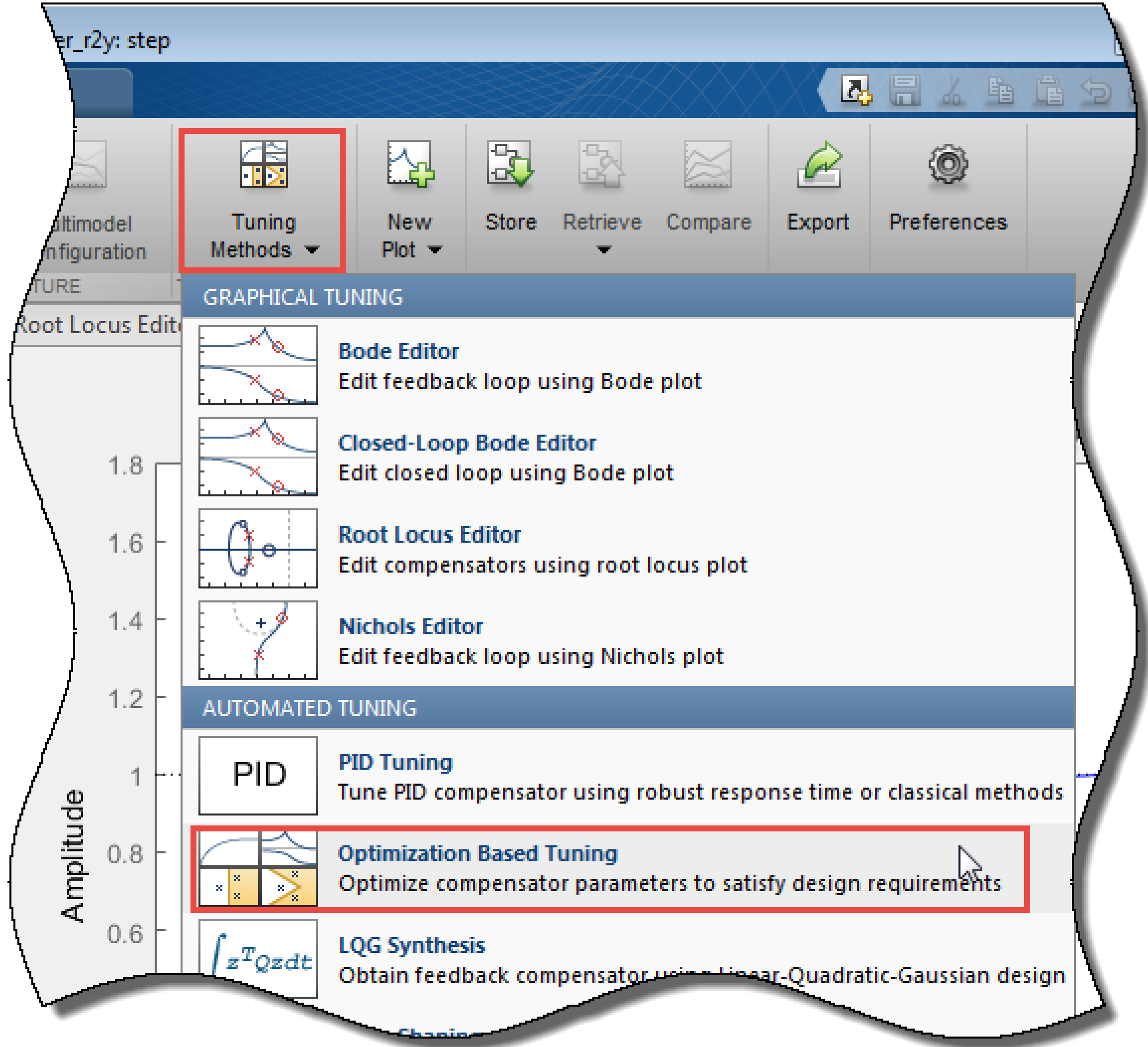
To choose the architecture for the control system you are designing, in the app click **Edit Architecture**. This example uses the default architecture. In this system, the plant model, *G*, is the open-loop transfer function `open_loopTF`. The prefilter, *F*, and the sensor, *H*, are set to `1`, and the compensator, *C*, is the compensator that is designed using response optimization methods.



Open Optimization Based Tuning Method

There are several possible methods for designing a SISO system; this example uses an automated approach that uses response optimization methods.

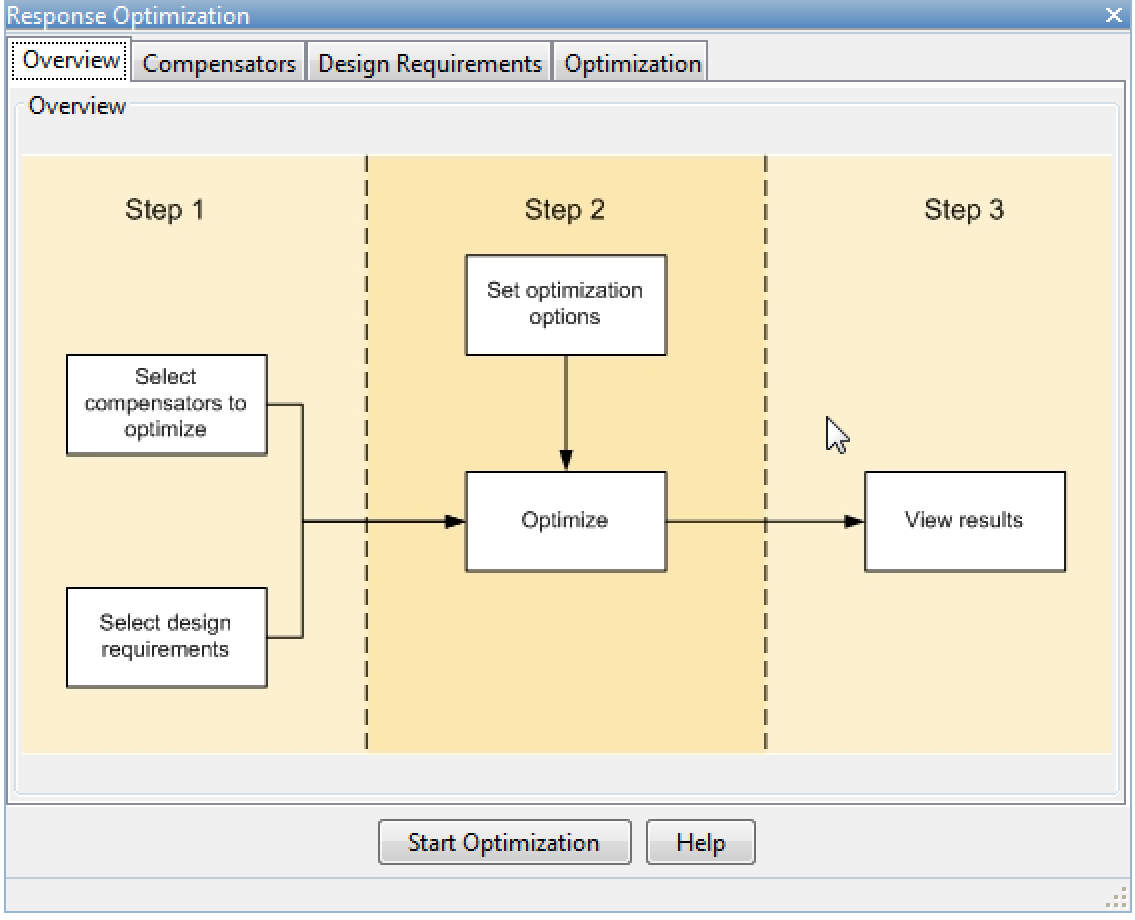
To create a response optimization task, in the **Tuning Methods** drop-down list, select `Optimization Based Tuning`.



The Response Optimization window has four tabs. Except for the first tab, each tab corresponds to a step in the response optimization process:

- **Overview** — Schematic diagram of the response optimization process.
- **Compensators** — Select and configure the compensator elements that you want to tune. See “Select Tunable Compensator Elements” on page 5-33.
- **Design requirements** — Select the design requirements that you want the system to meet after tuning the compensator elements. See “Add Design Requirements” on page 5-34.
- **Optimization** — Configure optimization options, and view the progress of the response optimization. See “Optimize the System Response” on page 5-42.

Note When optimizing responses in the app, you cannot add uncertainty to parameters or compensator elements.



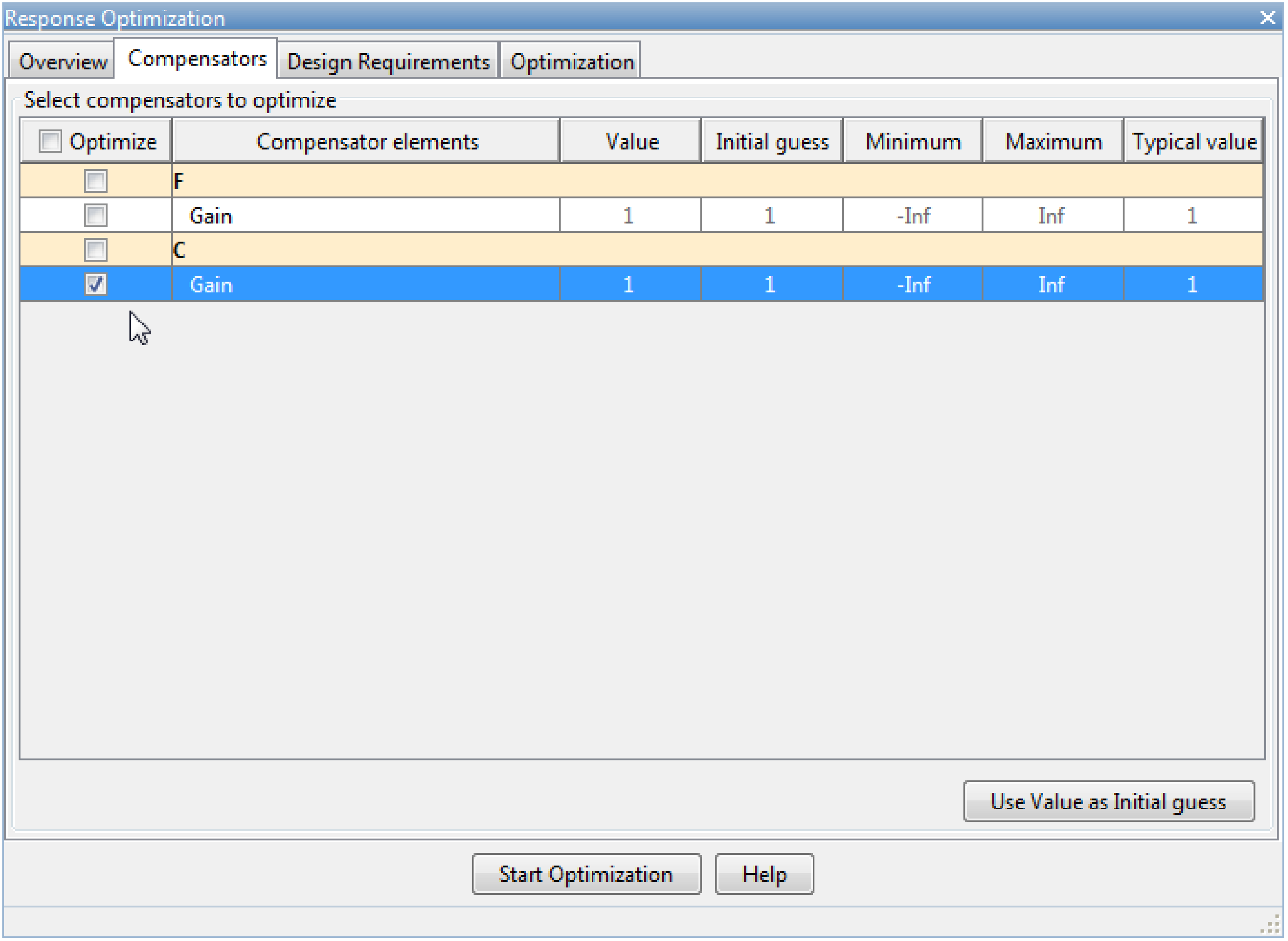
Select Tunable Compensator Elements

You can tune compensator elements or parameters within compensators in your system to meet the design requirements you specify.

To specify the compensator elements to tune:

1. In the Response Optimization window, select the **Compensators** tab.
2. In the **Compensators** tab, select the check boxes in the **Optimize** column that correspond to the compensator elements to tune.

   In this example, select **Gain** in the compensator **C**.



Add Design Requirements

You can use both frequency-domain and time-domain design requirements to tune parameters in a control system.

This example uses the design specifications described in "Design Requirements" on page 5-27. Create design requirements to meet these specifications:

- "Settling Time Design Requirement" on page 5-35
- "Overshoot Design Requirement" on page 5-36
- "Rise Time Design Requirement" on page 5-37
- "Actuator Limit Design Requirement" on page 5-39

After you add the design requirements, you can select a subset of requirements for controller design, as described in "Select the Design Requirements to Use During Response Optimization" on page 5-41. In the **Design requirements** tab of the Response Optimization window, you can create design requirements and select the requirements you want to use for optimization.

Settling Time Design Requirement

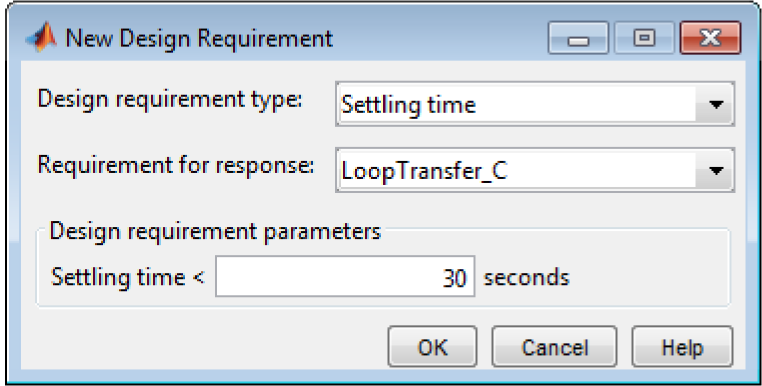
The first design requirement is to have a settling time of 30 seconds or less. This specification can be represented on a root locus diagram as a constraint on the real parts of the poles of the open-loop system.

To add the settling time design requirement:

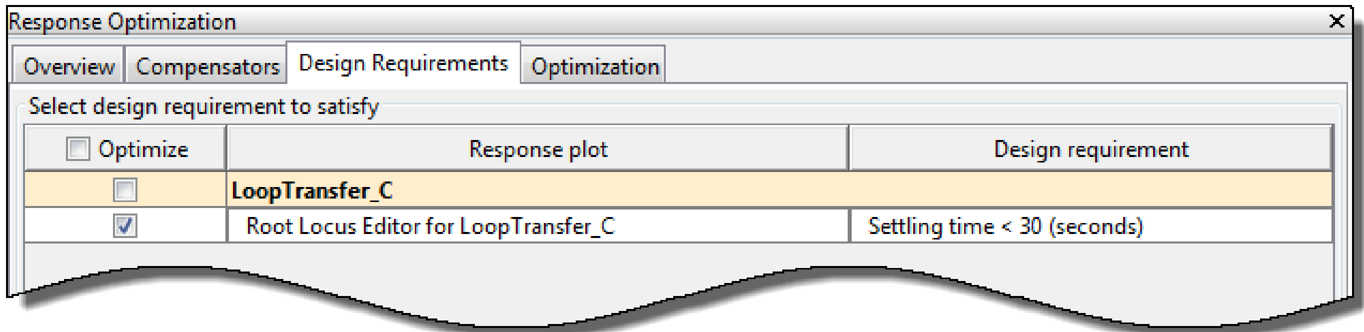
1. In the **Design requirements** tab, click **Add new design requirement**. A New Design Requirement dialog box opens.

   In this dialog box, you can specify new design requirements, and add them to a new or existing plot.
2. Add a design requirement to the existing root locus diagram.

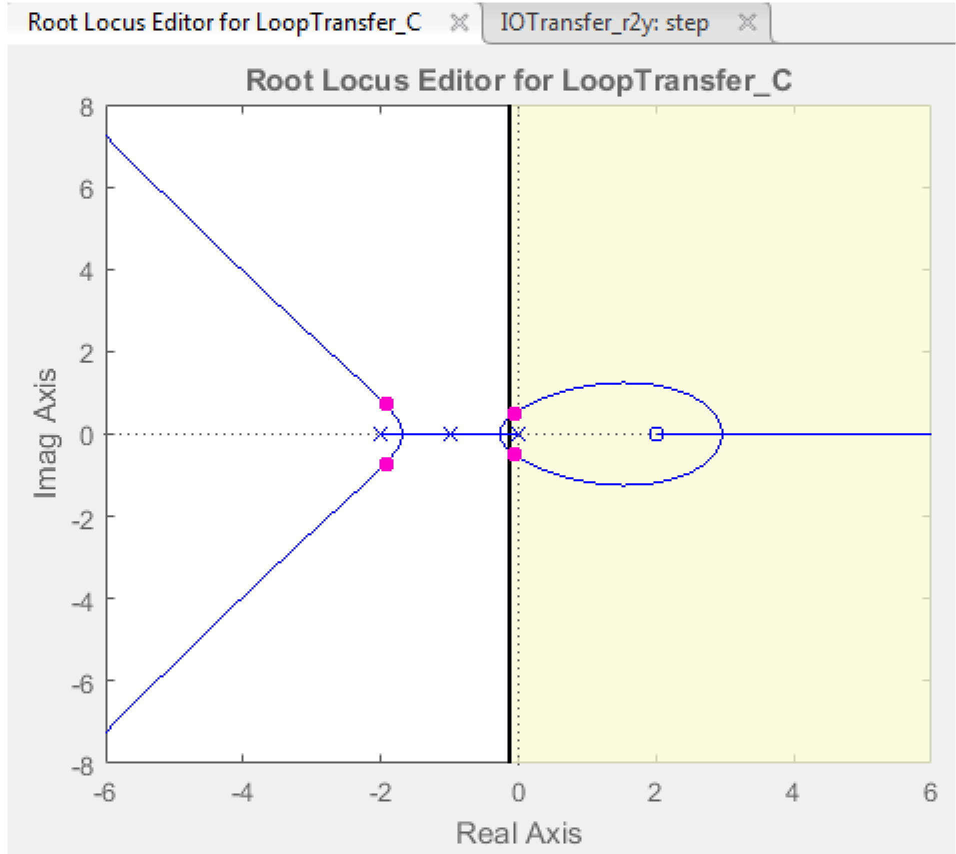
   a. In the **Design requirement type** drop-down list, select `Settling time`.
   b. In the **Requirement for response** drop-down list, select `LoopTransfer_C`.
   c. Specify **Settling time** as `30` seconds.
   d. Click **OK**.



The settling time design requirement is listed in the **Design Requirements** tab of the Response Optimization window.



In the app, the design requirement appears on the root locus plot as a vertical line.



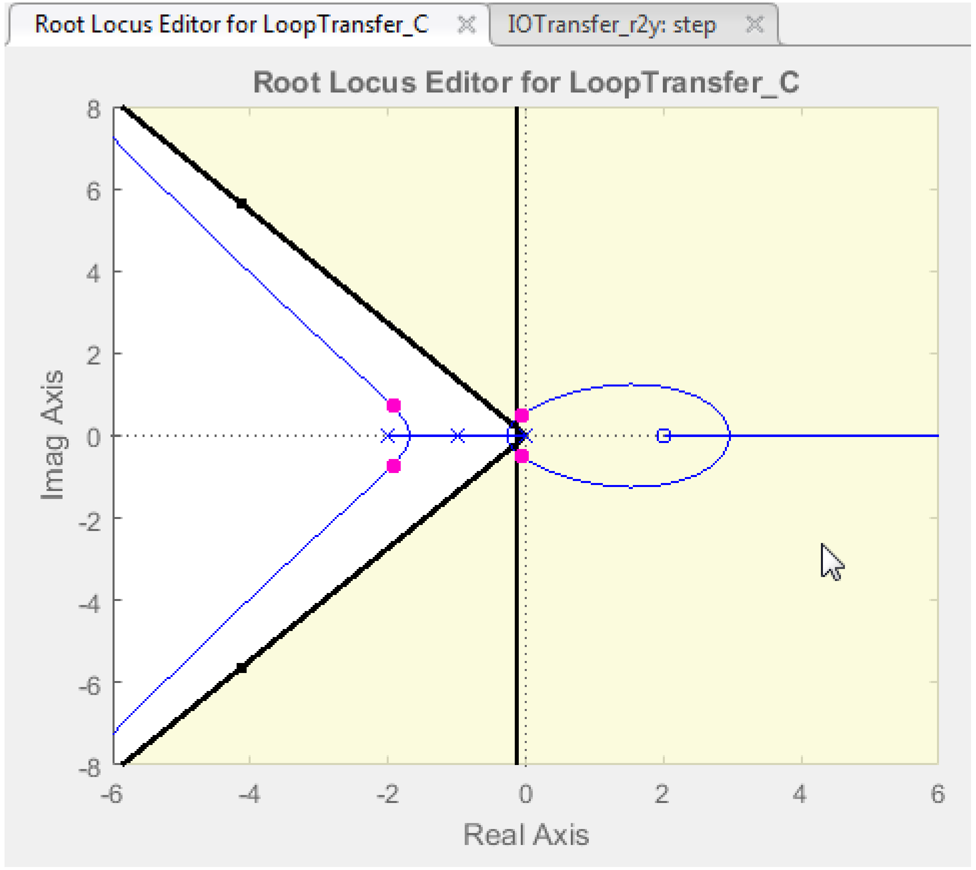
Overshoot Design Requirement

The second design requirement is to have a percentage overshoot of 10% or less. This requirement is related to the damping ratio on a root locus diagram. In addition to adding a design requirement with the **Add new design requirement** button, you can also right-click directly on the plots to add the requirement.

To add this design requirement:

1. In the **Control System Designer** app, right-click within the white space of the root-locus diagram. Select **Design Requirements** > **New** to open the New Design Requirement dialog box.
2. In the **Design requirement type** drop-down list, select `Percent overshoot`.
3. Specify **Percent overshoot** as `10`.
4. Click **OK**.

In the app, the design requirement appears on the root-locus plot as two lines radiating at an angle from the origin.

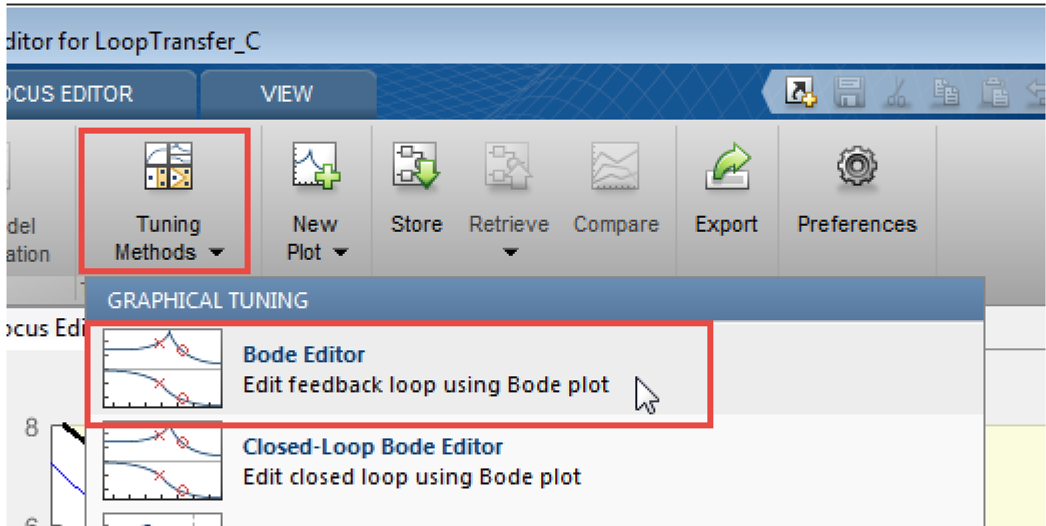


Rise Time Design Requirement

The third design requirement is to have a rise time of 10 seconds or less. This requirement corresponds to a lower limit on a Bode Magnitude diagram.

To add this design requirement:

1 In the app, in the **Tuning Methods** drop-down list, select `Bode Editor`.



2 In the Select Response to Edit dialog box, specify **Select Response to Edit** as `LoopTransfer_C`, and click **Plot**.

   A Bode plot is displayed in a **Bode Editor**.

3 Right-click within the white space of the open-loop Bode plot, and select **Design Requirements** > **New**, to open the New Design Requirement dialog box.

4 Specify the design requirement to represent the rise time, and add it to the new Bode plot.

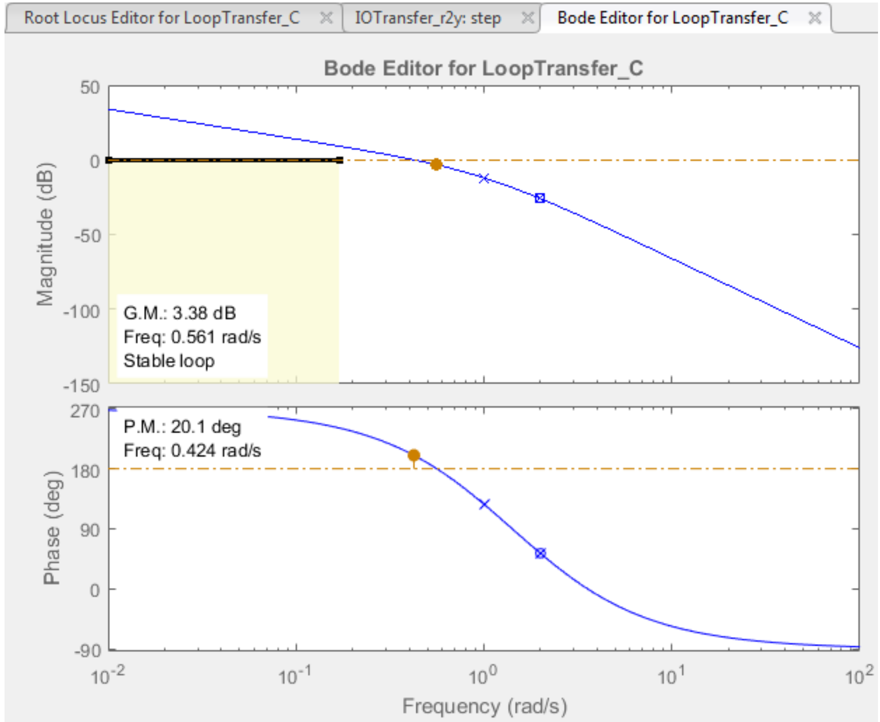
   a In the **Design requirement type** drop-down list, select `Lower gain limit`.

   b Specify the **Frequency** range as `1e-2` to `0.17`.

   c Specify the **Magnitude** range as `0` to `0`.

   d Click **OK**.

   The design requirement appears on the plot as a horizontal line.



Actuator Limit Design Requirement

The fourth design requirement is to limit the actuator signal to within ±0.7.

To add this design requirement:

1. In the Response Optimization window, in the **Design requirements**, click **Add new design requirement**. A New Design Requirement dialog box opens.
2. Create a time-domain design requirement to represent the upper limit on the actuator signal, and add it to a new step response plot:

    a. In the **Design requirement type** drop-down list, select `Step response upper amplitude limit`.

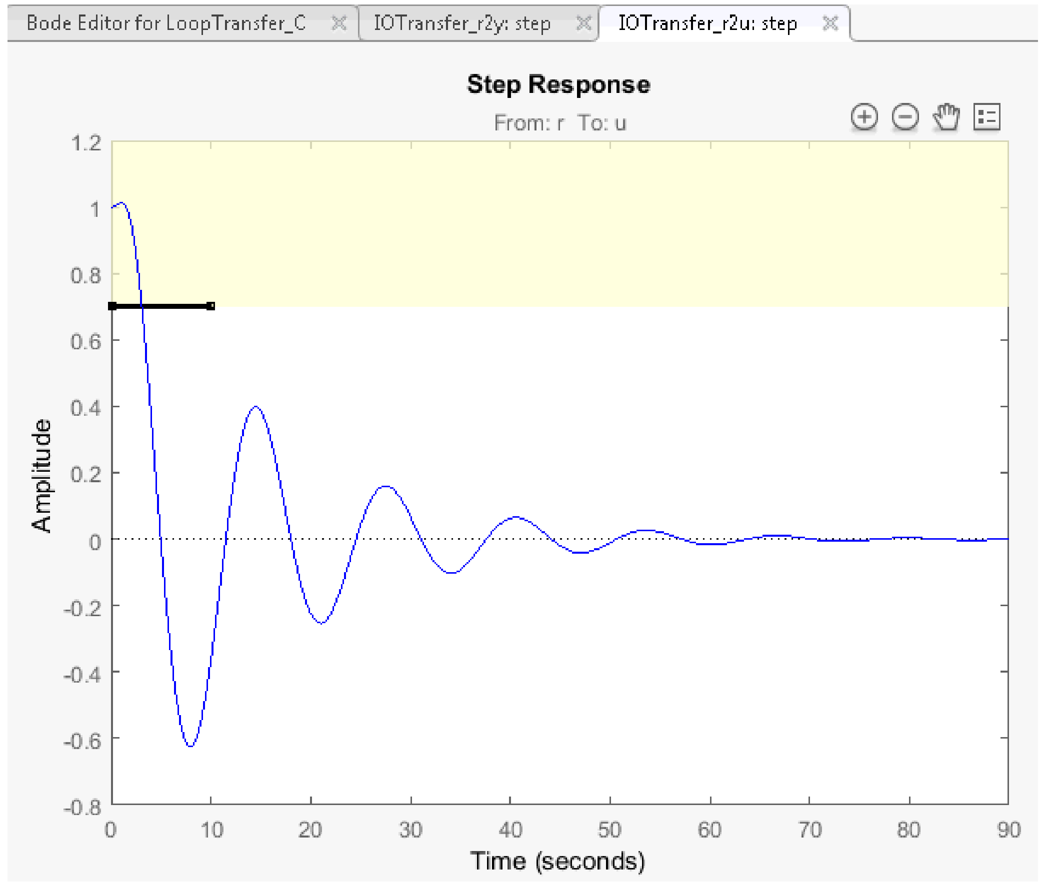
    b. In the **Requirement for response** drop-down list, select `IOTransfer_r2u`.

    c. Specify the **Time** range as `0` to `10`.

    d. Specify the **Amplitude** range as `0.7` to `0.7`.

    e. Click **OK**. A second step response plot for the closed-loop response from `r` to `u` is generated in the app. The plot contains a horizontal line representing the upper limit on the actuator signal.

    f. To extend this limit for all times (to $t = \infty$), right-click in the yellow shaded area, and select **Extend to inf**.



To add the corresponding design requirement for the lower limit on the actuator signal:

1. In the Response Optimization window, in the **Design requirements**, click **Add new design requirement**. A New Design Requirement dialog box opens.
2. Create a time-domain design requirement to represent the lower limit on the actuator signal, and add it to the step response plot:

   a. In the **Design requirement type** drop-down list, select `Step response lower amplitude limit`.

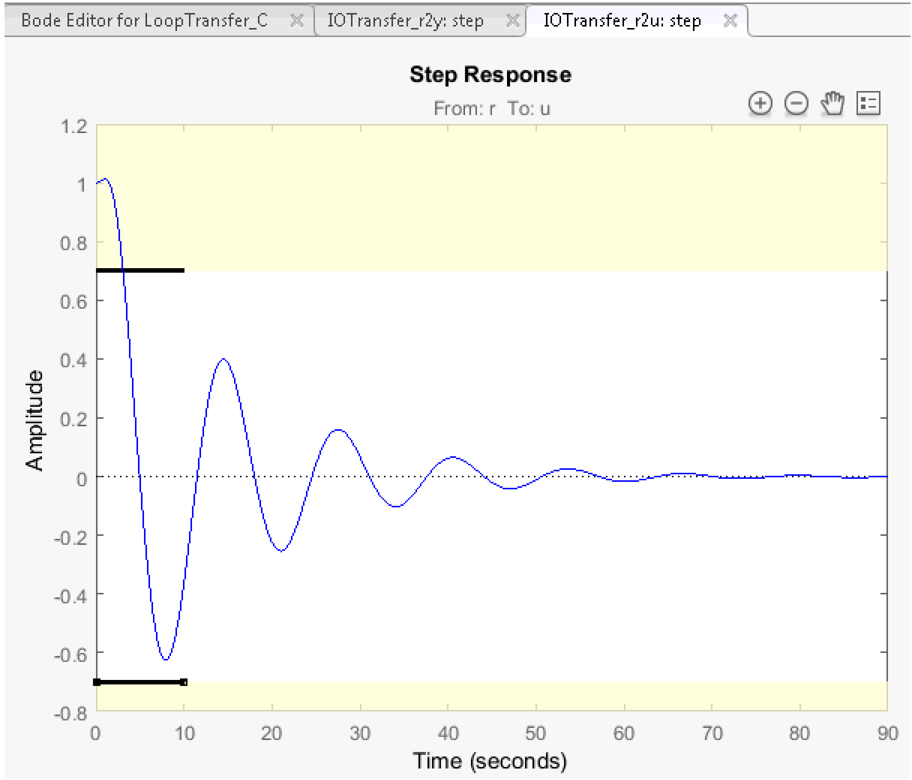
   b. In the **Requirement for response** drop-down list, select `IOTransfer_r2u`.

   c. Specify the **Time** range as `0` to `10`.

   d. Specify the **Amplitude** range as `-0.7` to `-0.7`.

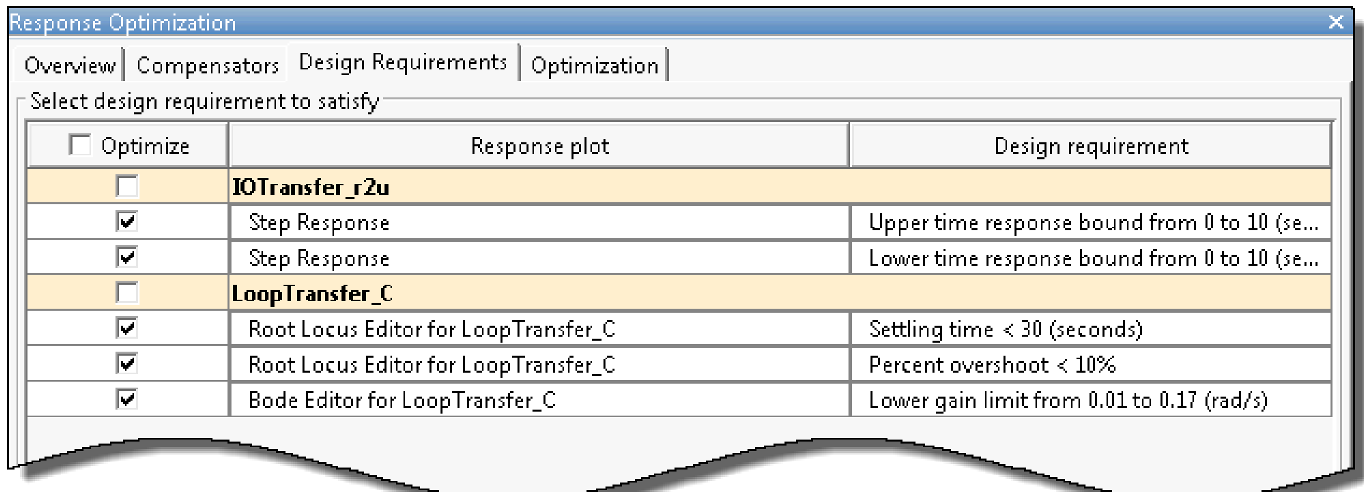
   e. Click **OK**. The step response plot now contains a second horizontal line representing the lower limit on the actuator signal.

   f. To extend this limit for all times (to $t = \infty$), right-click in the yellow shaded area of the design requirement, and select **Extend to inf**.



Select the Design Requirements to Use During Response Optimization

The table in the **Design requirements** tab lists all the specified design requirements. Select the design requirements you want to use in the response optimization. This example uses all the current design requirements.

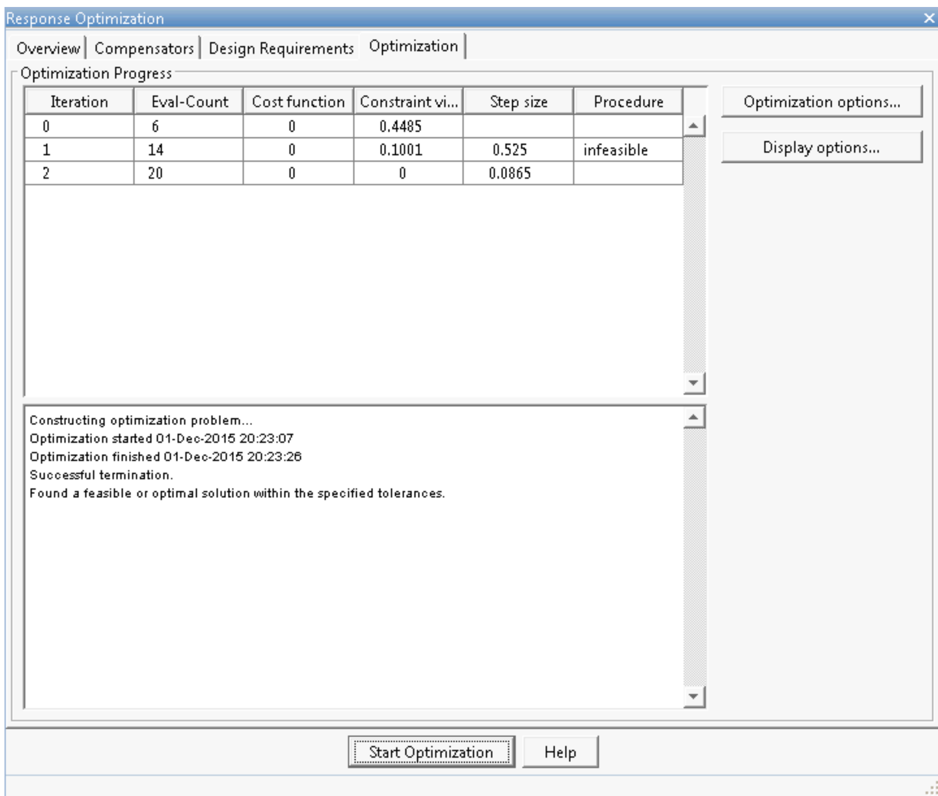


Optimize the System Response

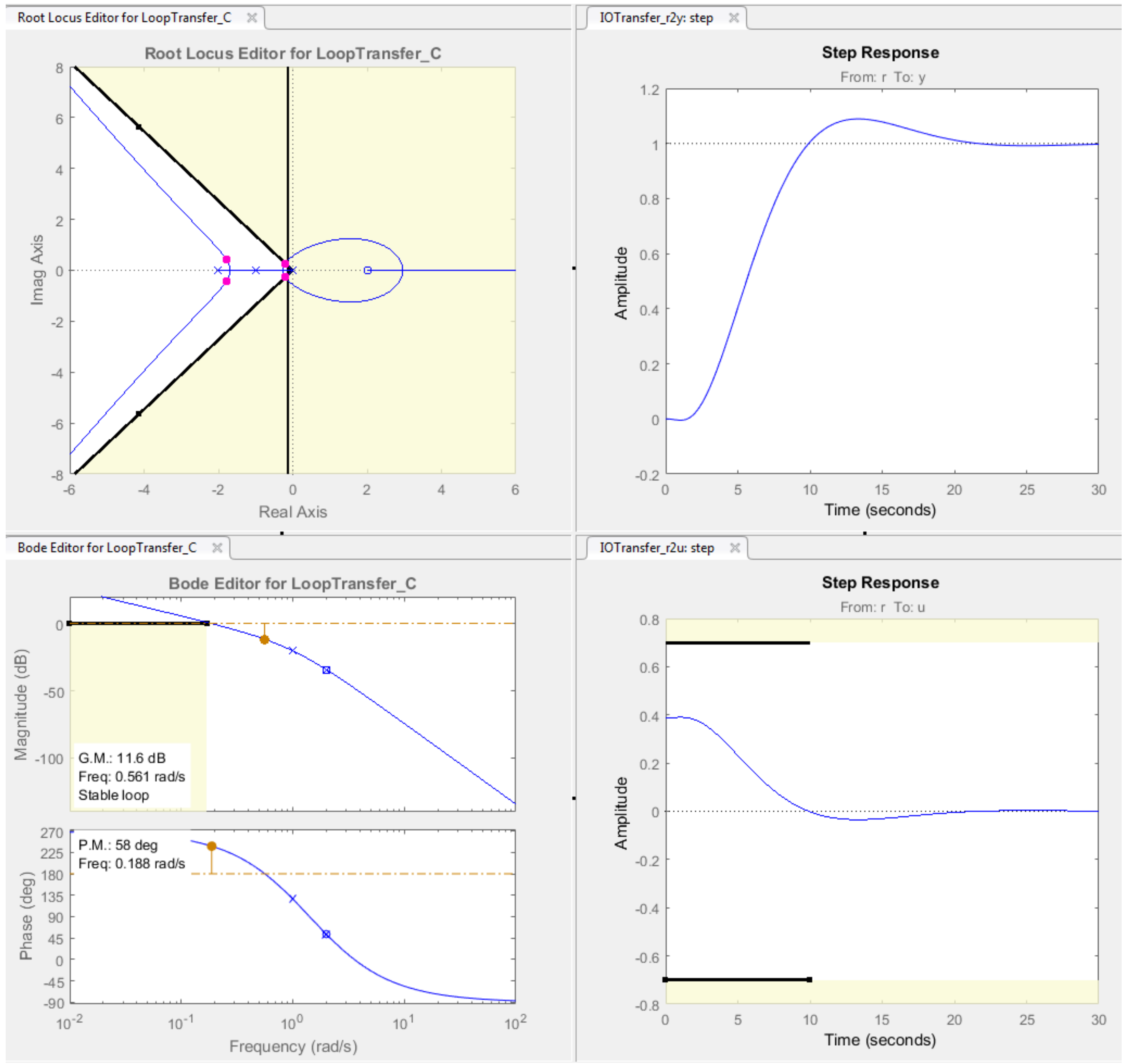
After you select the compensator elements to tune and add design requirements, you can optimize the system response.

To optimize the response of the system, in the **Optimization** tab of the Response Optimization window, click **Start Optimization**.

The **Optimization** tab displays the progress of the optimization.



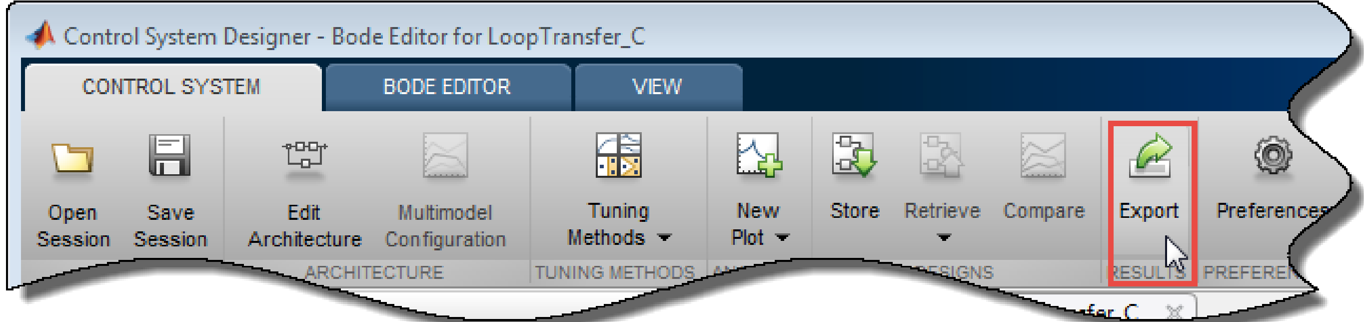
The status message indicates that the optimization solver found a solution that meets the design requirements within the tolerances. Verify that the design requirements are satisfied.



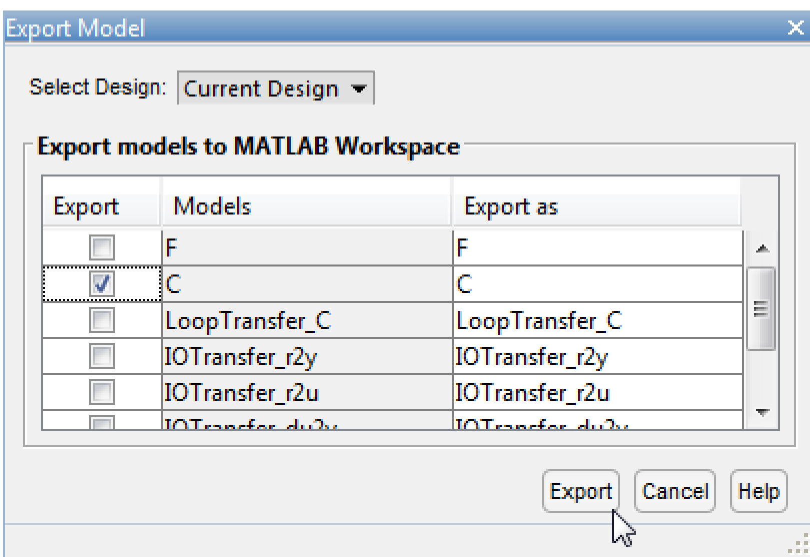
Create and Display the Closed-Loop System

After designing a compensator, you can export it to the MATLAB workspace and create a model of the full closed-loop system. To export the tuned compensator:

1 In the app, select **Export**.



2 In the Export Model dialog box, select **C**, the compensator you designed, and click **Export**.



At the command line, enter the following command to create the closed-loop system, `CL`, from the open-loop transfer function, `open_loopTF`, and the compensator, `C`:

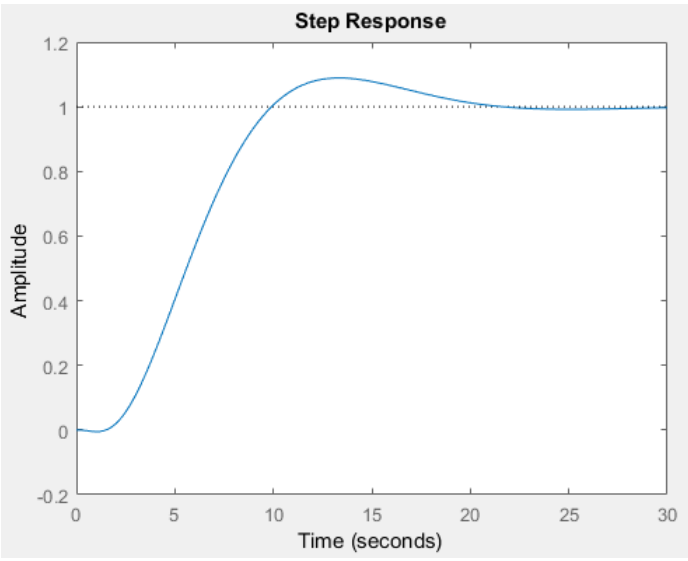
```
CL = feedback(C*open_loopTF,1)
```

The following model is returned:

```
CL =

                 -0.19414 (s-2)
  ---------------------------------------------
  (s^2 + 0.409s + 0.1136) (s^2 + 3.591s + 3.418)

Continuous-time zero/pole/gain model.
```

To create a step response plot of the closed-loop system, enter the following command.

```
step(CL);
```



See Also

More About

- "Design Optimization-Based Controllers for LTI Systems" on page 5-26
- "Time-Domain Simulations in Control System Designer App" on page 5-25

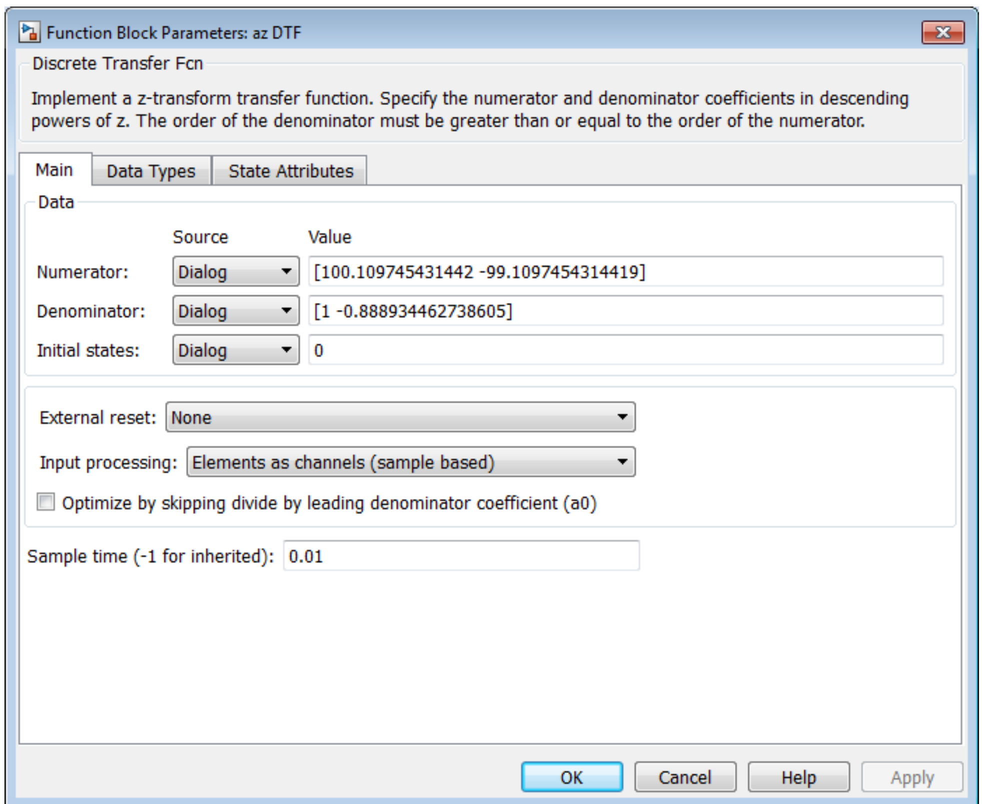
Design Linear Controllers for Simulink Models

When you have Control System Toolbox and Simulink Control Design software, you can perform frequency-domain optimization of Simulink models.

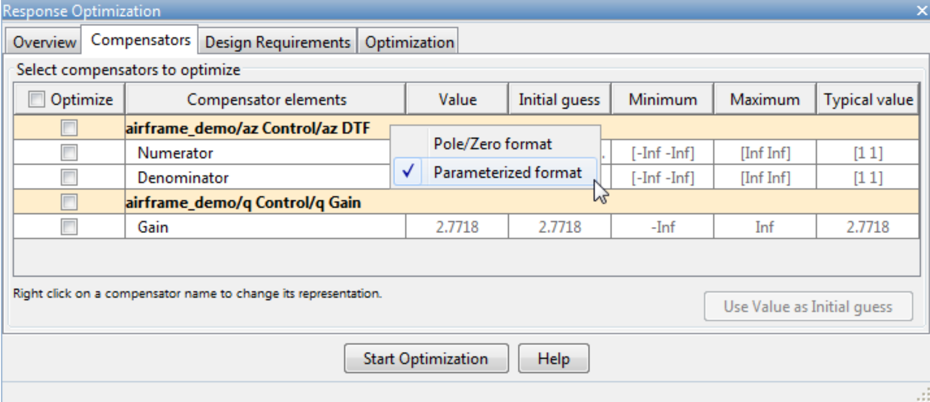
You can use Simulink Control Design software to configure the **Control System Designer** app with compensators, inputs, outputs, and loops computed from a Simulink model. For more information, see topics in the “Classical Control Design” (Simulink Control Design) category.

After you configure the **Control System Designer** app, use Simulink Design Optimization software to optimize the controller parameters of the linearized Simulink model. For an example of optimization-based control design for a model linearized using Simulink Control Design software, see “Design Optimization-Based PID Controller for Linearized Simulink Model (GUI)”.

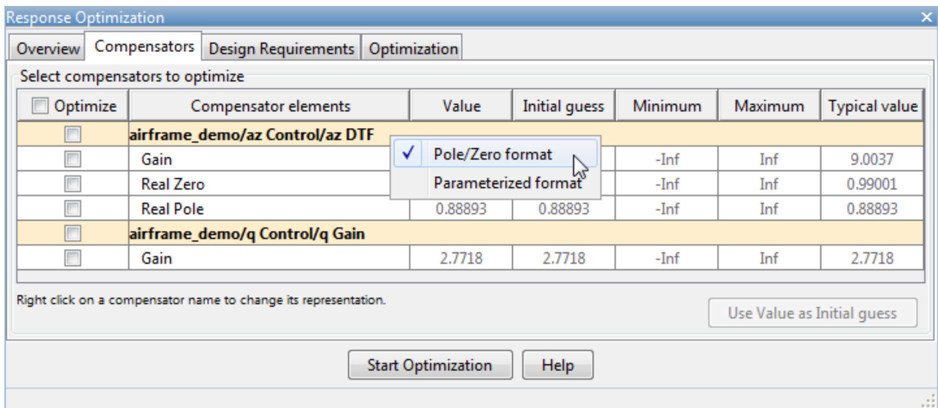
When tuning compensators derived from Simulink Control Design software, the tuning of compensators from a Simulink model is done through the masks of the Simulink blocks representing each compensator. When selecting parameters to optimize, you can tune the compensator in the pole, zero, or gain format, or in a format consistent with the Simulink block mask.



Mask of a Simulink Compensator Block



Response Optimization Compensators Tab — Parameterized Format



Response Optimization Compensators Tab — Pole/Zero Format

Note You cannot change the compensator format if the compensator is not a Simulink block.

See Also

Related Examples

- “Design Optimization-Based PID Controller for Linearized Simulink Model (GUI)”

Enforcing Time and Frequency Requirements on a Single-Loop Controller Design

This example shows how to use Simulink® Design Optimization™ to tune a compensator in a Simulink model. You will add performance requirements to further refine and optimize an initial compensator design performed with Simulink® Control Design™ (see “Single Loop Feedback/ Prefilter Compensator Design” (Simulink Control Design)).

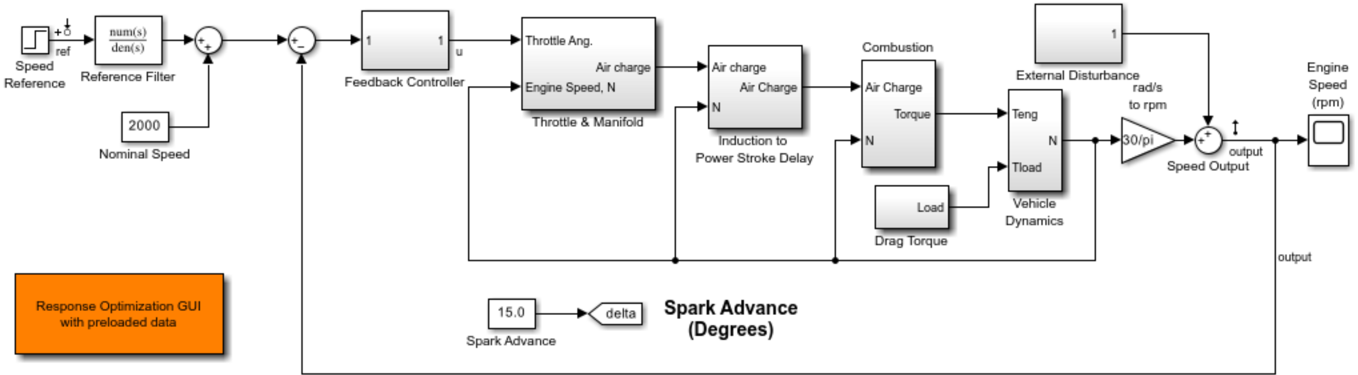
Using Simulink Design Optimization software you can graphically specify design and performance requirements for your system by positioning bounds on response plots such as Bode, Nichols, Pole/ Zero, Step, or Impulse. Then, using optimization-based methods you can automatically tune compensator elements to satisfy the design requirements. Compensator elements that are tunable via optimization-based tuning include gains, poles, and zeros.

This example requires Simulink® Control Design™.

Opening the Model

Open the model using the command below, and double click on the orange block to launch the **Control System Designer** app.

```
open_system('speedctrl_demo')
```



Design Overview

This example designs a single feedback loop for the speed control of an engine. A preliminary PI controller design has been created using Simulink Control Design (see “Single Loop Feedback/ Prefilter Compensator Design” (Simulink Control Design)) and is used as a starting point to further refine the design using response optimization. This example will tune the controller to satisfy the following time-domain and frequency-domain performance specifications:

Requirement 1. A lower amplitude limit on the step response output of -0.1 and a 3 second rise time to reach 95% of the set-point value.

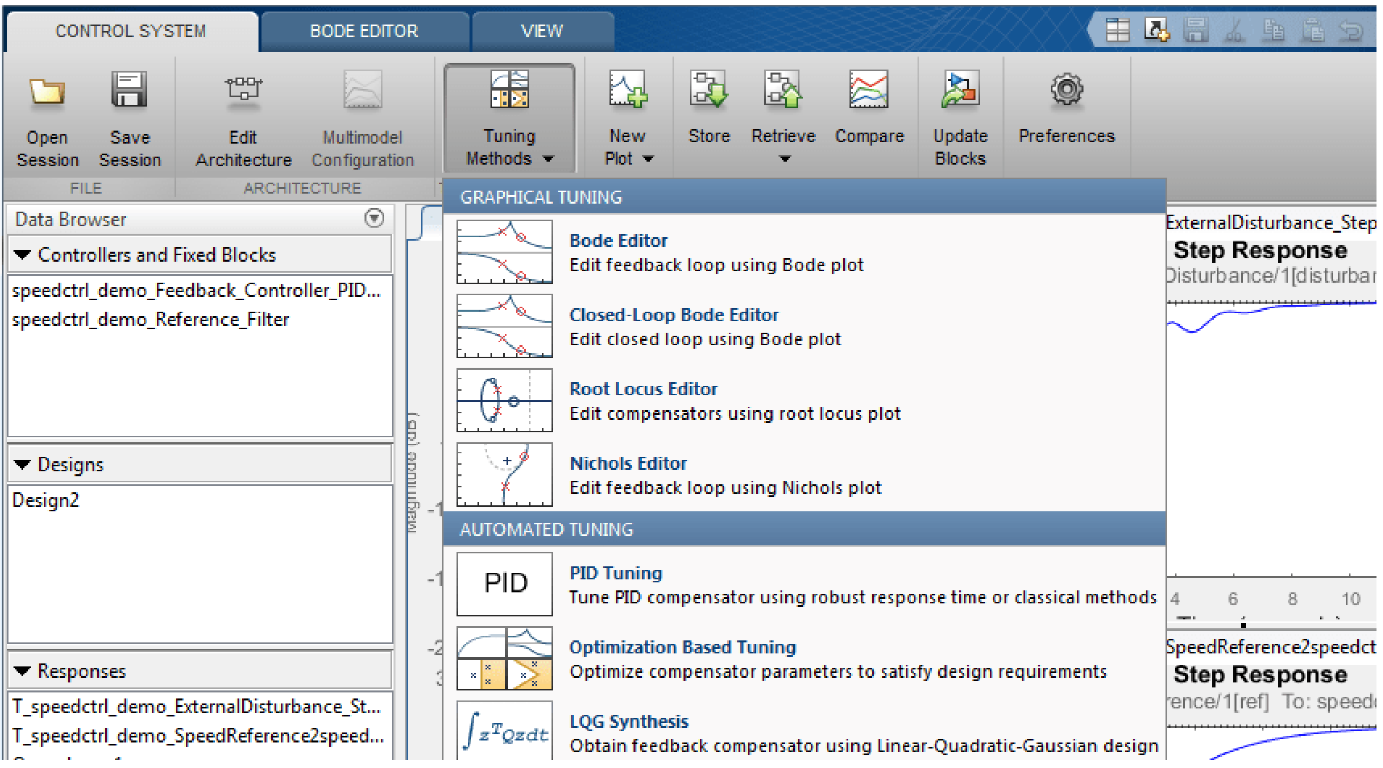
Requirement 2. A maximum overshoot of 1% for the unit step response from `Speed Reference` to `Speed Output`.

Requirement 3. A minimum loop gain of 10db over the frequency range 1e-4 to 1 rad/sec to ensure good output disturbance rejection and reference tracking over this frequency range.

Requirement 4. A maximum loop gain of -10db over the frequency range 10 to 1e4 rad/sec to ensure adequate high frequency noise rejection, and together with the low frequency requirement, to ensure a loop bandwidth of between 1 and 10 rad/sec.

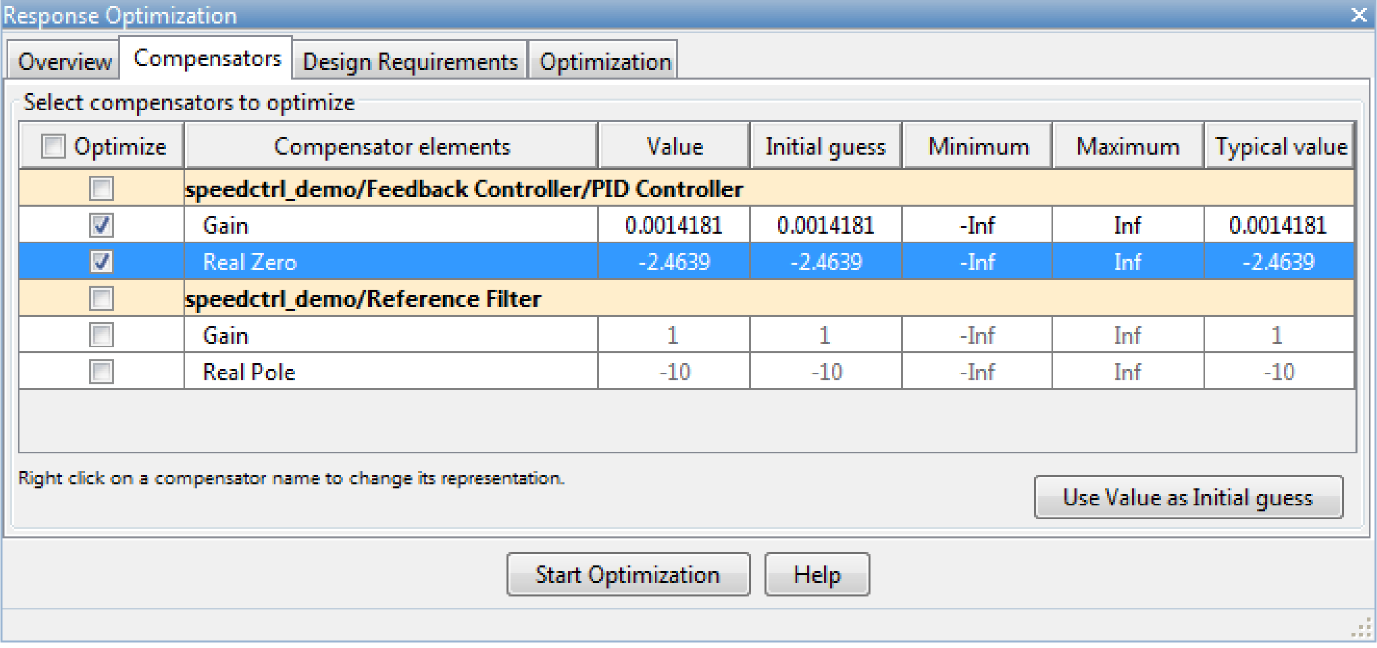
Launching Simulink Design Optimization

Both time- and frequency-domain response optimization are integrated into the Control System Designer app. In the **Control System** tab, in the **Tuning Methods** drop-down list, select **Optimization Based Tuning**.



Configuring an Optimization

The first step in configuring an optimization is to select the compensator elements to tune. For this example select the `Gain` and `Real Zero` of the PID controller; the reference filter is not tuned.



Adding Design Requirements

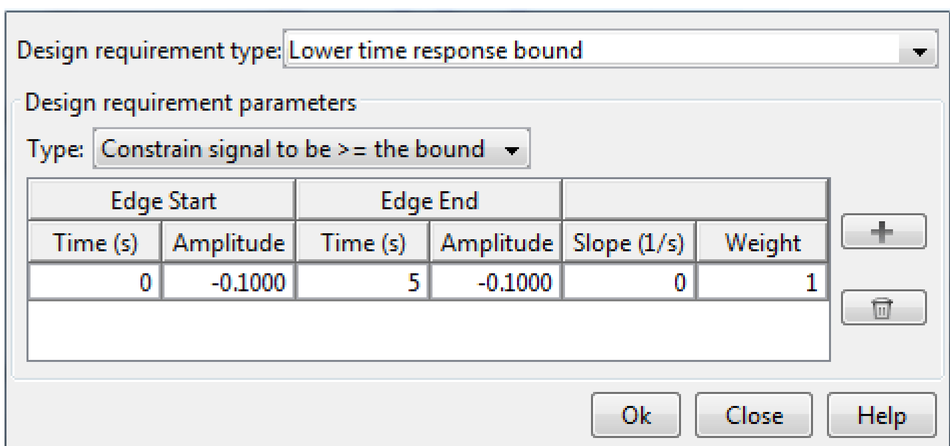
The next step is to create the design requirements that the optimization should satisfy. Design requirements are visualized on system response plots. You can add response plots by using the **Graphical Tuning** or the **New Plot** drop down lists in the Control System Designer app. The “Getting Started with the Control System Designer” (Control System Toolbox) example shows how to use the Control System Designer.

There are two ways to add requirements; you can add them using the **Add new design requirement** button on the **Design Requirements** tab in the **Response Optimization** window or by right clicking on a response plot and selecting **Design Requirements->New**.

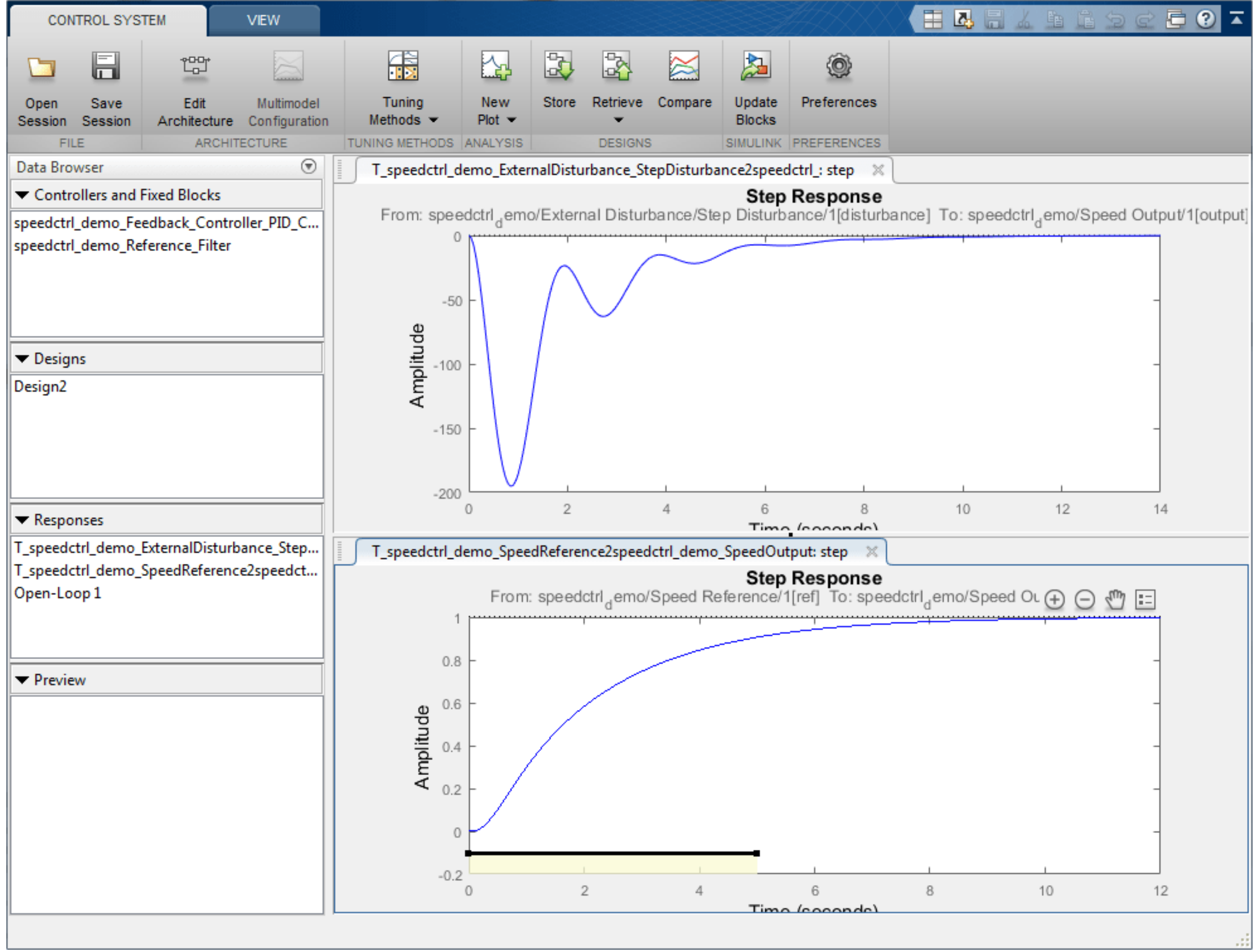
To add **Requirement 1** to limit the lower amplitude of the output resulting from a step input,

1. Right click on the lower step response plot and select **Design Requirements->New** .

2. Specify the lower limit as -0.1 over the time range 0 to 5 seconds.

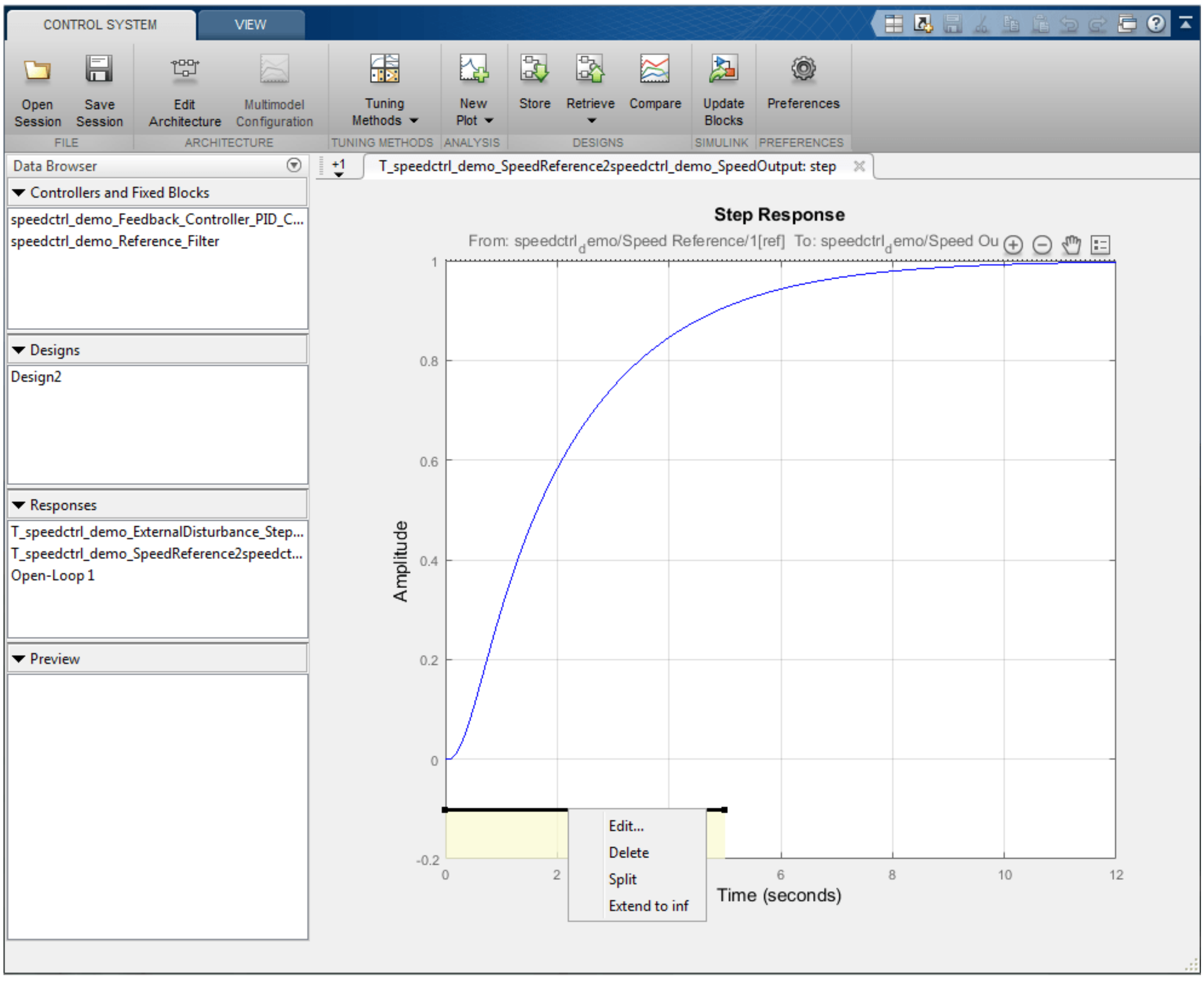


This creates the lower amplitude limit on the step response plot as shown in the next figure.

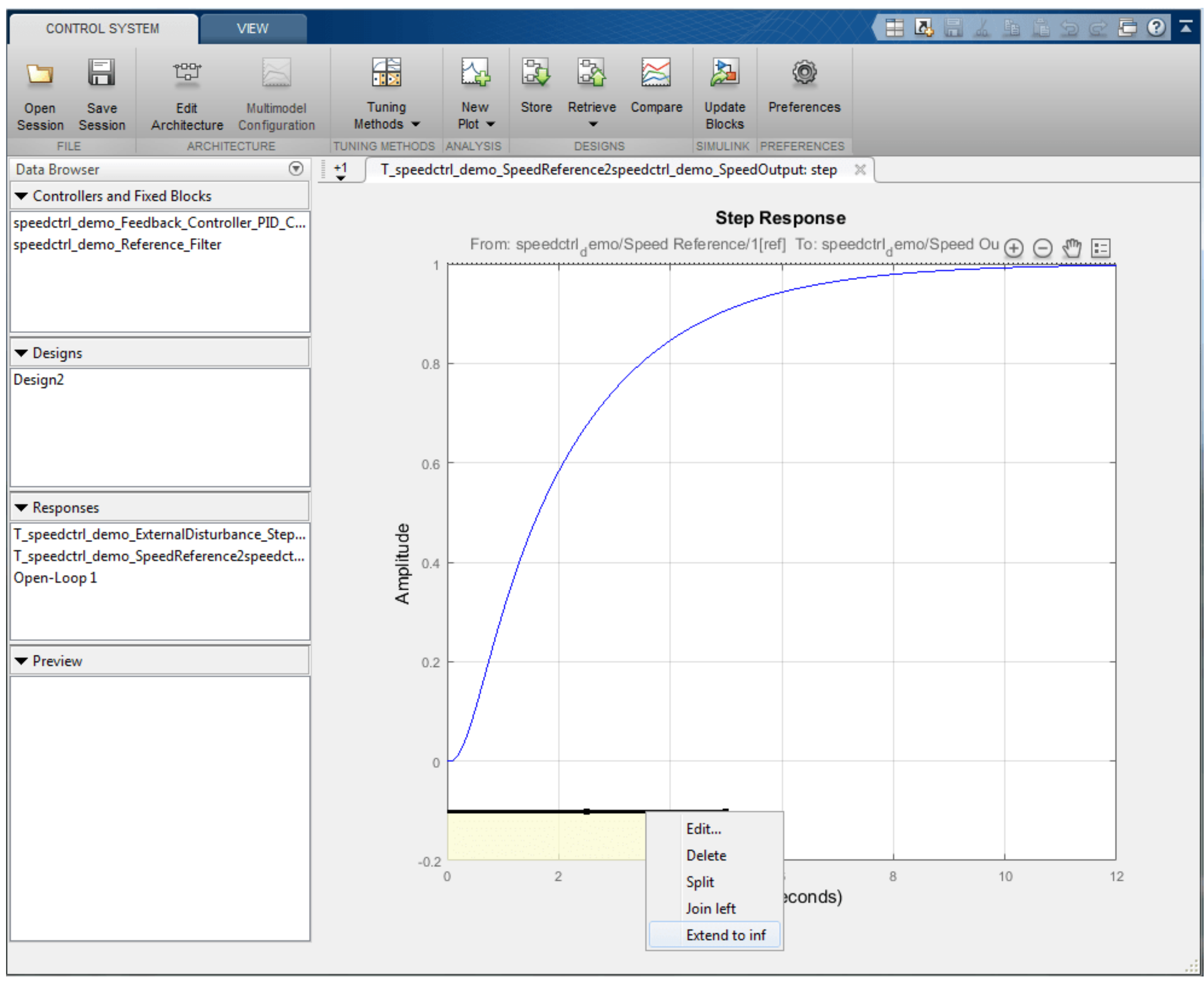


To add the rise time requirement to the step response, you can graphically manipulate the lower amplitude requirement on the step response plot.

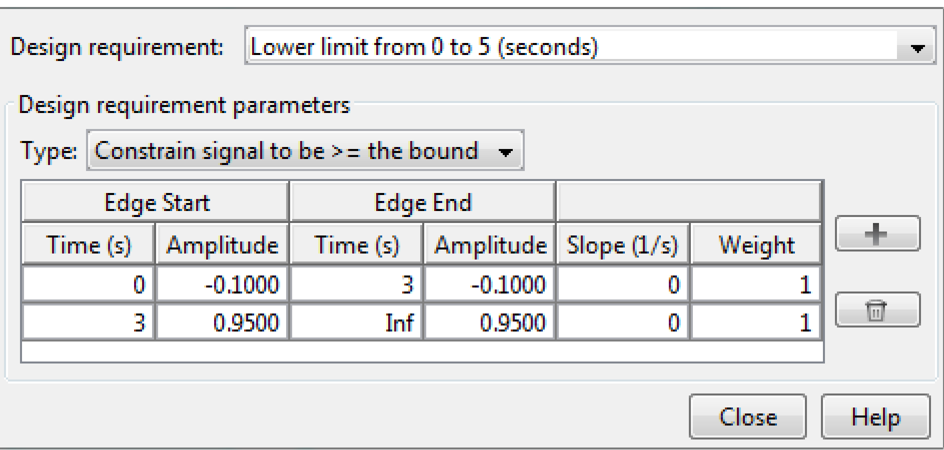
1. Right click the lower amplitude limit requirement and select **Split** to split a segment into two pieces.



2. Right click the second segment of the requirement and select **Extend to inf** to extend it to infinity.

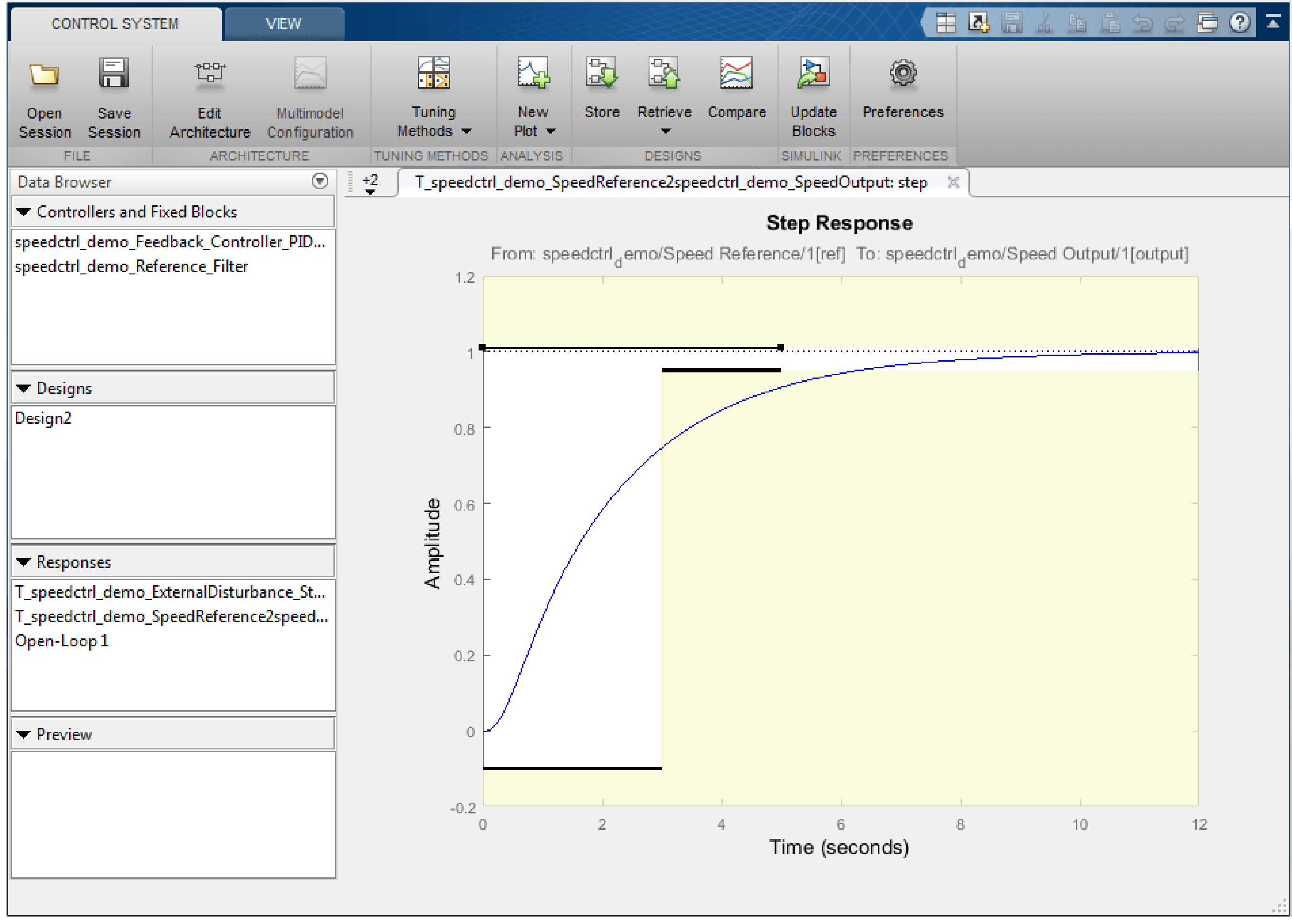


3. Right click the second segment of requirement, select **Edit**, and set the values to represent a 95% rise time at 3 seconds.



Alternatively you can left click the second segment of the requirement and drag it into position.

Next add **Requirement 2** for maximum overshoot to the step response plot. The time-domain constraints on the step response plot are shown in the next figure.

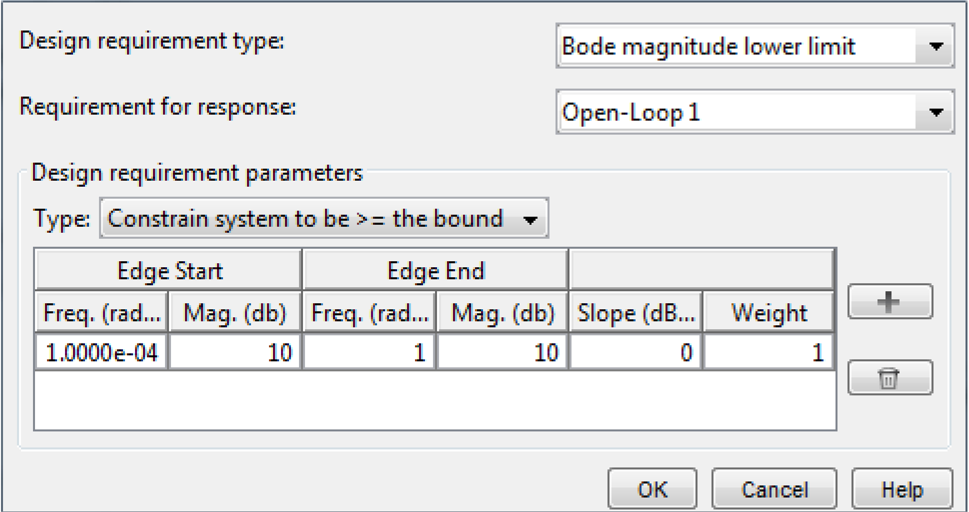


The plot shows the lower amplitude limit of -0.1, maximum overshoot and 95% of the unit step response value of 1.01 and 0.95 respectively.

To add **Requirement 3** for minimum loop gain,

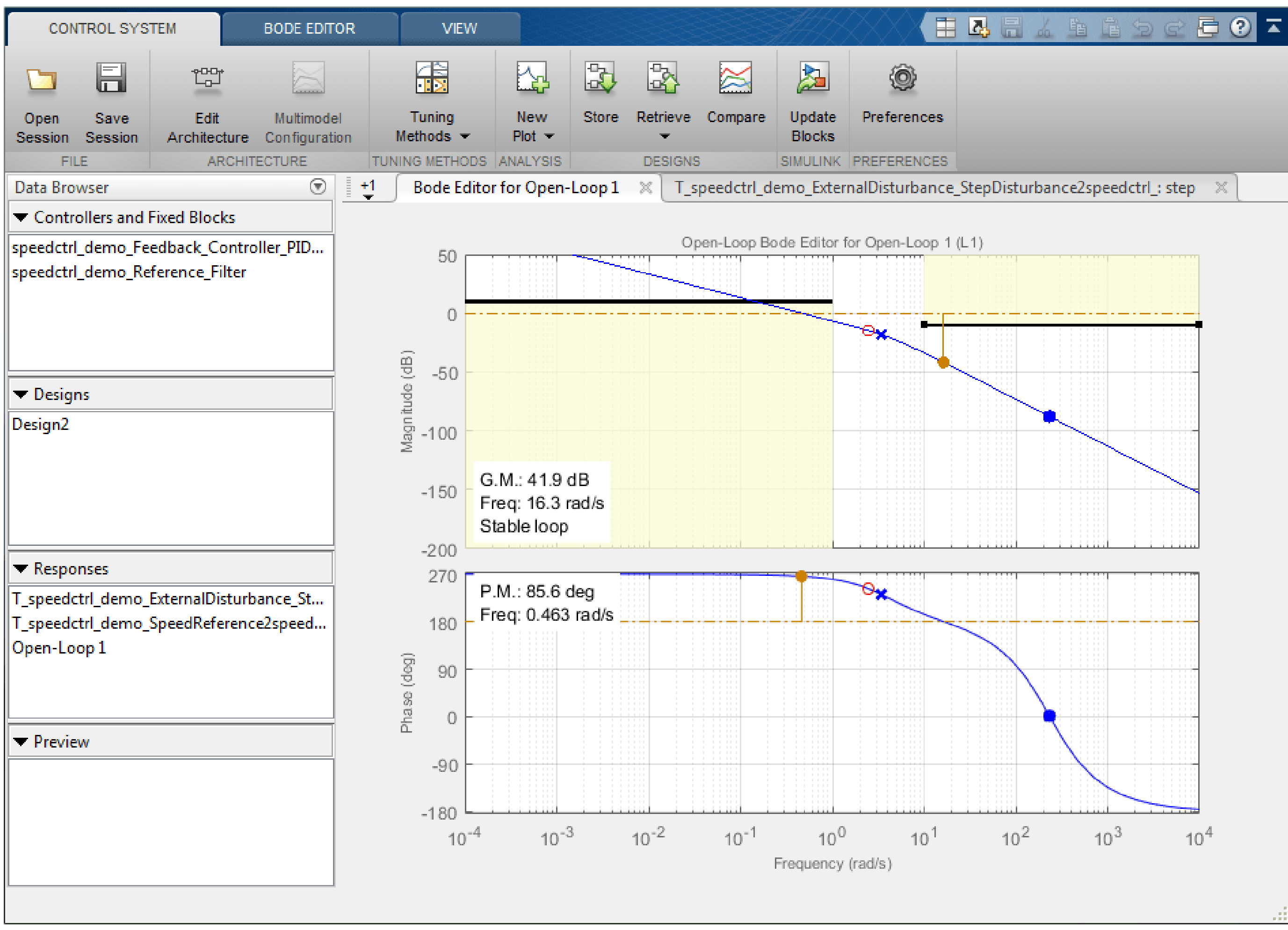
1. Click **Add new design requirement** in the **Design Requirements** tab of the **Response Optimization** window.

2. Specify the Bode magnitude lower limit for the open loop as 10db over the frequency range 1e-4 to 1 rad/sec.

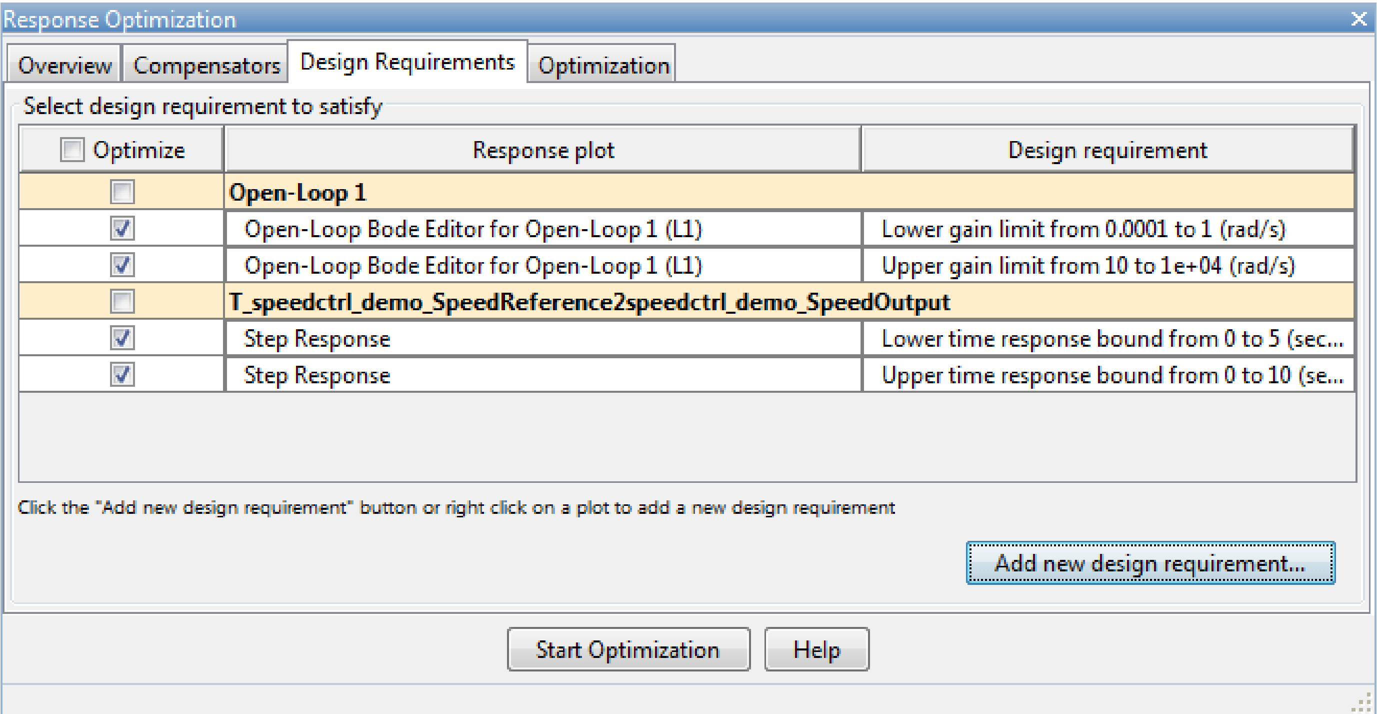


This creates the minimum loop gain constraint on the Bode magnitude plot as shown in the next figure.

Add **Requirement 4** for the maximum loop gain to the Bode magnitude plot to satisfy the overall design specifications. The Bode magnitude plot shows the minimum and maximum loop gain over the specified frequency range.

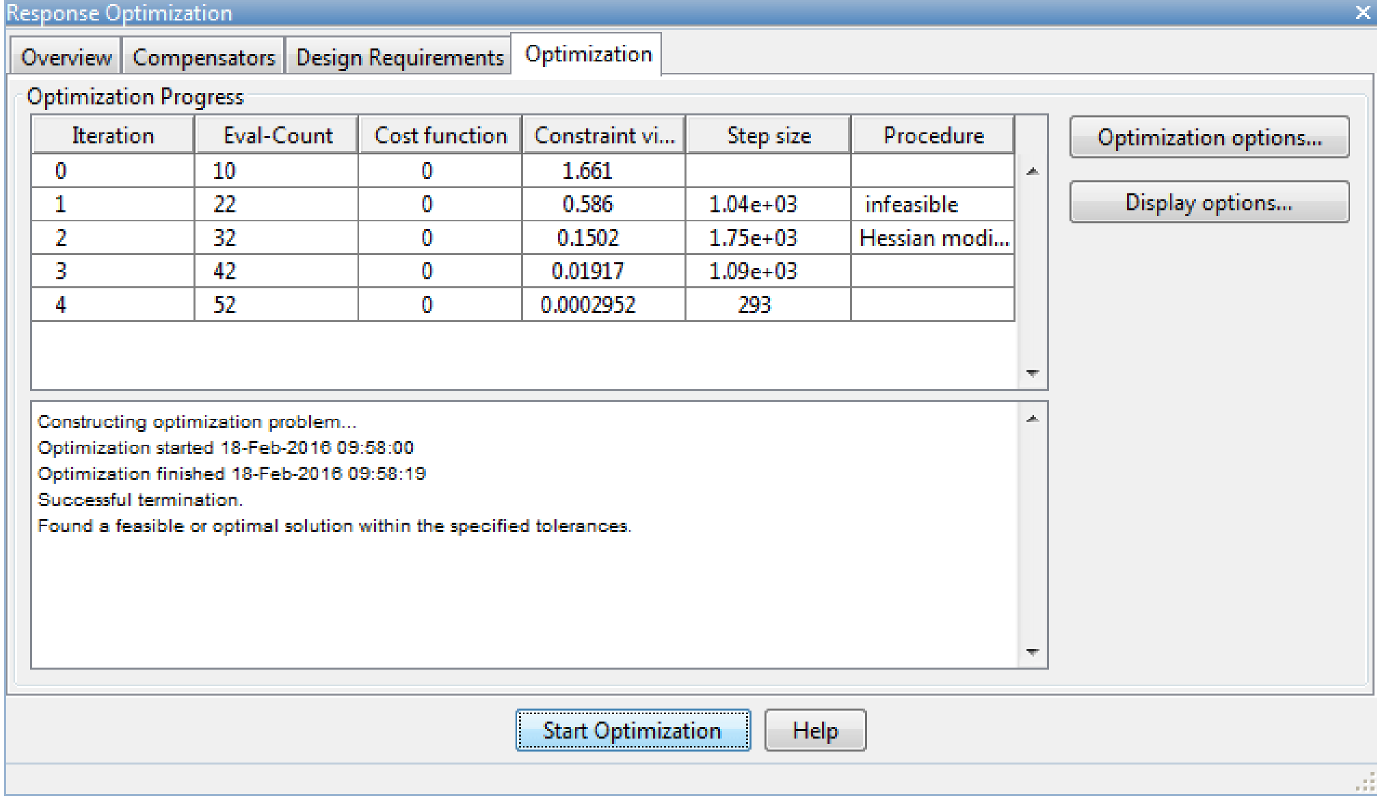


Select the design requirements for optimization from the **Design Requirements** tab. After you have selected the requirements, the **Design Requirements** table appears as shown next:



Running an Optimization

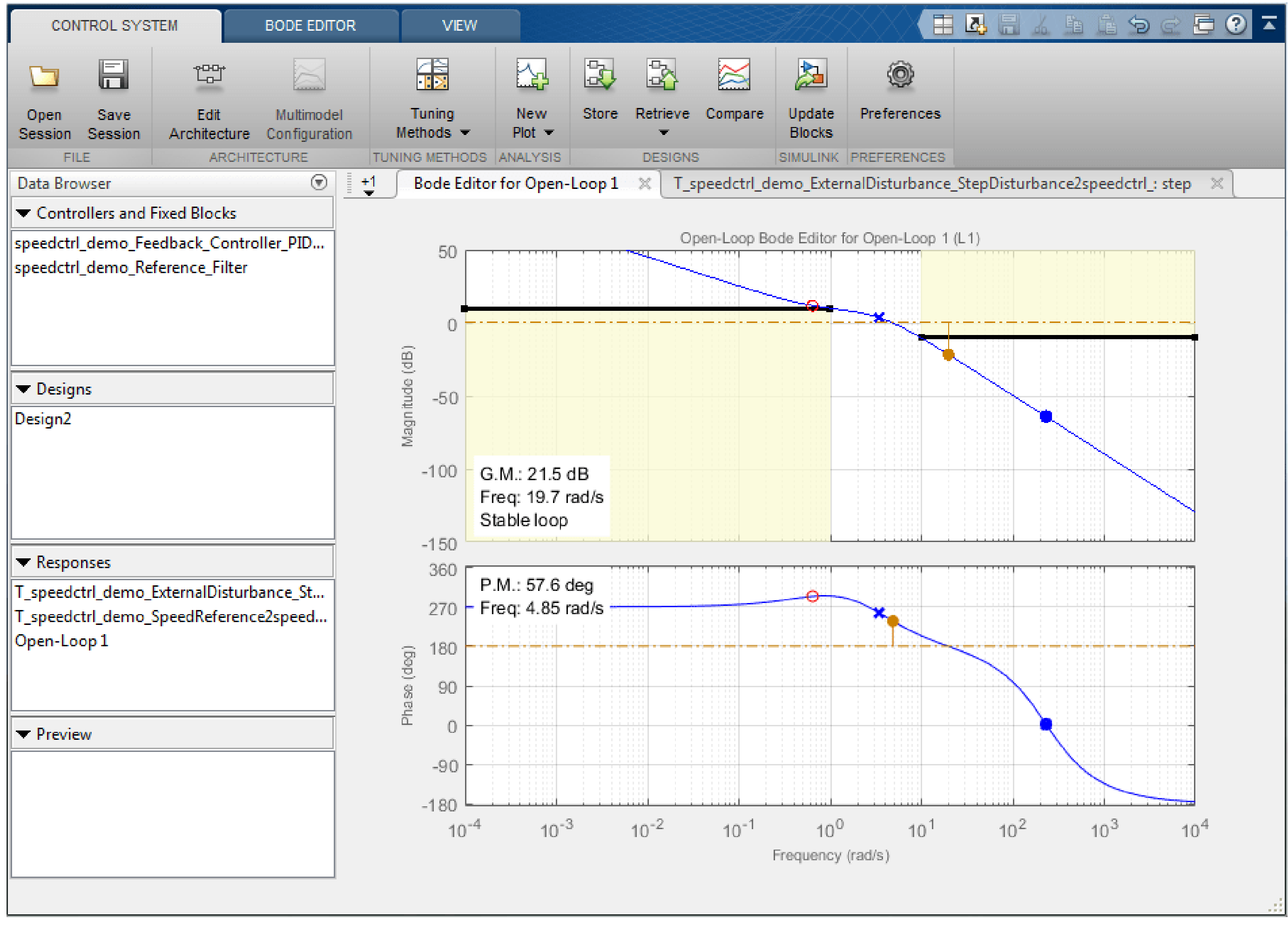
After defining the design requirements and selecting the compensator elements to tune, the optimization is ready to run. Select the **Optimization** tab and click the **Start Optimization** button. During optimization the response plots update and numerical progress data is displayed in the **Optimization** tab.

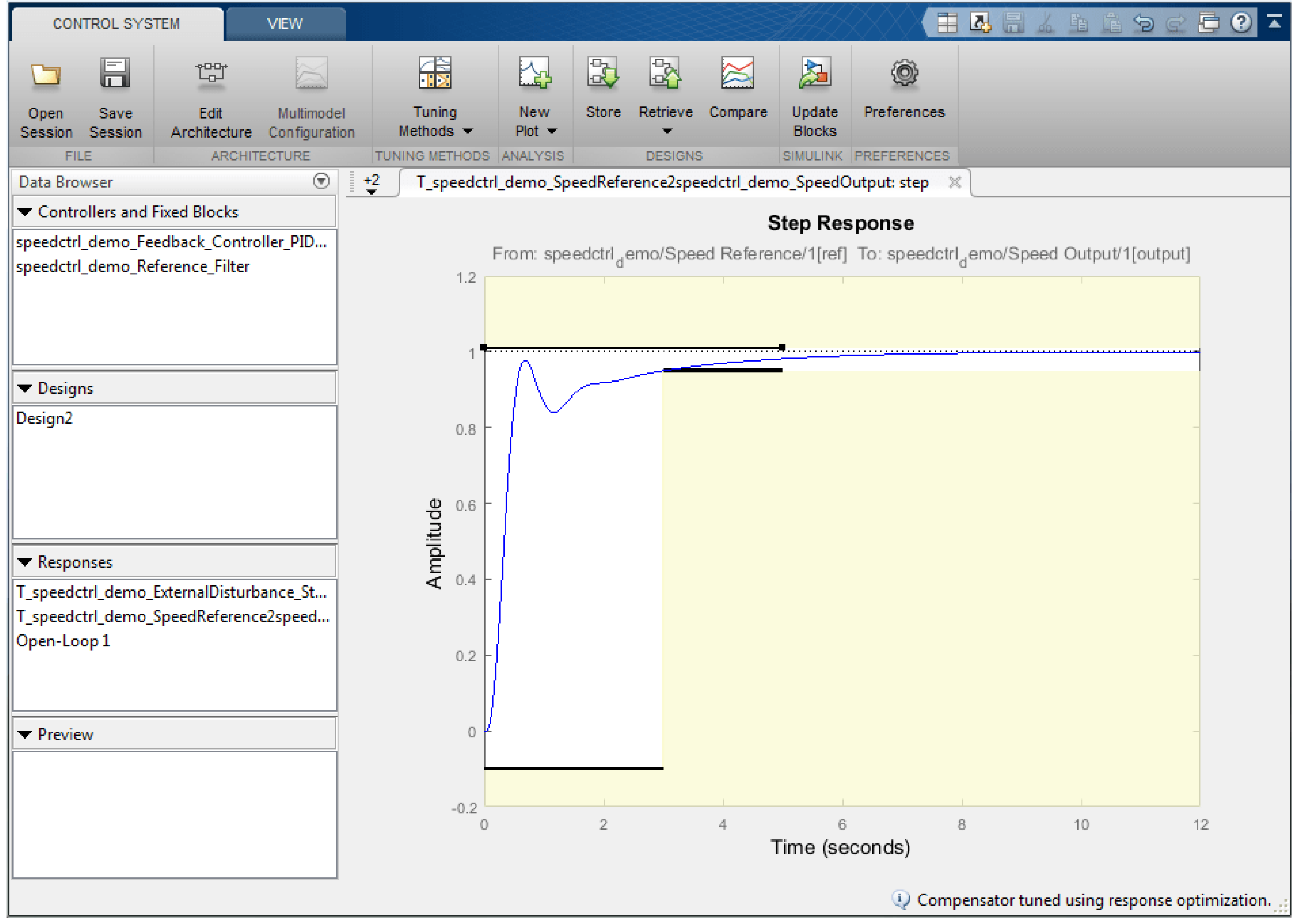


Inspecting and Verifying the Final Design

You can check how well the optimized design meets the specified design requirements by viewing the optimized responses (shown below).

To verify the compensator design on the full non-linear Simulink model, return to the **Control System Designer** and click the **Update Simulink Block Parameters** button to write the compensator back to the Simulink model. You can now simulate the Simulink model with the newly designed compensator.


CONTROL SYSTEM
BODE EDITOR
VIEW
Open Session
Save Session
Edit Architecture
Multimodel Configuration
Tuning Methods
New Plot
Store
Retrieve
Compare
Update Blocks
Preferences
FILE
ARCHITECTURE
TUNING METHODS
ANALYSIS
DESIGNS
SIMULINK
PREFERENCES
Data Browser
Controllers and Fixed Blocks
speedctrl_demo_Feedback_Controller_PID...
speedctrl_demo_Reference_Filter
Designs
Design2
Responses
T_speedctrl_demo_ExternalDisturbance_St...
T_speedctrl_demo_SpeedReference2speed...
Open-Loop 1
Preview
Bode Editor for Open-Loop 1
T_speedctrl_demo_ExternalDisturbance_StepDisturbance2speedctrl_: step
Open-Loop Bode Editor for Open-Loop 1 (L1)
Magnitude (dB)
G.M.: 21.5 dB
Freq: 19.7 rad/s
Stable loop
Phase (deg)
P.M.: 57.6 deg
Freq: 4.85 rad/s
Frequency (rad/s)




```
bdclose('speedctrl_demo')
```

See Also

Related Examples

- “Design Optimization to Meet Time-Domain and Frequency-Domain Requirements (GUI)” on page 3-76

More About

- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43

Airframe Controller Tuning

This example shows how to design two feedback loops in a cascaded control system to track reference signals. The design uses the body rate (q) as an inner feedback loop and the acceleration (az) as an outer feedback signal. This example is based on the Simulink® Control Design™ example "Cascaded Multiloop Feedback Design" (Simulink Control Design).

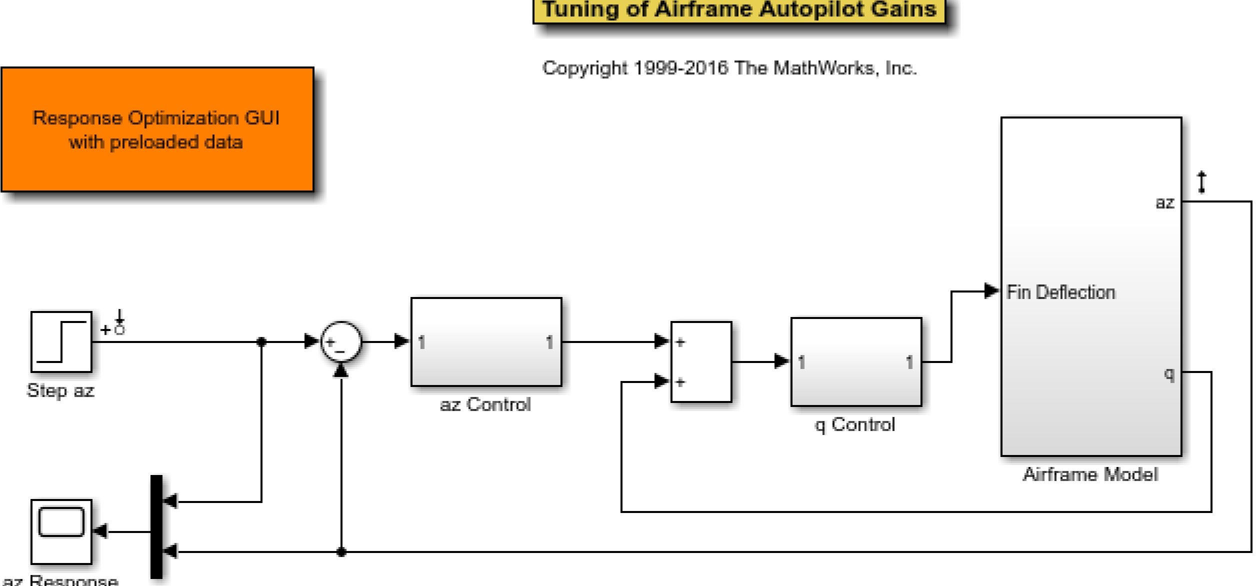
After loading the model and pre-configured **Control System Designer** app session, you can design a new controller using Response Optimization.

Requires Simulink® Control Design™.

Opening the Model

Open the model using the following command, and double click on the orange block to launch the **Control System Designer**.

```
open_system('airframe_demo')
```



Design Overview

The goal of the design is to have an overall rise time of under 0.5 seconds for the outer feedback loop. A preliminary design is done using Simulink Control Design (see "Cascaded Multiloop Feedback Design" (Simulink Control Design).) and is used as a starting point for optimization. The controller must satisfy the following requirements:

- A Gain Margin >= 10db and Phase Margin >= 50 degrees for the inner feedback loop.
- A Gain Margin >= 10db and Phase Margin >= 60 degrees for the outer feedback loop.
- An overshoot of at most 1%, a 80% rise time of 0.5 seconds, and a 99% rise time of 0.6 seconds for the step response of the outer loop.

These design requirements have been added to the Control System Designer app. To complete the design using response optimization, in the **Control System** tab, in the **Tuning Methods** drop-down list, select **Optimization Based Tuning**. In the **Response Optimization** window, click **Start Optimization**.

```
bdclose('airframe_demo')
```

See Also

More About

- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43

DC Motor Controller Tuning

This example shows how to design a PI control system to control the speed of a DC motor. It is based on the Control System Toolbox™ “DC Motor Control” (Control System Toolbox) example.

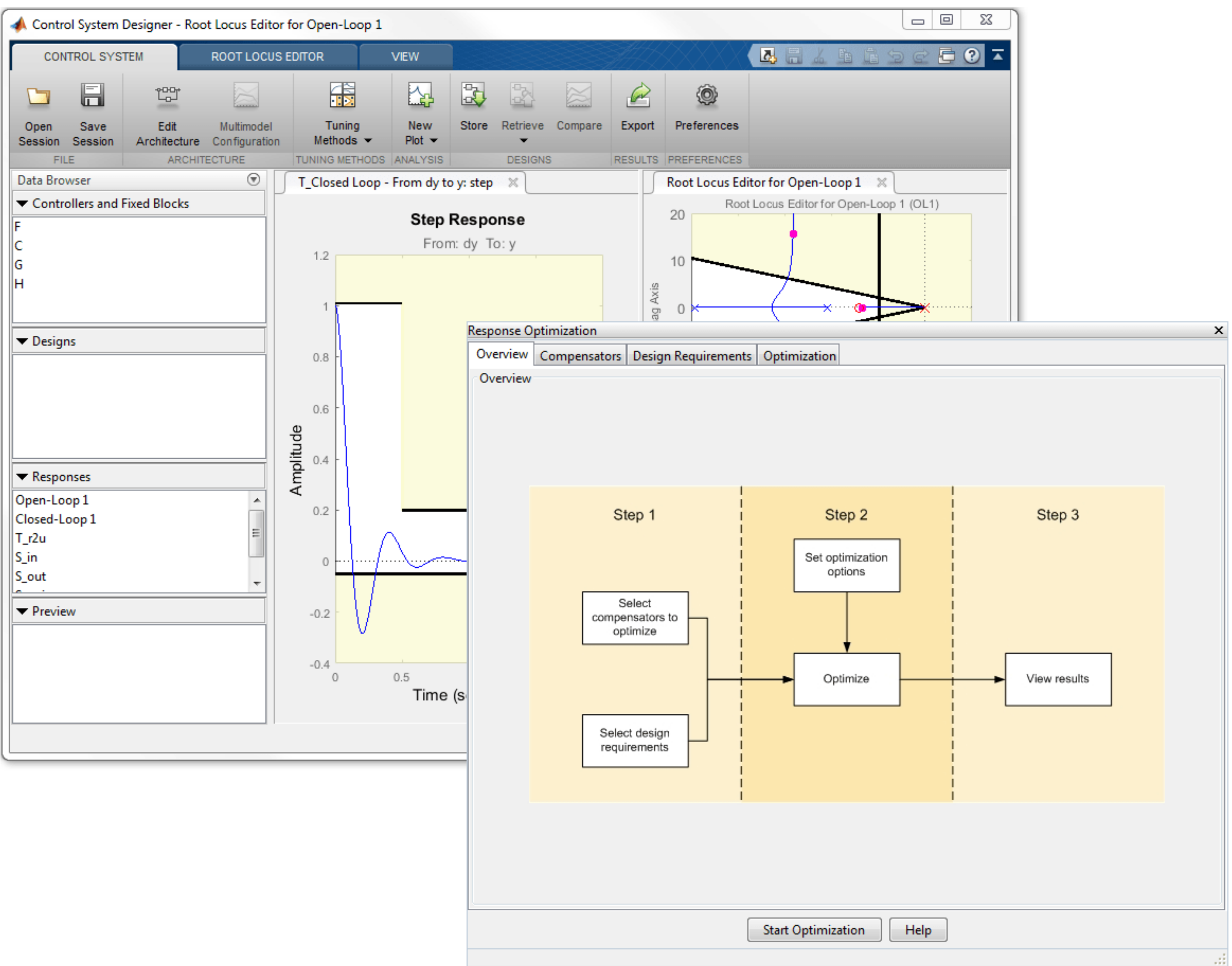
After loading the model and pre-configured **Control System Designer**, you can design a new controller using Response Optimization.

Requires Control System Toolbox™.

Opening the Model and Control System Designer

Open the model and pre-configured Control System Designer using the command

```
controlSystemDesigner('dcmotor_demoproject')
```



Design Overview

The goal of the overall design is to track a reference change in speed with minimal overshoot and to reject output disturbances. The controller must satisfy the following requirements:

- The closed-loop poles of the control loop are restricted to a region on the root locus plot that implies less than a 5% overshoot.
- The closed-loop poles of the control loop are restricted to a region on the root locus plot that implies a settling time less than 2 seconds.
- The output (y) of a unit step output disturbance is reduced by 80% within 0.5 seconds and by 95% within 1 second.

These design requirements have been added to the Control System Designer. To complete the design, using response optimization, click the **Start Optimization** button within the **Response Optimization** dialog.

See Also

More About

- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43

Hydraulic Piston Regulator Tuning

This example shows how to tune a lead-lag regulator for a simplified hydraulic piston. The piston model is given by:

```
PlantModel = zpk(10,[0,0,-10],-1);
```

An initial controller design using the Control System Toolbox™ yields a controller:

```
Controller = zpk(-0.15, -3.5, 0.15);
```

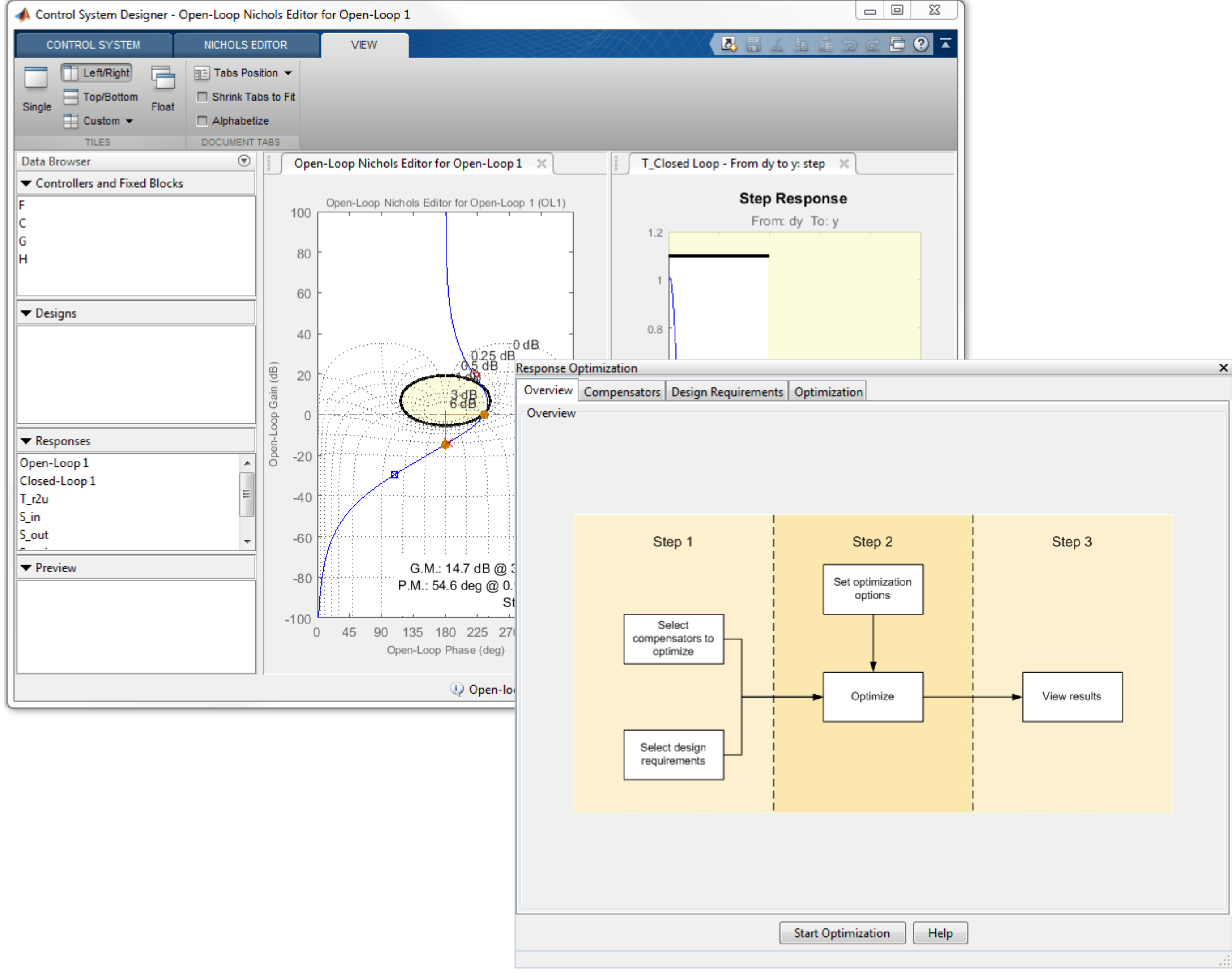
After loading the model and pre-configured Control System Designer, you can design a new controller using Response Optimization.

Requires Control System Toolbox.

Opening the Model and Control System Designer

Open the model and pre-configured Control System Designer using the command

```
controlSystemDesigner('piston_demoproject');
```



Design Overview

The goal of the design is to fine tune the designed regulator to better reject disturbances. The controller must satisfy the following requirements:

- The closed-loop peak gain must be less than 1db; this ensures good regulation with minimum overshoot.
- The output (y) resulting from a unit step output disturbance (dy) must be reduced by 99% within 10 seconds and no more than a 20% overshoot is allowed.

These design requirements have been added to the Control System Designer. To complete the design, using response optimization, click **Start Optimization** button in the **Response Optimization** window.

See Also

More About

- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Frequency-Domain Design Requirements in the App” on page 3-43

Lookup Tables

- “What are Adaptive Lookup Tables?” on page 6-2
- “How to Estimate Lookup Table Values” on page 6-4
- “Estimate Constrained Values of a Lookup Table” on page 6-5
- “Estimate Lookup Table Values from Data” on page 6-17
- “Building Models Using Adaptive Lookup Table Blocks” on page 6-28
- “Selecting an Adaptation Method” on page 6-31
- “Model Engine Using n-D Adaptive Lookup Table” on page 6-33
- “Using Adaptive Lookup Tables in Real-Time Environment” on page 6-43
- “Design Optimization Using Lookup Table Requirements for Gain Scheduling (Code)” on page 6-44
- “Design Optimization Using Lookup Table Requirements for Gain Scheduling (GUI)” on page 6-59
- “2-D Adaptive Lookup Table Generation” on page 6-70
- “Engine Volumetric Efficiency Surface Matching” on page 6-71

What are Adaptive Lookup Tables?

Lookup Tables

Lookup tables store numeric data in a multidimensional array format. In the simpler two-dimensional case, lookup tables can be represented by matrices. Each element of a matrix is a numerical quantity, which can be precisely located in terms of two indexing variables. At higher dimensions, lookup tables can be represented by multidimensional matrices, whose elements are described in terms of a corresponding number of *indexing variables*.

Lookup tables provide a means to capture the dynamic behavior of a physical (mechanical, electronic, software) system. The behavior of a system with M inputs and N outputs can be approximately described by using N lookup tables, each consisting of an array with M dimensions.

You usually generate lookup tables by experimentally collecting or artificially creating the input and output data of a system. In general, you need as many indexing parameters as the number of input variables. Each indexing parameter may take a value within a predetermined set of data points, which are called the *breakpoints*. The set of all breakpoints corresponding to an indexing variable is called a *grid*. Thus, a system with M inputs is gridded by M sets of breakpoints. The software uses the breakpoints to locate the array elements, where the output data of the system are stored. For a system with N outputs, the software locates the N array elements and then stores the corresponding data at these locations.

After you create a lookup table using the input and output measurements as described previously, you can use the corresponding multidimensional array of values in applications without having to remeasure the system outputs. In fact, you need only the input data to locate the appropriate array elements in the lookup table because the software reads the approximate system output from the data stored at these locations. Therefore, a lookup table provides a suitable means of capturing the input-output mapping of a *static* system in the form of numeric data stored at predetermined array locations.

Adaptive Lookup Tables

Statically defined lookup tables, as described in “Lookup Tables” on page 6-2, cannot accommodate the *time-varying* behavior (characteristics) of a physical plant. Static lookup tables establish a permanent and static mapping of input-output behavior of a physical system. Conversely, the behavior of actual physical systems often varies with time due to wear, environmental conditions, and manufacturing tolerances. With such variations, the static mapping of input-output behavior of a plant described by the lookup table may no longer provide a valid representation of the plant characteristics.

Adaptive lookup tables incorporate the time-varying behavior of physical plants into the lookup table generation and maintenance process while providing all of the functionality of a regular lookup table.

The adaptive lookup table receives the input and output measurements of a plant's behavior, which are then used to dynamically create and update the content of the underlying lookup table. In addition to requiring the input data to create the lookup table, the adaptive lookup table also uses the output data of the plant to recalculate the table values. For example, you can collect the output data of the plant by placing sensors at appropriate locations in a physical system.

The software uses the input measurements to locate the array elements by comparing these input values with the breakpoints defined for each indexing variable. Next, it uses the output

measurements to recalculate the numeric value stored at these array locations. However, unlike a regular table, which only stores the array data before the actual use of the lookup table, the adaptive table continuously improves the content of the lookup table. This continuous improvement of the table data is referred to as the adaptation process or learning process.

The adaptation process involves statistical and signal processing algorithms to recapture the input-output behavior of the plant. The adaptive lookup table always tries to provide a valid representation of the plant dynamics even though the plant behavior may be time varying. The underlying signal processing algorithms are also robust against reasonable measurement noise and they provide appropriate filtering of noisy output measurements.

See Also

Adaptive Lookup Table (1D Stair-Fit) | Adaptive Lookup Table (2D Stair-Fit) | Adaptive Lookup Table (nD Stair-Fit)

Related Examples

- “Model Engine Using n-D Adaptive Lookup Table” on page 6-33

More About

- “About Lookup Table Blocks”
- “Building Models Using Adaptive Lookup Table Blocks” on page 6-28

How to Estimate Lookup Table Values

You can use lookup table Simulink blocks to approximate a system's behavior, as described in “About Lookup Table Blocks”. After you build your system using lookup tables, you can use Simulink Design Optimization software to estimate the table values from measured I/O data.

Estimating lookup table values is an example of estimating parameters which are matrices or multi-dimensional arrays. The workflow for estimating parameters of a lookup table consist of the following tasks:

1. Creating a Simulink model using lookup table blocks.
2. Importing the measured input and output (I/O) data from which you want to estimate the table values.
3. Analyzing and preparing the I/O data for estimation.
4. Estimating the lookup table values.
5. Validating the estimated table values using a validation data set.

See Also

Related Examples

- “Estimate Lookup Table Values from Data” on page 6-17
- “Estimate Constrained Values of a Lookup Table” on page 6-5

Estimate Constrained Values of a Lookup Table

Objectives

This example shows how to estimate constrained values of a lookup table in the **Parameter Estimator**. Apply monotonically increasing constraints to the lookup table output values, and use the **Parameter Estimator** to estimate the table values.

About the Data

In this example, use `lookup_increasing.mat`, which contains the measured I/O data for estimating the lookup table values. The MAT-file includes the following variables:

- `xdata1` — Input data consisting of 602 uniformly sampled data points in the range `[-5,5]`.
- `ydata1` — Output data corresponding to the input data samples.
- `time1` — Time vector.

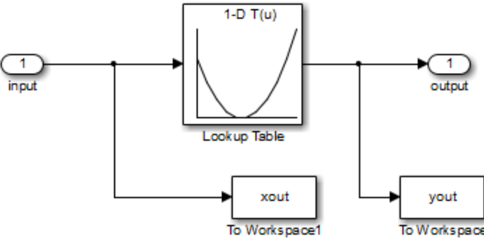
Use the I/O data to estimate monotonically increasing output values of the lookup table in the `lookup_increasing` Simulink model.

Lookup Table Output

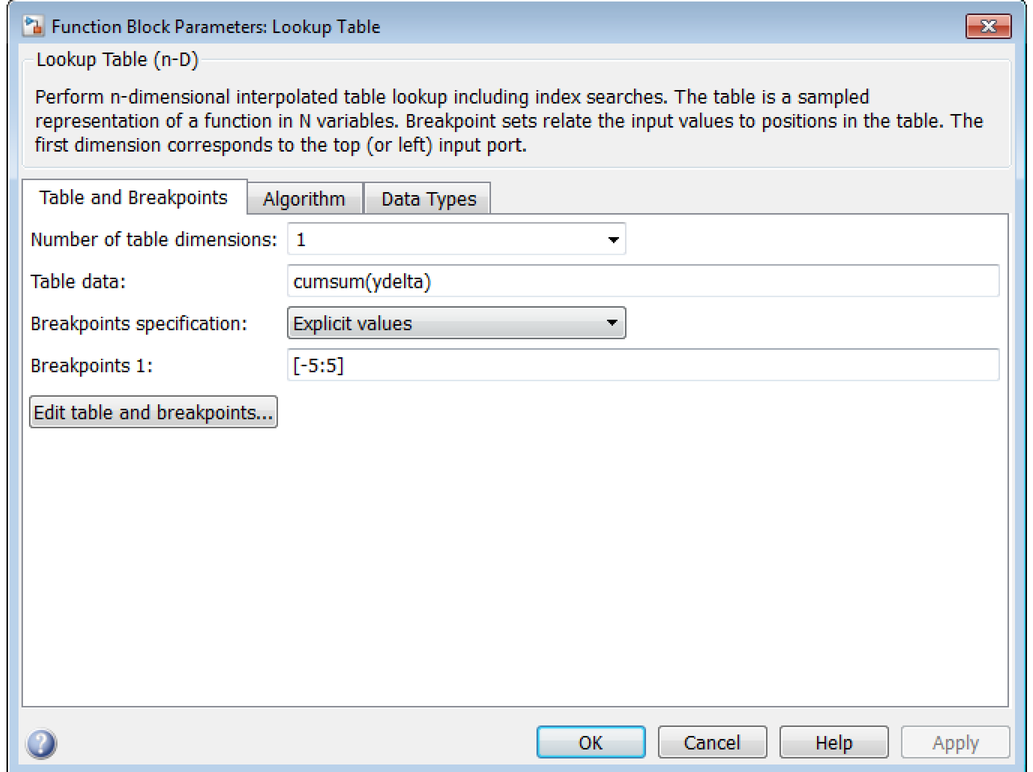
1 Open the lookup table model by typing the following command at the MATLAB prompt:

```
lookup_increasing
```

This command opens the Simulink model, and loads the estimation data in the MATLAB workspace.



2 View the table output values by double-clicking the Lookup Table block.



The table contains 11 output values at breakpoints `[-5:5]`, specified in the Function Block Parameters dialog box. To learn more about how to specify the table values, see “Enter Breakpoints and Table Data”.

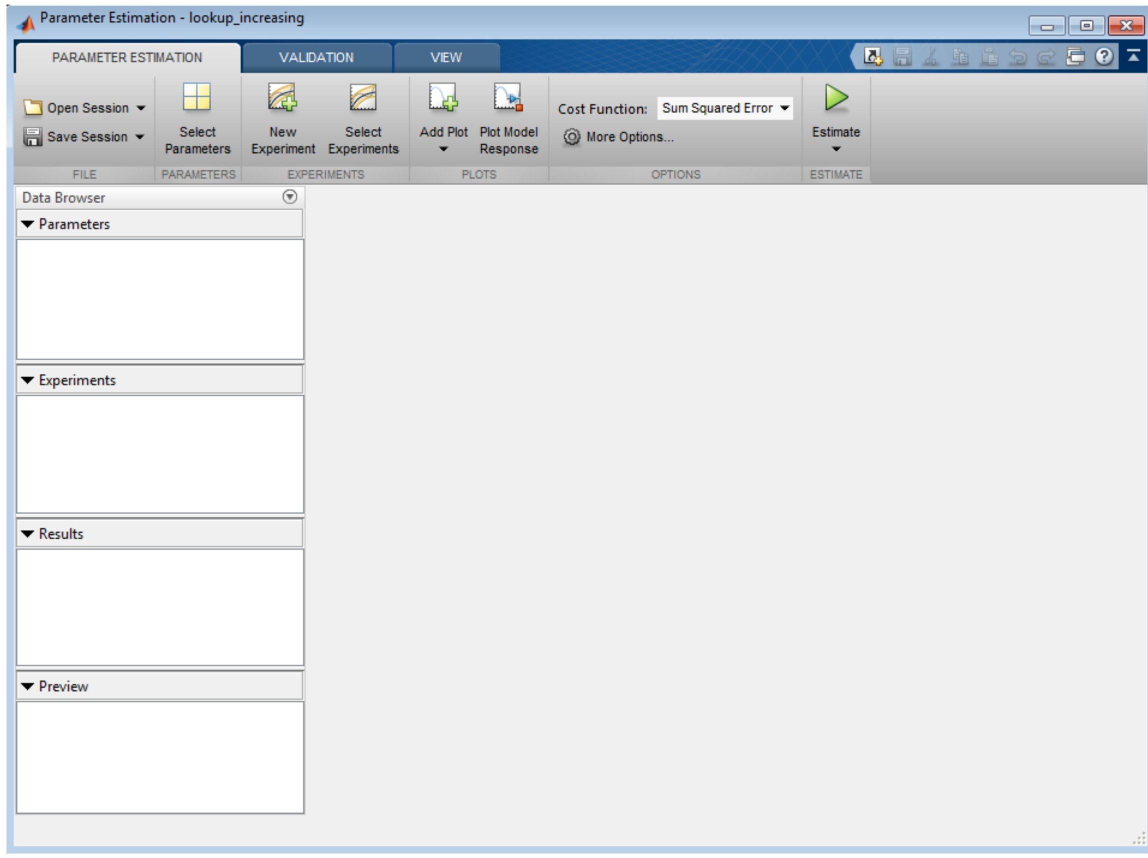
The **Table data** field shows that the table output values are the cumulative sum of the values stored in variable `ydelta`. Thus, if y_n are the 11 table output values, `ydelta` is (y_1, y_2-y_1, y_3-y_2, ..., y_{11}-y_{10}). The initial `ydelta` values are loaded from `lookup_increasing.mat`.

The initial table output values are not monotonically increasing. To ensure monotonically increasing table output values, the difference between adjacent table output values should be positive. To do so, estimate `ydelta` in the **Parameter Estimator** using the measured I/O estimation data, and constrain `ydelta(2:end)` to be positive during estimation.

Estimate the Monotonically Increasing Table Values Using Default Settings

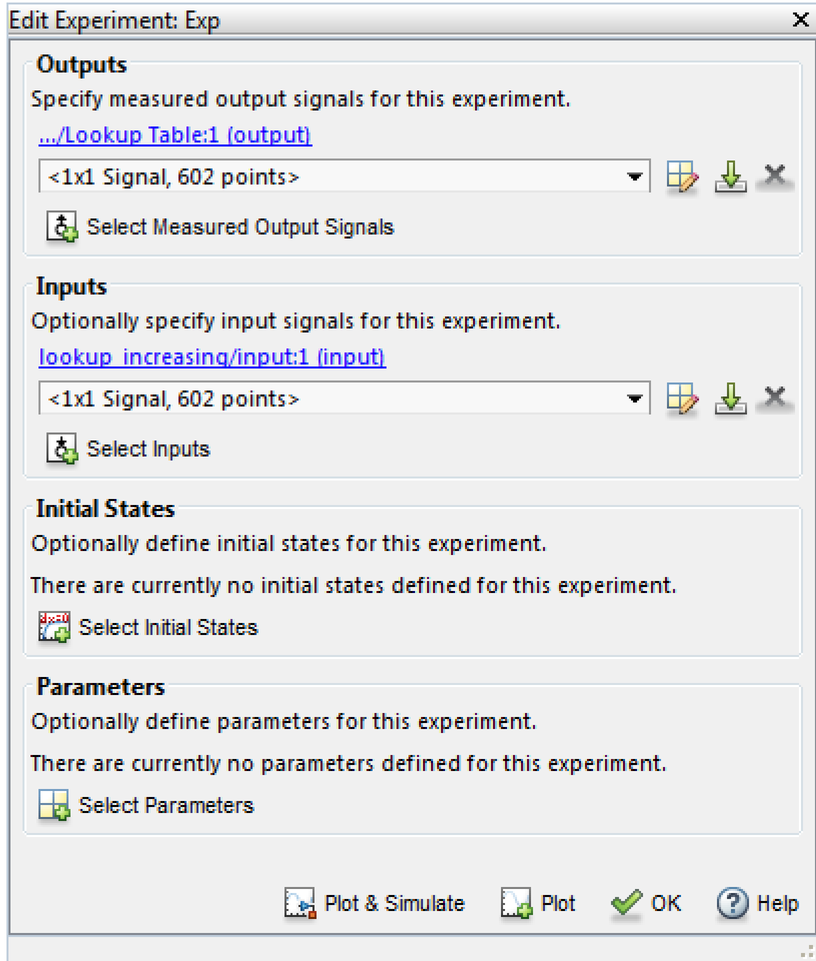
1 Open a parameter estimation session.

In the Simulink model, select **Parameter Estimator** from the **Apps** tab, in the gallery, under **Control Systems** to open a session with the name **lookup_increasing** in the **Parameter Estimator**.



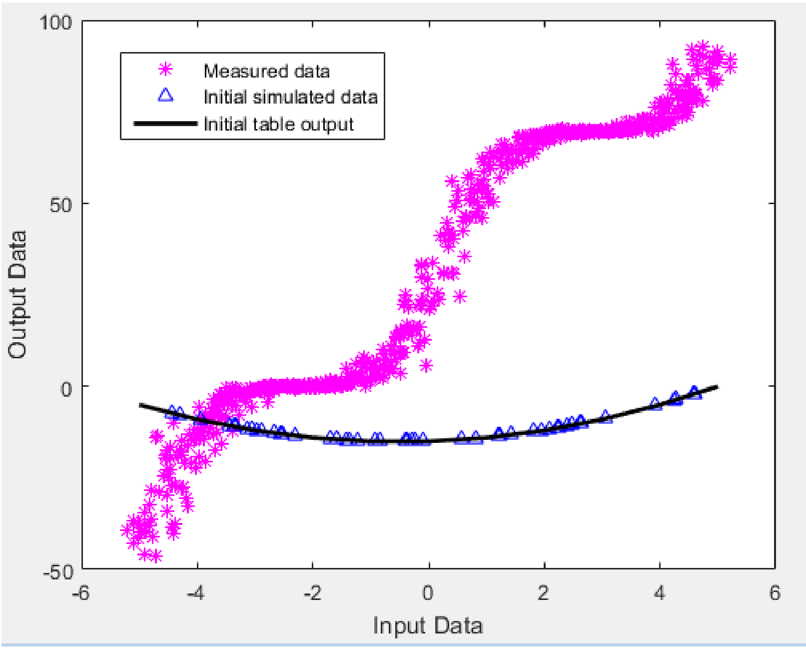
2 Create an experiment and import the I/O data.

On the **Parameter Estimation** tab, click **New Experiment**. Type `[time1,ydata1]` in **Outputs** and `[time1,xdata1]` in **Inputs** of the Edit Experiment dialog box. Click **OK**. A new experiment with name `Exp` is created in the **Experiments** area of the app. Rename the experiment `EstimationData` by right-clicking the default experiment name, `Exp`, and selecting `Rename`. For more information, see “Import Data for Parameter Estimation” on page 1-5.



3 Run an initial simulation to view the measured data, simulated model values, and the initial table values by typing the following commands at the MATLAB prompt.

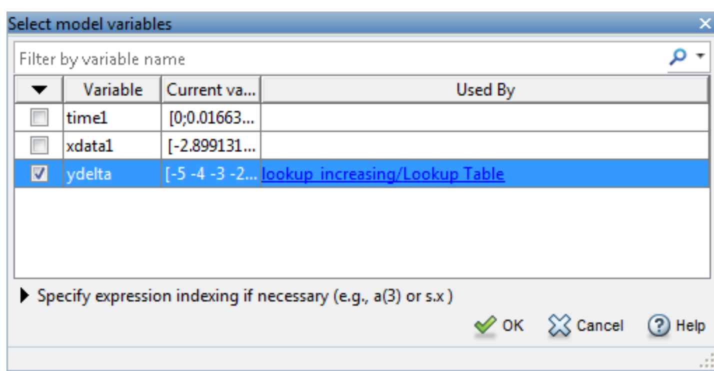
```
sim('lookup_increasing')
figure(1); plot(xdata1,ydata1,'m*',xout,yout,'b^')
hold on; plot(-5:5,cumsum(ydelta),'k','LineWidth',2)
xlabel('Input Data'); ylabel('Output Data');
legend('Measured data','Initial simulated data','Initial table output')
```



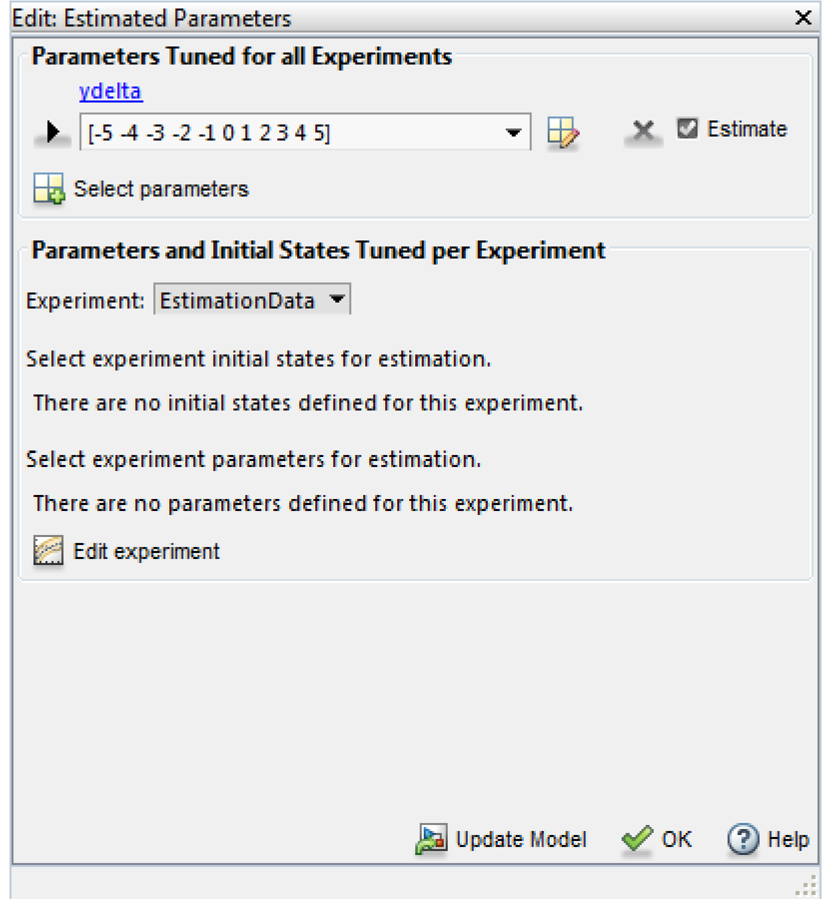
The initial table output values and simulated data do not match the measured data.

4 Select parameter for estimation.

On the **Parameter Estimation** tab, click **Select Parameters**. The Edit: Estimated Parameters dialog box opens. In the **Parameters Tuned for all Experiments** panel, click **Select parameters** to open the Select Model Variables dialog box. Check the box next to `ydelta`, and click **OK**.

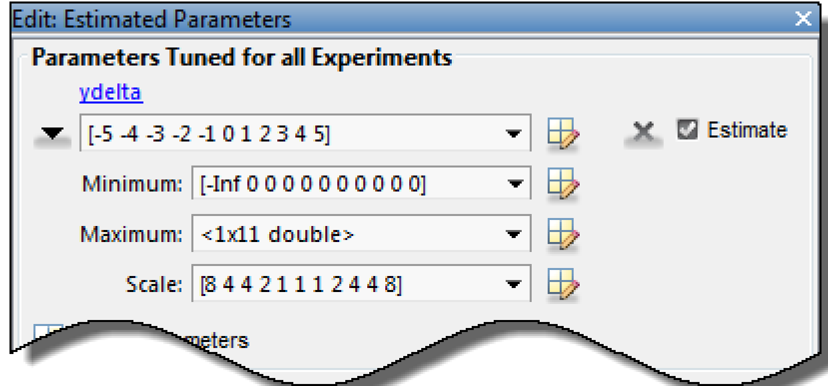


The `ydelta` values are selected for estimation by default in the Edit: Estimated Parameters dialog box.



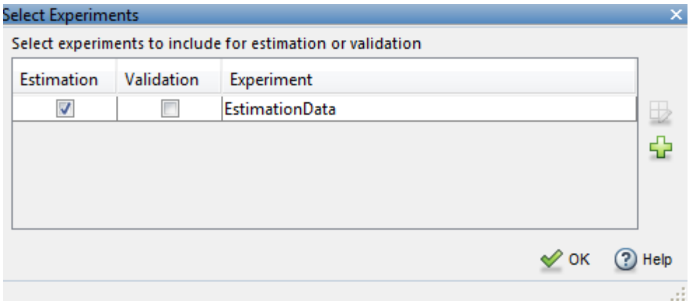
5 Apply a monotonically increasing constraint on the table output values. For more details about the table, see “Lookup Table Output” on page 6-5.

In the Edit: Estimated Parameters dialog box, click the arrow next to the `ydelta` values. In the expanded menu, set **Minimum** `ydelta` values to `[-Inf,zeros(1,10)]`. Thus, while the first value in `ydelta` can by anything, subsequent values which are the difference between adjacent table output values, must be positive.



6 Select `EstimationData` experiment for estimation.

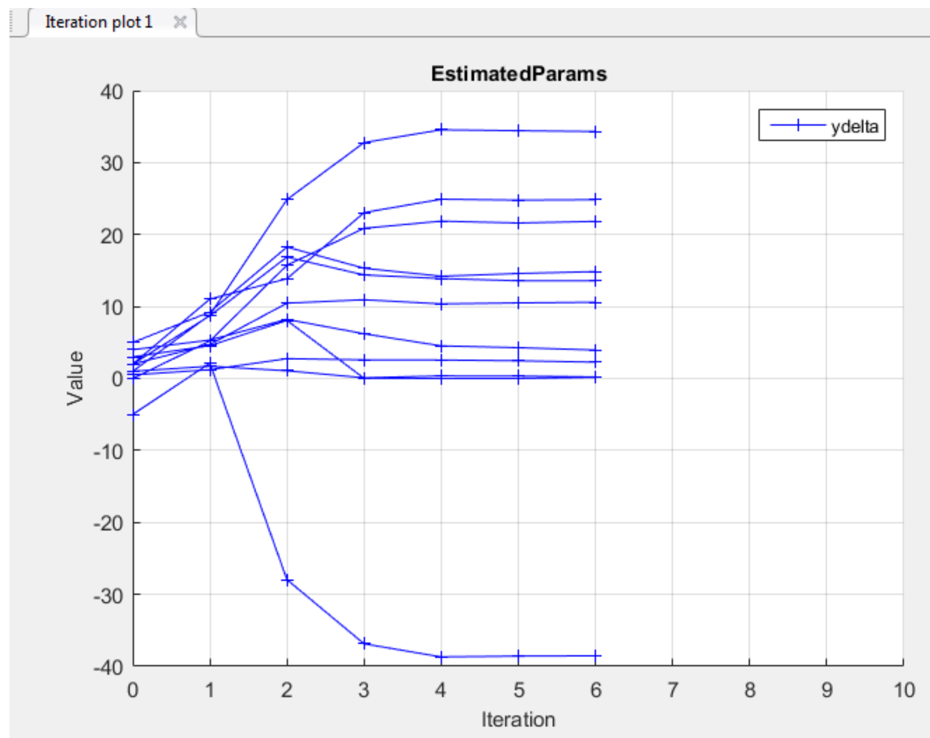
On the **Parameter Estimation** tab, click **Select Experiment**. By default, `EstimationData` is selected for estimation. If not, check the box under the **Estimation** column, and click **OK**.



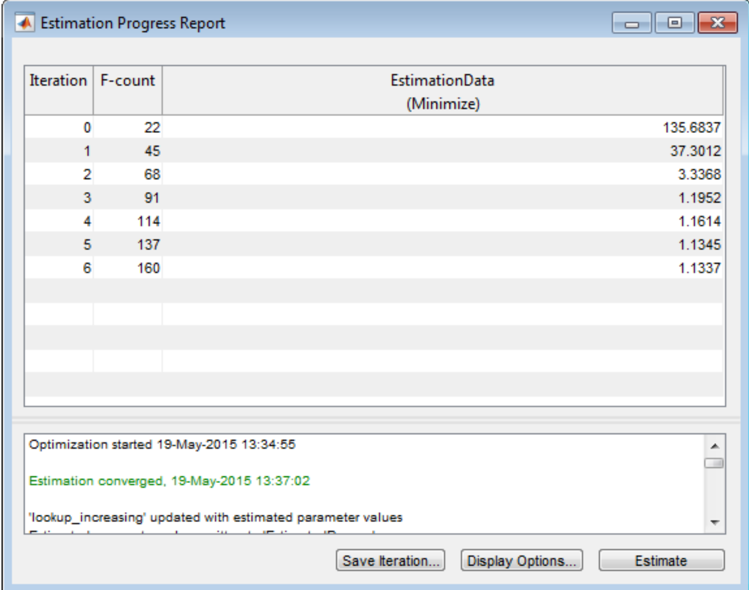
7 Estimate the table values using default settings.

On the **Parameter Estimation** tab, click **Estimate**.

The **Parameter Trajectory** plot shows the change in the parameter values at each iteration.



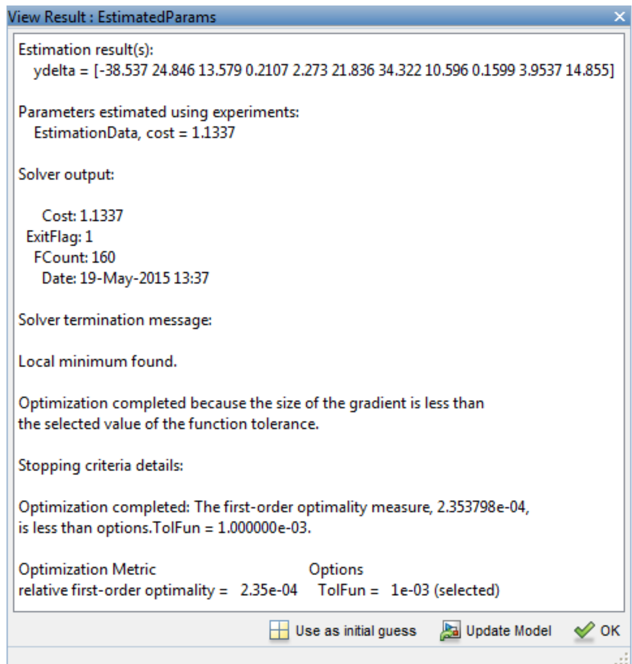
The Estimation Progress Report shows the iteration number, number of times the objective function is evaluated, and value of the cost function at the end of each iteration.



Estimation Progress Report

Iteration	F-count	EstimationData (Minimize)
0	22	135.6837
1	45	37.3012
2	68	3.3368
3	91	1.1952
4	114	1.1614
5	137	1.1345
6	160	1.1337

The estimated parameters are saved in a new variable, `EstimatedParams`, in the **Results** area of the app. To view the estimated parameters, right-click `EstimatedParams` and select **Open**.



The estimated `ydelta(2:end)` values are positive. Thus, the output of the table, which is the cumulative sum of the values stored in `ydelta`, is monotonically increasing.

Validate the Estimation Results

After you estimate the table values, as described in “Estimate the Monotonically Increasing Table Values Using Default Settings” on page 6-6, you use another measured data set to validate and check

that you have not over-fit the model. You can plot and examine the following plots to validate the estimation results:

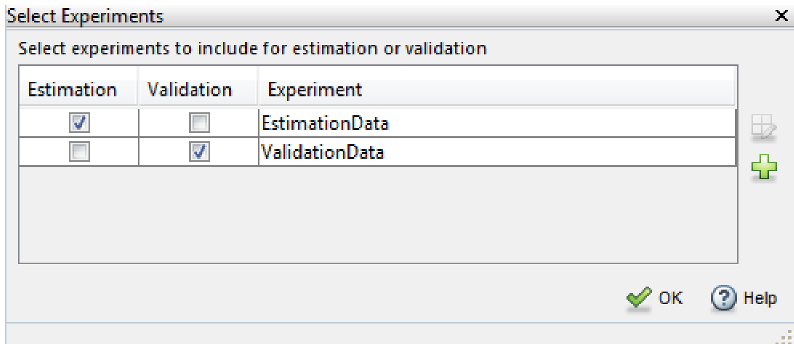
- Residuals plot
- Measured and simulated data plots

1 Create an experiment to use for validation and import the validation I/O data.

   On the **Parameter Estimation** tab, click **New Experiment**. Type `[time2,ydata2]` in **Outputs** and `[time2,xdata2]` in **Inputs** of the Edit Experiment dialog box. Name the experiment `ValidationData` by right-clicking the default experiment name, `Exp`, in the **Experiments** area of the app, and selecting `Rename`. For more information, see “Import Data for Parameter Estimation” on page 1-5.

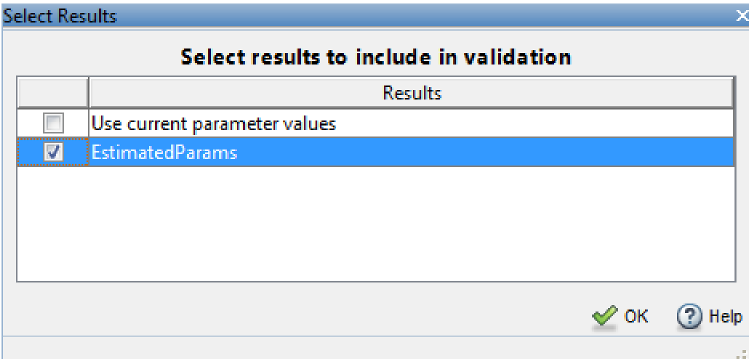
2 Select the experiment for validation.

   Click **Select Experiments** on the **Parameter Estimation** tab. The `ValidationData` experiment is selected for estimation by default. Clear **Estimation** and select the box for **Validation**.



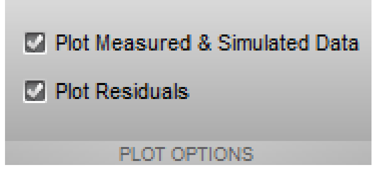
3 Select the results to validate.

   On the **Validation** tab, click **Select Results to Validate**. Clear `Use current parameter values`, select `EstimatedParams`, and click **OK**.



4 Select the plots to display during validation.

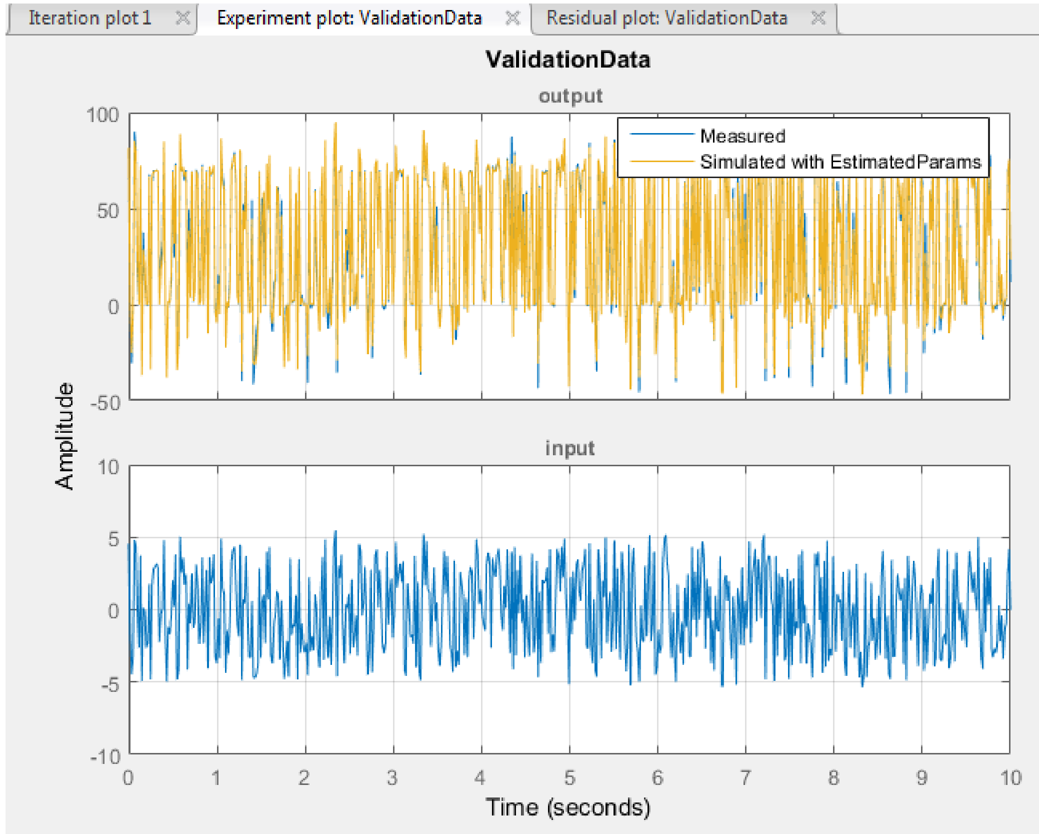
   The **Parameter Estimator** displays the experiment plot after validation by default. Add the residuals plot by selecting the corresponding box on the **Validation** tab.



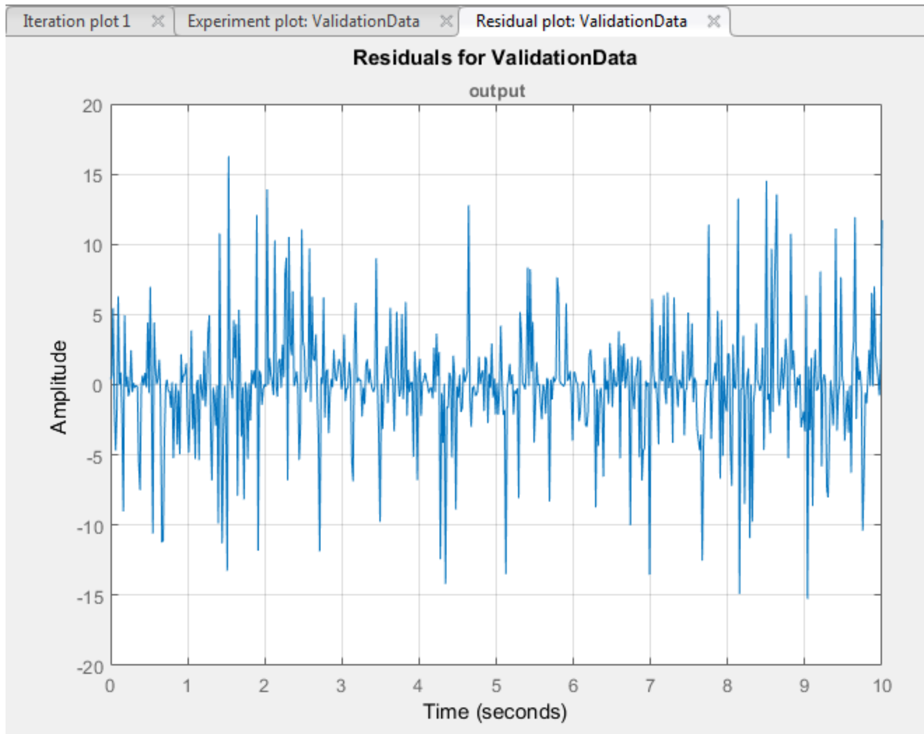
Click **Validate**.

5 Examine the plots.

   a The experiment plot shows the data simulated using estimated parameters agrees with the measured validation data.



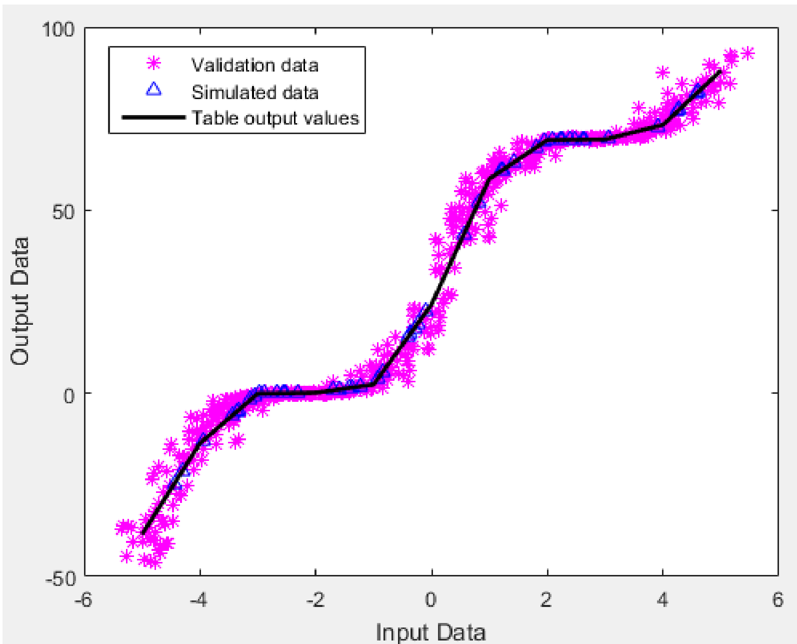
   b To view the residuals plot, click **Residual plot: ValidationData** tab.



The residuals, which show the difference between the simulated and measured data, lie within 15% of the maximum output variation. This indicates a good match between the measured and simulated table data values.

c Plot and examine the validation data, simulated data, and estimated table values.

```
sim('lookup_increasing')
figure(2); plot(xdata2,ydata2,'m*',xout,yout,'b^')
hold on; plot(-5:5,cumsum(ydelta),'k','LineWidth', 2)
xlabel('Input Data'); ylabel('Output Data');
legend('Validation data','Simulated data','Table output values');
```



The table output values match both the measured data and the simulated table values. The table output values cover the entire range of input values, which indicates that all the lookup table values have been estimated.

See Also

Related Examples

- "Estimate Lookup Table Values from Data" on page 6-17

Estimate Lookup Table Values from Data

Objectives

This example shows how to estimate lookup table values from time-domain input-output (I/O) data in the **Parameter Estimator**.

About the Data

In this example, use the I/O data in `lookup_regular.mat` to estimate the values of a lookup table. The MAT-file includes the following variables:

- `xdata1` — Consists of 63 uniformly-sampled input data points in the range [0,6.5]
- `ydata1` — Consists of output data corresponding to the input data samples
- `time1` — Time vector

Use the I/O data to estimate the lookup table values in the `lookup_regular` Simulink model. The lookup table in the model contains ten values, which are stored in the MATLAB variable `table`. The initial table values comprise a vector of 0s. To learn more about how to model a system using lookup tables, see “Guidelines for Choosing a Lookup Table”.

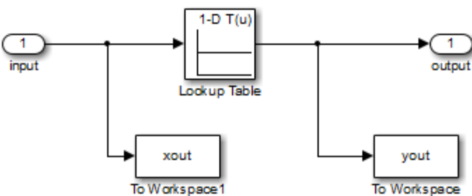
Open a Parameter Estimation Session

To estimate the lookup table values, open a Parameter Estimation session.

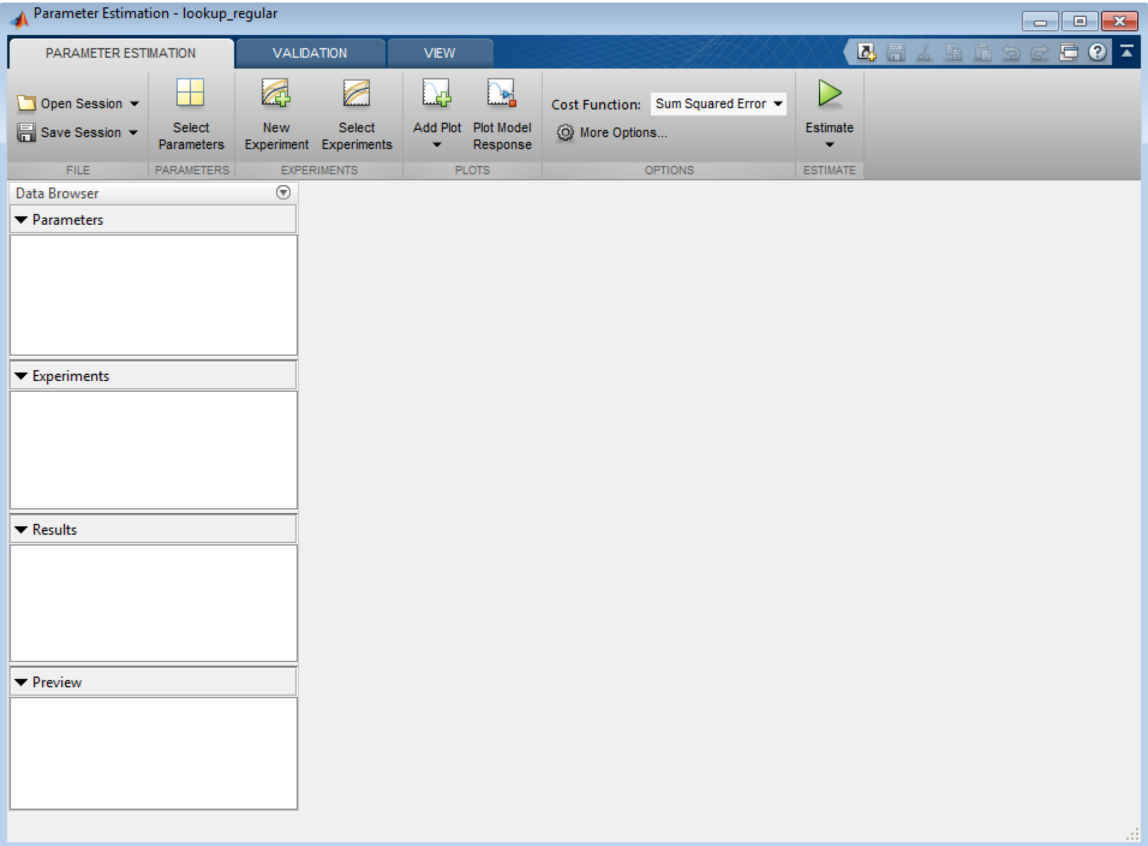
1. Open the lookup table model by typing the following command at the MATLAB prompt:

   ```
   lookup_regular
   ```

   This command opens the Simulink model, and loads the estimation data into the MATLAB workspace.

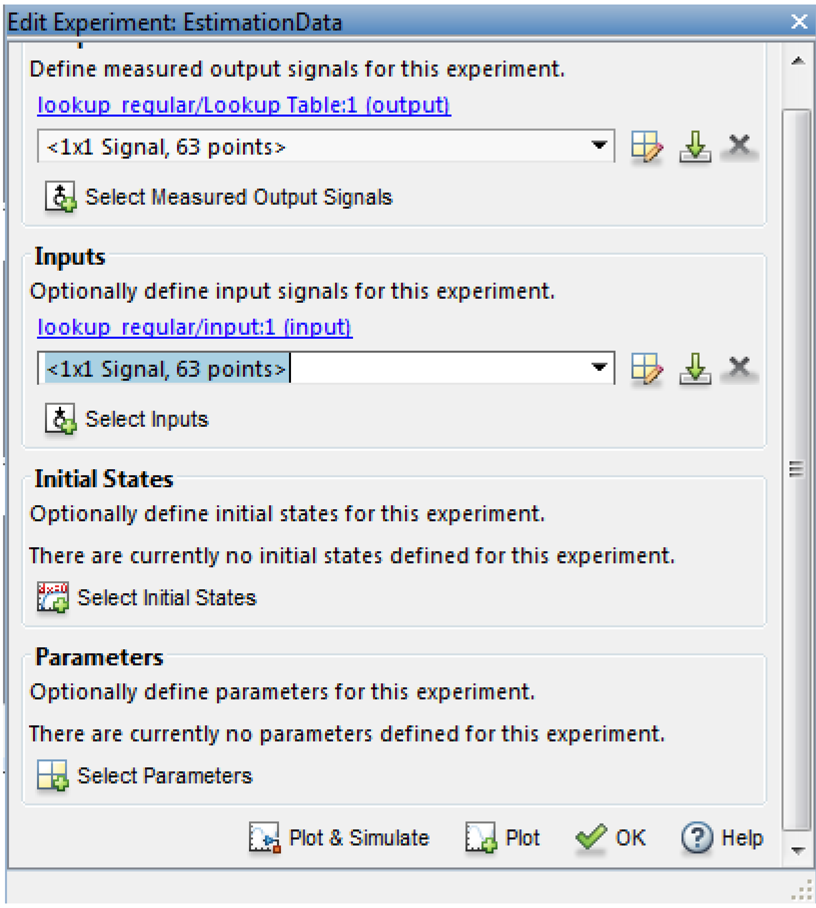
2. In the Simulink model, select **Parameter Estimator** from the **Apps** tab, in the gallery, under **Control Systems** to open a new session with name **lookup_regular** in the **Parameter Estimator**.



Estimate the Table Values Using Default Settings

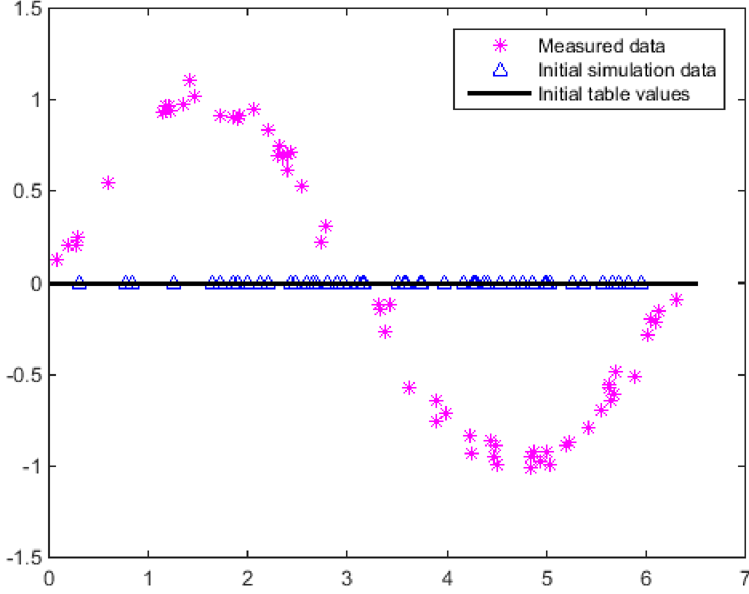
Use the following steps to estimate the lookup table values.

1 Create a new experiment by clicking **New Experiment** on the **Parameter Estimation** tab. Name it `EstimationData`. Then import the I/O data, `xdata1` and `ydata1`, and the time vector, `time1`, into the experiment. To do this open the experiment editor by right-clicking `EstimationData` and selecting **Edit...**. Type `[time1,ydata1]` in the output dialog box and `[time1,xdata1]` in the input dialog box in the experiment editor. For more information, see “Import Data for Parameter Estimation” on page 1-5. After you import the data the experiment looks as follows:



2 Run an initial simulation to view the I/O data, simulated output, and the initial table values. To do so, type the following commands at the MATLAB prompt:

```
sim('lookup_regular')
figure(1); plot(xdata1,ydata1, 'm*', xout, yout,'b^')
hold on; plot(linspace(0,6.5,10), table, 'k', 'LineWidth', 2);
legend('Measured data','Initial simulation data','Initial table values');
```

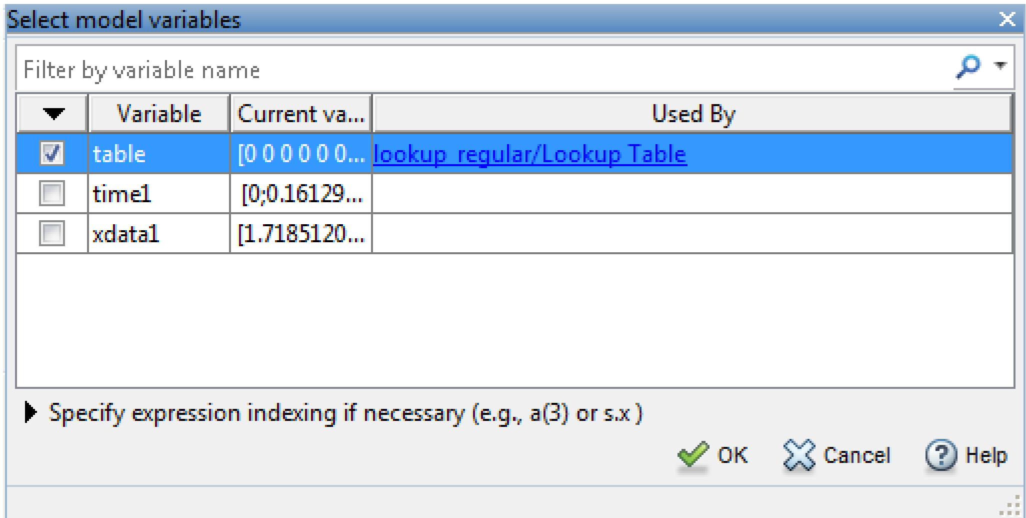


The x-axis and y-axis of the figure represent the input and output data, respectively. The figure shows the following plots:

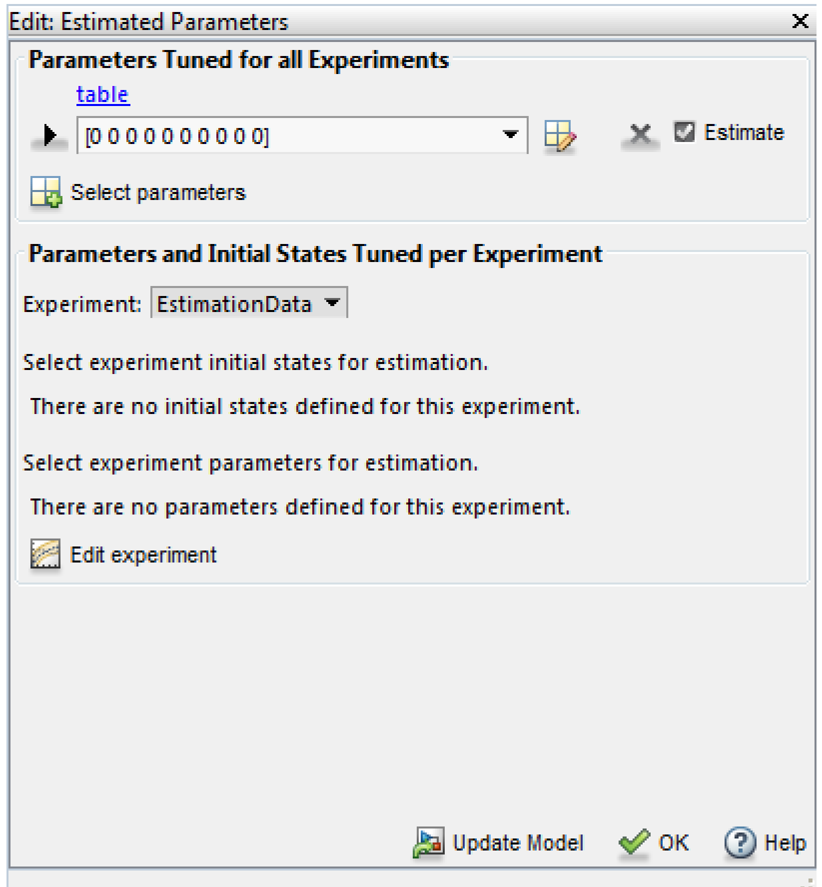
- Measured data — Represented by the magenta stars (*).
- Initial table values — Represented by the black line.
- Initial simulation data — Represented by the blue deltas (Δ).

You can see that the initial table values and simulated data do not match with the measured data.

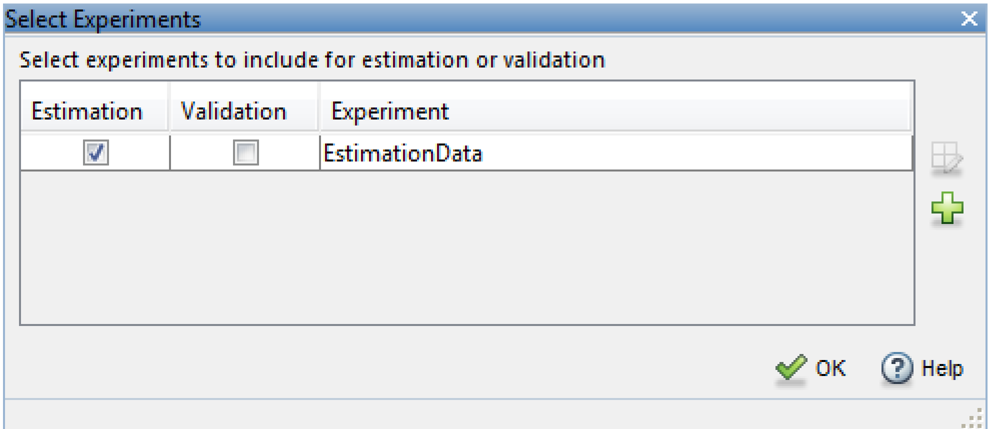
3 To select the table values to estimate, on the **Parameter Estimation** tab, click the **Select Parameters** button to open the **Edit:Estimated Parameters** dialog. In the **Parameters Tuned for all Experiments** panel, click **Select parameters** to launch the Select Model Variables dialog. Check the box next to table, and click **OK**.



The **Edit:Estimated Parameters** window now looks as follows. The table values are selected for estimation by default.

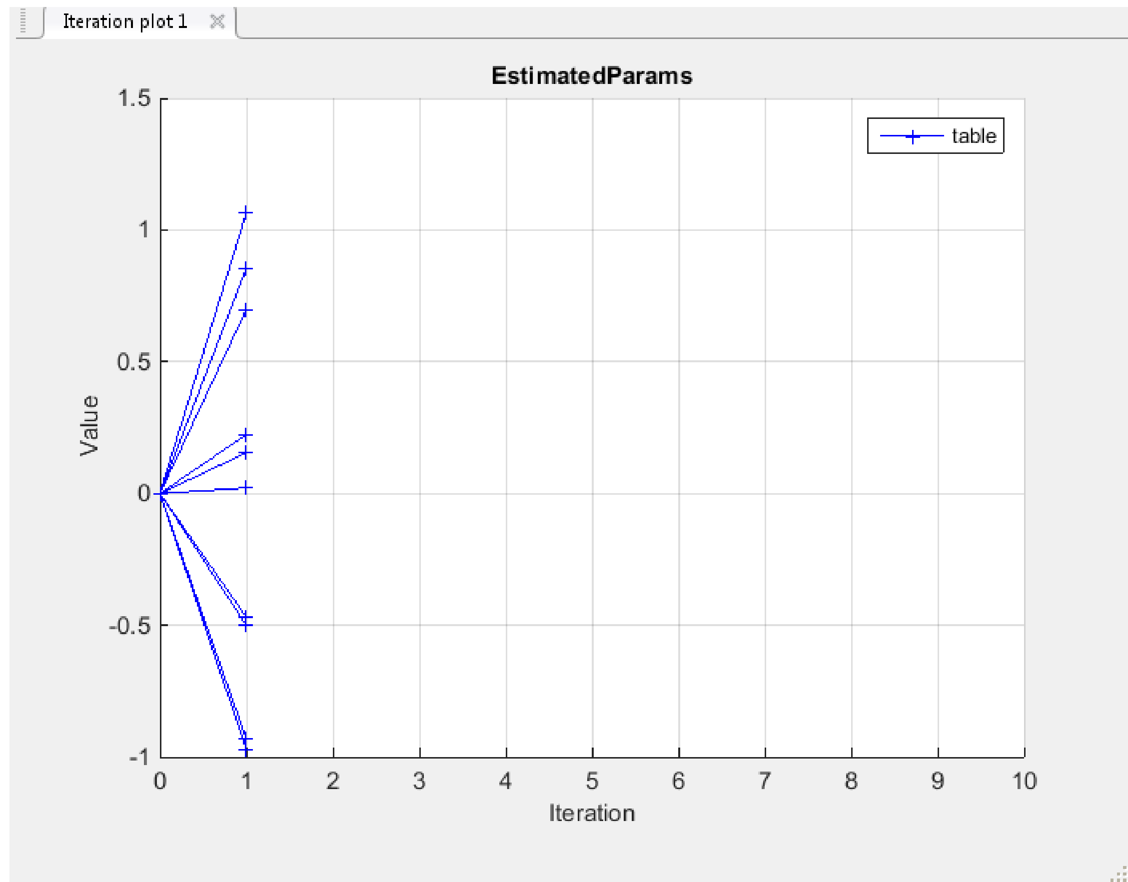


4 On the **Parameter Estimation** tab, click **Select Experiment**. `EstimationData` is selected for estimation by default. If not, check the box under the **Estimation** column, and click **OK**.

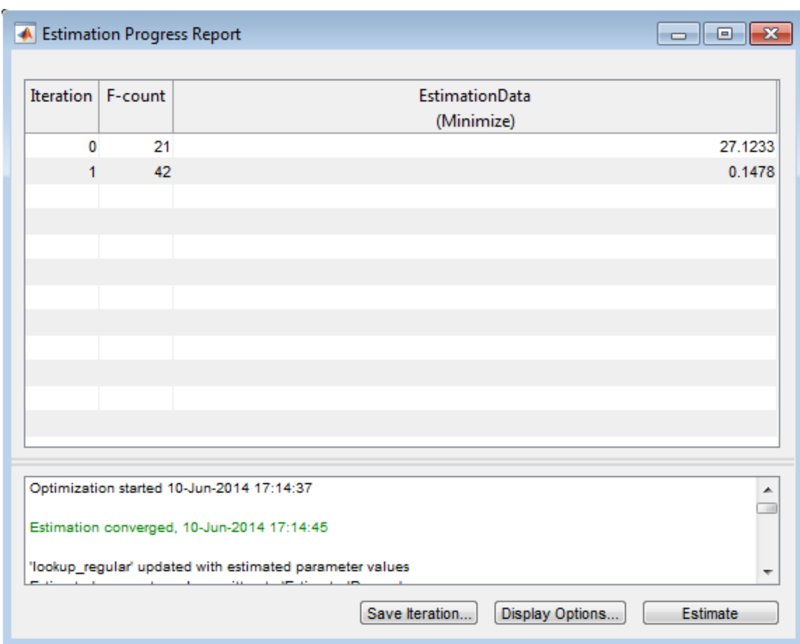


5 To estimate the table values using the default settings, on the **Parameter Estimation** tab, click **Estimate** to open the **Parameter Trajectory** plot and **Estimation Progress Report** window. The **Parameter Trajectory** plot shows the change in the parameter values at each iteration.

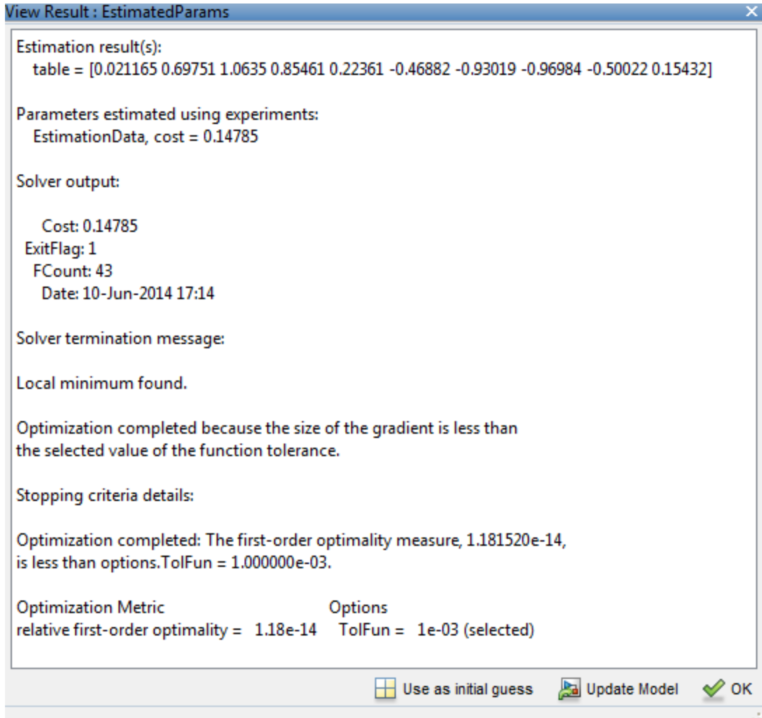
After the estimation converges, the **Parameter Trajectory** plot looks like this:



The **Estimation Progress Report** shows the iteration number, number of times the objective function is evaluated, and the value of the cost function at the end of each iteration. After the estimation converges, the **Estimation Progress Report** looks like this:



The estimated parameters are saved in `EstimatedParams` in the **Results** section of the **Data Browser** pane on the left. To view the results, right-click on `EstimatedParams` and then select **Open**. The report resembles the following.



This report includes the estimated parameter values, the final value of the cost function, and other optimization results. You can see that the optimization stopped when the size of the gradient, 1.18e-14 was less than the criteria value, 1e-3.

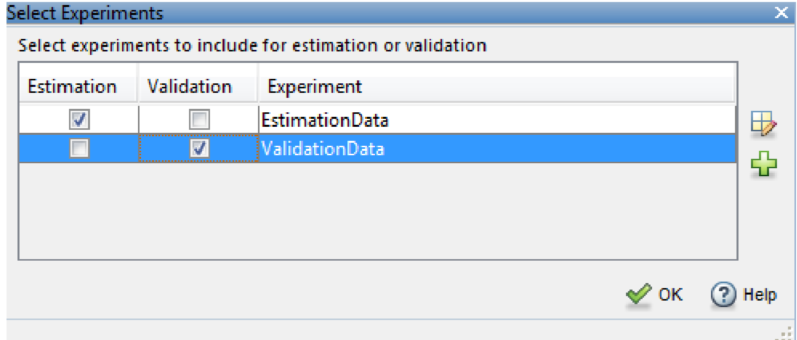
Validate the Estimation Results

After you estimate the table values, as described in “Estimate the Table Values Using Default Settings” on page 6-18, you must use another data set to validate that you have not over-fitted the model. You can plot and examine the following plots to validate the estimation results:

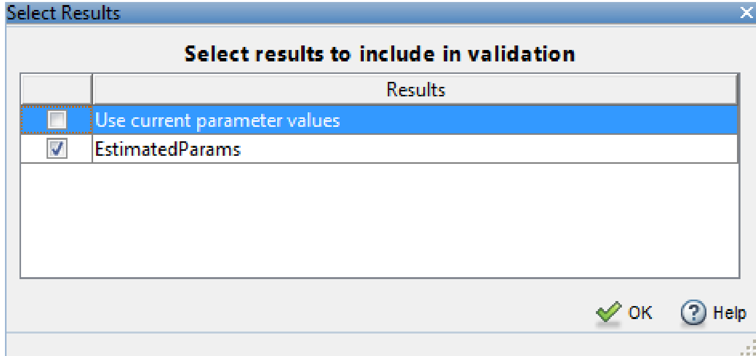
- Residuals plot
- Measured and simulated data plots

To validate the estimation results:

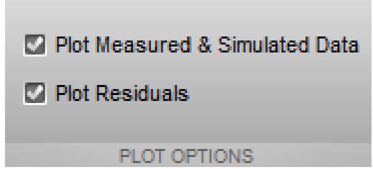
1. Create a new experiment to use for validation. Name it `ValidationData`. Import the validation I/O data, `xdata2` and `ydata2`, and time vector, `time2` in the `ValidationData` experiment. To do this open the experiment editor by right-clicking `ValidationData` and selecting **Edit...**. Then, type `[time2,ydata2]` in the output dialog box and `[time2,xdata2]` in the input dialog box in the experiment editor. For more information, see “Import Data for Parameter Estimation” on page 1-5.
2. To select the experiment for validation, on the **Parameter Estimation** tab, click **Select Experiments**. The `ValidationData` experiment is selected for estimation by default. Deselect the box for estimation and check it for validation.



3. To select results to use, on the **Validation** tab, click **Select Results to Validate**. Deselect `Use current parameter values` and select `EstimatedParams`, and click **OK**.



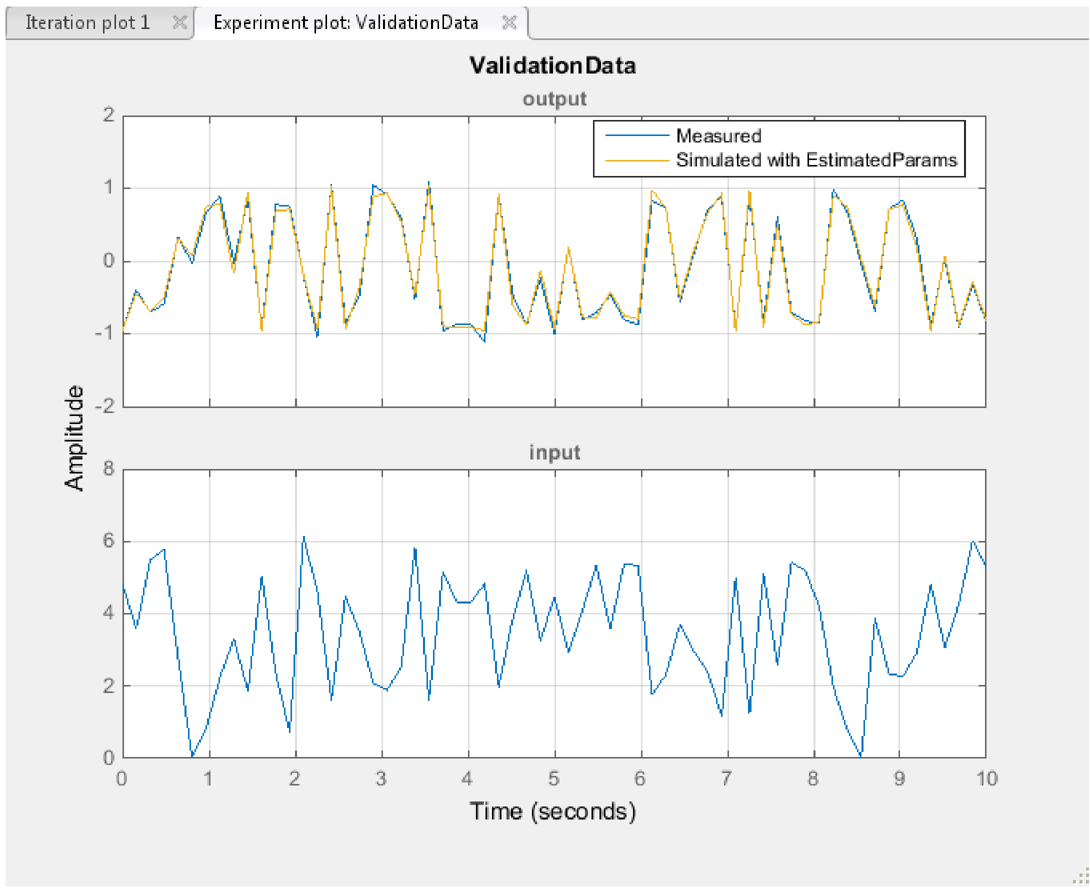
4. The **Parameter Estimator**, by default, displays the experiment plot after validation. Add the residuals plot by checking the corresponding box on the **Validation** tab.



To start validation, on the **Validation** tab, click **Validate**.

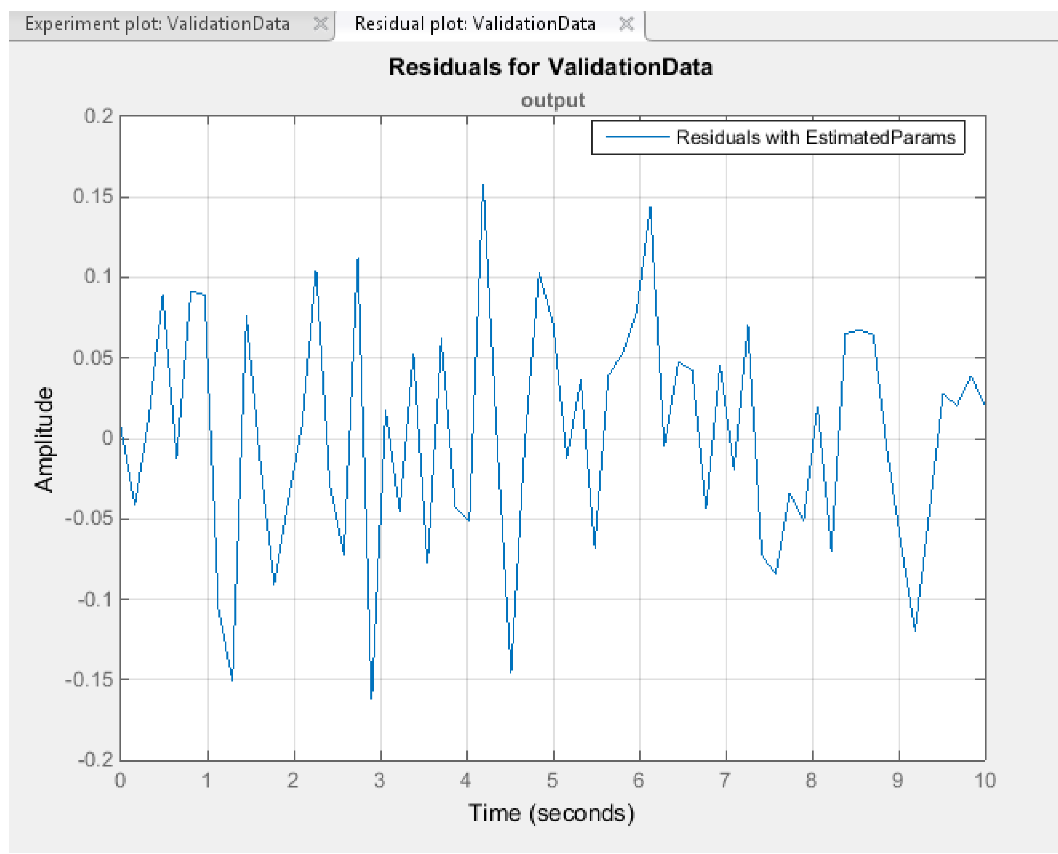
5 Examine the plots

a Experiment plot



You can see that the data simulated using the estimated parameters agrees with the measured validation data.

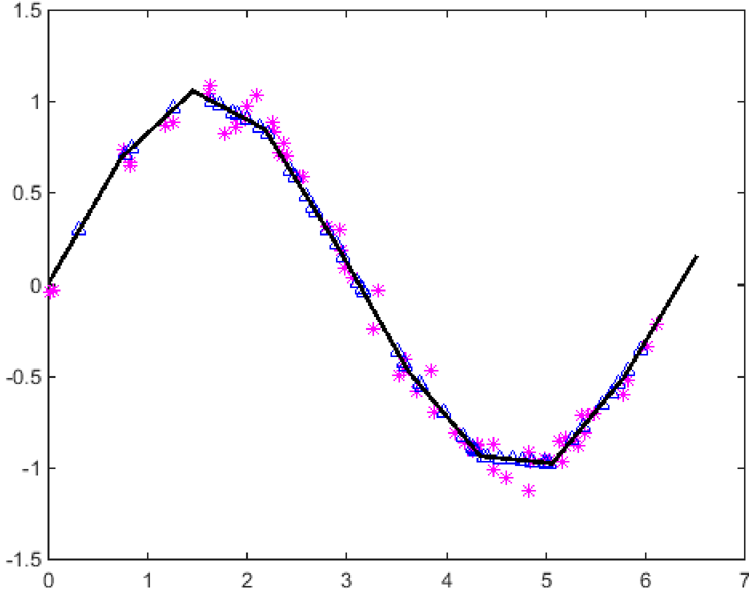
b Click Residual plot: ValidationData to open the residuals plot.



The residuals, which show the difference between the simulated and measured data, lie in the range [-0.15,0.15]— within 15% of the maximum output variation. This indicates a good match between the measured and the simulated table data values.

c Plot and examine the estimated table values against the validation data set and the simulated table values by typing the following commands at the MATLAB prompt.

```
sim('lookup_regular')
figure(2); plot(xdata2,ydata2, 'm*', xout, yout,'b^')
hold on; plot(linspace(0,6.5,10), table, 'k', 'LineWidth', 2)
```



The plot shows that the table values, displayed as the black line, match both the validation data and the simulated table values. The table data values cover the entire range of input values, which indicates that all the lookup table values have been estimated.

See Also

Related Examples

- "Estimate Constrained Values of a Lookup Table" on page 6-5

Building Models Using Adaptive Lookup Table Blocks

Simulink Design Optimization software provides blocks for modeling systems as adaptive lookup tables. You can use the adaptive lookup table blocks to create lookup tables from measured or simulated data. You build a model using the adaptive lookup table blocks, and then simulate the model to adapt the lookup table values to the time-varying I/O data. During simulation, the software uses the input data to locate the table values, and then uses the output data to recalculate the table values. The updated table values are stored in the adaptive lookup table block. For more information, see “What are Adaptive Lookup Tables?” on page 6-2.

The Adaptive Lookup Table library has the following blocks:

- Adaptive Lookup Table (1D Stair-Fit) — One-dimensional adaptive lookup table
- Adaptive Lookup Table (2D Stair-Fit) — Two-dimensional adaptive lookup table
- Adaptive Lookup Table (nD Stair-Fit) — Multidimensional adaptive lookup table

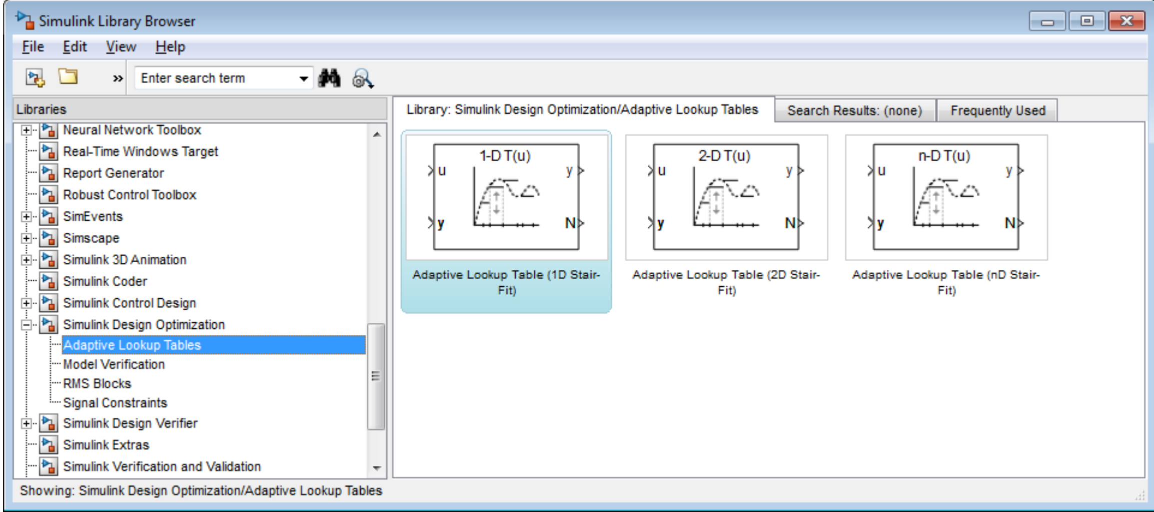
Note Use the Adaptive Lookup Table (nD Stair-Fit) block to create lookup tables of three or more dimensions.

To access the Adaptive Lookup Tables library:

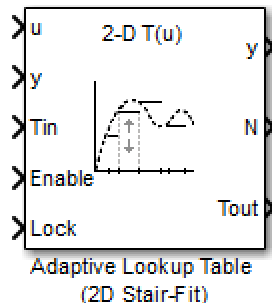
1. Open the Simulink Library Browser.

   At the MATLAB prompt, enter `slLibraryBrowser`.
2. Open the Simulink Design Optimization library.

   In the **Libraries** pane, expand the **Simulink Design Optimization** node.
3. In the Simulink Design Optimization library tree, click **Adaptive Lookup Tables**.



By default, the Adaptive Lookup Table blocks have two inputs and outputs. You can display additional inputs and outputs in a block by selecting the corresponding options in the Function Block Parameters dialog box. To learn more about the options, see the block reference pages.



Adaptive Lookup Table Block Showing Inputs and Outputs

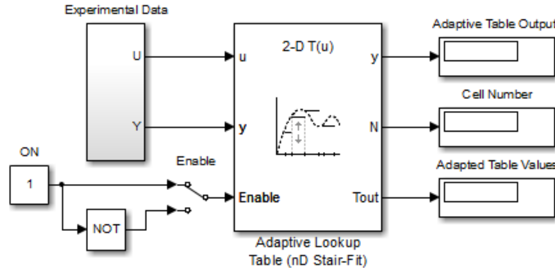
The 2-D Adaptive Lookup Table block has the following inputs and outputs:

- `u` and `y` — Input and output data of the system being modeled, respectively.

  For example, to model an engine's efficiency as a function of engine rpm and manifold pressure, specify `u` as the rpm, `y` as the pressure, and `y` as the efficiency signals.
- `Tin` — The initial table data.
- `Enable` — Signal to enable, disable, or reset the adaptation process.
- `Lock` — Signal to update only specified cells in the table.
- `y` — Value of the cell currently being adapted.
- `N` — Number of the cell currently being adapted.
- `Tout` — Values of the adapted table data.

For more information on how to use adaptive lookup tables, see "Model Engine Using n-D Adaptive Lookup Table" on page 6-33.

A typical Simulink diagram using an adaptive lookup table block is shown in the next figure.



Simulink Diagram Using an Adaptive Lookup Table

In this figure, the Experiment Data block imports a set of experimental data into Simulink through MATLAB workspace variables. The initial table is specified in the block mask parameters. When the simulation runs, the initial table begins to adapt to new data inputs and the resulting table is copied to the block's output.

See Also

Adaptive Lookup Table (1D Stair-Fit) | Adaptive Lookup Table (2D Stair-Fit) | Adaptive Lookup Table (nD Stair-Fit)

Related Examples

- “Model Engine Using n-D Adaptive Lookup Table” on page 6-33

More About

- “What are Adaptive Lookup Tables?” on page 6-2
- “Selecting an Adaptation Method” on page 6-31

Selecting an Adaptation Method

You specify the algorithm using the **Adaptation Method** drop-down list in the Function Block Parameters dialog box of an adaptive lookup table block. This section discusses the details of these algorithms.

Sample Mean

`Sample mean` provides the average value of n output data samples and is defined as:

$$\hat{y}(n) = \frac{1}{n}\sum_{i=1}^{n} y(i)$$

where $y(i)$ is the ith measurement collected within a particular *cell*. For each input data u, the sample mean at the corresponding cell is updated using the output data measurement, y. Instead of accumulating n samples of data for each cell, a recursive relation is used to calculate the sample mean. The recursive expression is obtained by the following equation:

$$\hat{y}(n) = \frac{1}{n}\left[\sum_{i=1}^{n-1} y(i) + y(n)\right] = \frac{n-1}{n}\left[\frac{1}{n-1}\sum_{i=1}^{n-1} y(i)\right] + \frac{1}{n}y(n) = \frac{n-1}{n}\hat{y}(n-1) + \frac{1}{n}y(n)$$

where $y(n)$ is the nth data sample.

Defining *a priori estimation error* as $e(n) = y(n) - \hat{y}(n-1)$, the recursive relation can be written as:

$$\hat{y}(n) = \hat{y}(n-1) + \frac{1}{n}e(n)$$

where $n \geq 1$ and the initial estimate $\hat{y}(0)$ is arbitrary.

In this expression, only the number of samples, n, for each cell— rather than n data samples—is stored in memory.

Sample Mean with Forgetting

The adaptation method “Sample Mean” on page 6-31 has an *infinite memory*. The past data samples have the same weight as the final sample in calculating the sample mean. `Sample mean (with forgetting)` uses an algorithm with a *forgetting factor* or **Adaptation gain** that puts more weight on the more recent samples. This algorithm provides robustness against initial response transients of the plant and an adjustable speed of adaptation. `Sample mean (with forgetting)` is defined as:

$$\hat{y}(n) = \frac{1}{\sum_{i=1}^{n}\lambda^{n-i}}\sum_{i=1}^{n}\lambda^{n-i}y(i)$$

$$= \frac{1}{\sum_{i=1}^{n}\lambda^{n-i}}\left[\sum_{i=1}^{n-1}\lambda^{n-i}y(i) + y(n)\right] = \frac{s(n-1)}{s(n)}\hat{y}(n-1) + \frac{1}{s(n)}y(n)$$

where $\lambda \in [0, 1]$ is the **Adaptation gain** and $s(k) = \sum_{i=1}^{k}\lambda^{n-i}$.

Defining *a priori estimation error* as $e(n) = y(n) - \widehat{y}(n-1)$, where $n \geq 1$ and the initial estimate $\widehat{y}(0)$ is arbitrary, the recursive relation can be written as:

$$\widehat{y}(n) = \widehat{y}(n-1) + \frac{1}{s(n)}e(n) = \widehat{y}(n-1) + \frac{1-\lambda}{1-\lambda^n}e(n)$$

A small value of λ results in faster adaptation. A value of 0 indicates short memory (last data becomes the table value), and a value of 1 indicates long memory (average all data received in a cell).

Model Engine Using n-D Adaptive Lookup Table

Objectives

In this example, you learn how to capture the time-varying behavior of an engine using an n-D adaptive lookup table. You accomplish the following tasks using the Simulink software:

- Configure an adaptive lookup table block to model your system.
- Simulate the model to update the lookup table values dynamically.
- Export the adapted lookup table values to the MATLAB workspace.
- Lock a specific cell in the table during adaptation.
- Disable the adaptation process and use the adaptive lookup table as a static lookup table.

About the Data

In this example, you use the data in `vedata.mat` which contains the following variables measured from an engine:

- `X` — 10 input breakpoints for intake manifold pressure in the range [10,100]
- `Y` — 36 input breakpoints for engine speed in the range [0,7000]
- `Z` — 10x36 matrix of table data for engine volumetric efficiency

  To learn more about breakpoints and table data, see “Anatomy of a Lookup Table”.

The output volumetric efficiency of the engine is time varying, and a function of two inputs—intake manifold pressure and engine speed. The data in the MAT-file is used to generate the time-varying input and output (I/O) data for the engine.

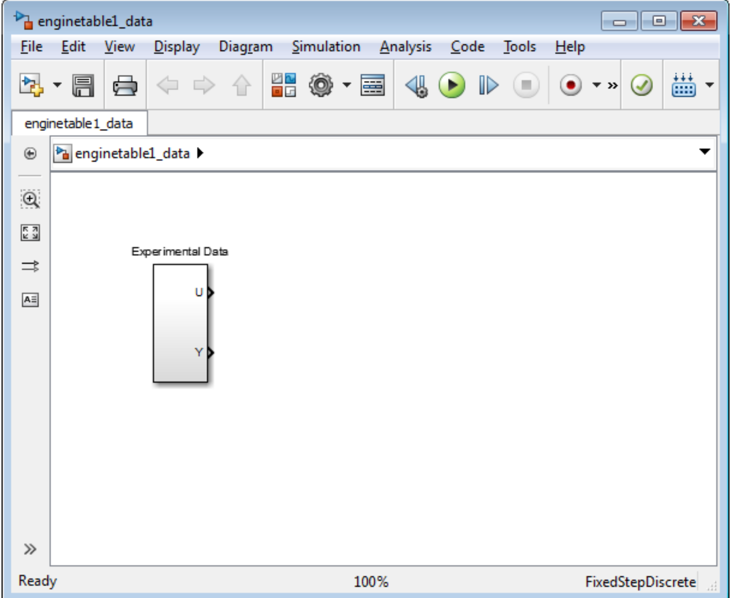
Building a Model Using Adaptive Lookup Table Blocks

In this portion of the tutorial, you learn how to build a model of an engine using an Adaptive Lookup Table block.

1. Open a preconfigured Simulink model by typing the model name at the MATLAB prompt:

   ```
   enginetable1_data
   ```

   The Experimental Data subsystem in the Simulink model generates time-varying I/O data during simulation.



This command also loads the variables X, Y and Z into the MATLAB workspace. To learn more about this data, see "About the Data" on page 6-33.

2 Add an Adaptive Lookup Table block to the Simulink model.

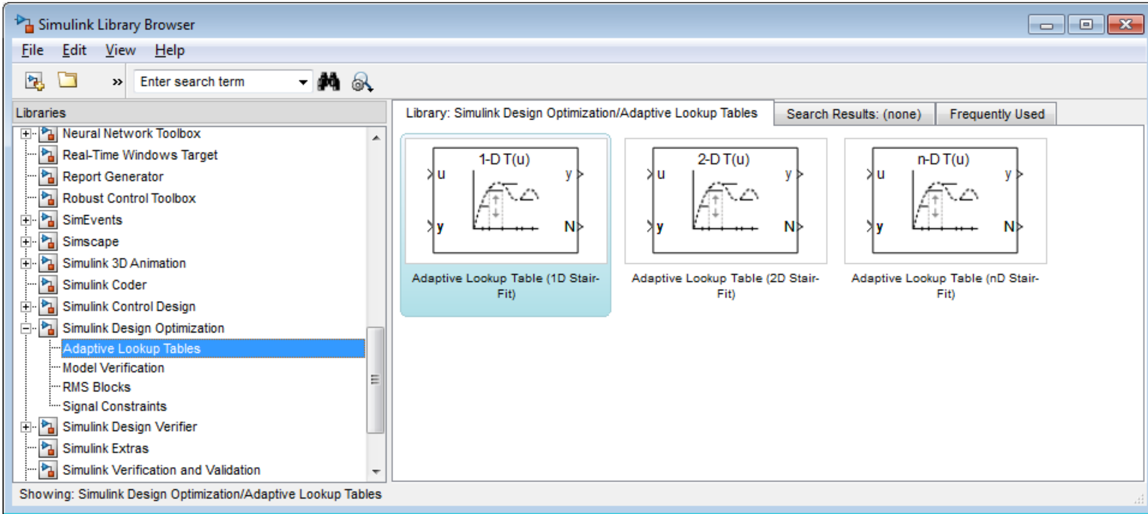
   a Open the Simulink Library Browser.

   At the MATLAB prompt, enter `slLibraryBrowser`.

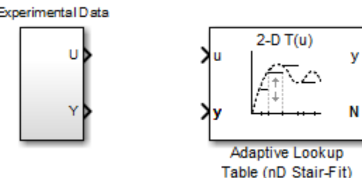
   b Open the Simulink Design Optimization library.

   In the **Libraries** pane, expand the **Simulink Design Optimization** node.

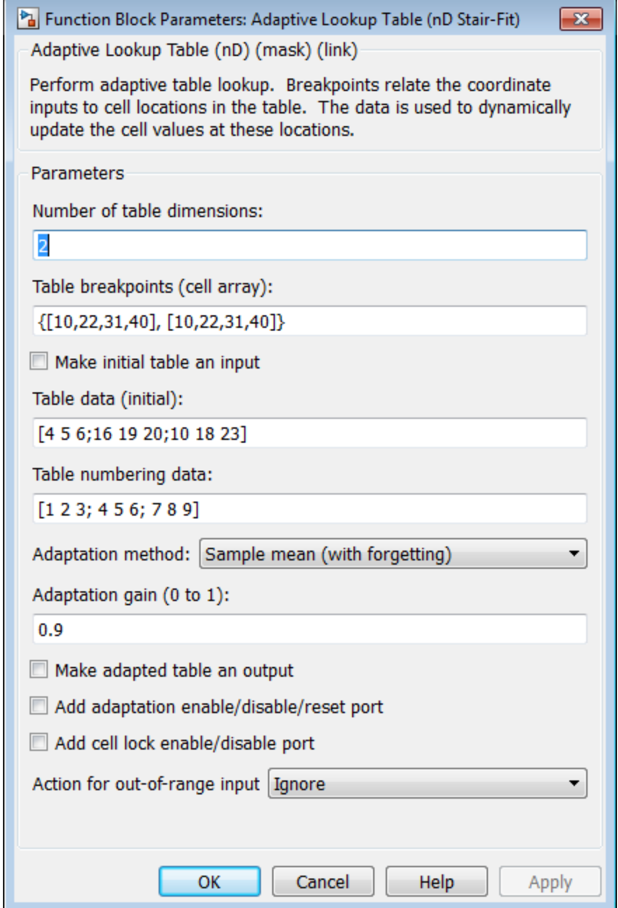
   c In the Simulink Design Optimization library tree, click **Adaptive Lookup Tables**.



   d Drag and drop the Adaptive Lookup Table (nD Stair-Fit) block from the Adaptive Lookup Tables library to the Simulink model window.



3 Double-click the Adaptive Lookup Table (nD Stair-Fit) block to open the Function Block Parameters: Adaptive Lookup Table (nD Stair-Fit) dialog box.



4 In the Function Block Parameters dialog box:

a Specify the following block parameters:

- **Table breakpoints (cell array)** — Enter `{[X; 110], [Y; 7200]}` to specify the range of input breakpoints.
- **Table data (initial)** — Enter `rand(10,36)` to specify random numbers as the initial table values for the volumetric efficiency.
- **Table numbering data** — Enter `reshape(1:360,10,36)` to specify a numbering scheme for the table cells.

b Verify that `Sample mean (with forgetting)` is selected in the **Adaptation method** drop-down list.

c Enter `0.98` in the **Adaptation gain (0 to 1)** field to specify the *forgetting factor* for the `Sample mean (with forgetting)` adaptation algorithm.

An adaptation gain close to 1 indicates high robustness of the lookup table values to input noise. To learn more about the adaptation gain, see "Sample Mean with Forgetting" on page 6-31 in "Selecting an Adaptation Method" on page 6-31.

d Select the **Make adapted table an output** check box.

This action adds a new port named `Tout` to the Adaptive Lookup Table block. You use this port to plot the table values as they are being adapted.

e Select the **Add adaptation enable/disable/reset port** check box.

This action adds a new port named `Enable` to the Adaptive Lookup Table block. You use this port to enable or disable the adaptation process.

f Select the **Add cell lock enable/disable port** check box.

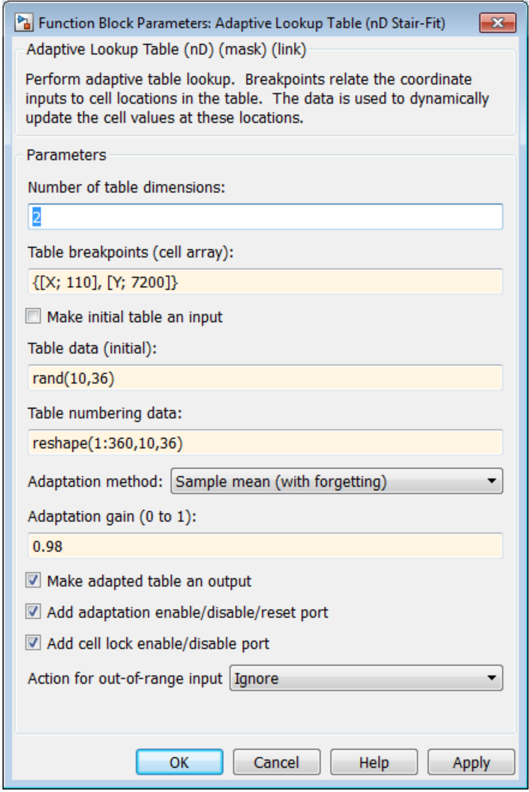
This action adds a new port named `Lock` to the Adaptive Lookup Table block. You use this port to lock a cell during the adaptation process.

g Verify that `Ignore` is selected in the **Action for out-of-range** drop-down list.

This selection specifies that the software ignores any time-varying inputs outside the range of input breakpoints during adaptation.

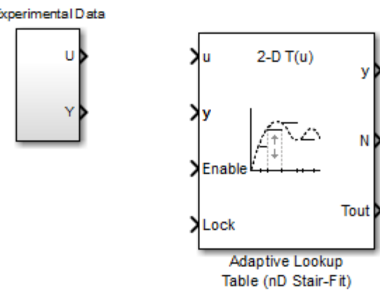
Tip To learn more, see Adaptive Lookup Table (nD Stair-Fit) block reference page.

After you configure the parameters, the block parameters dialog box looks like the following figure.

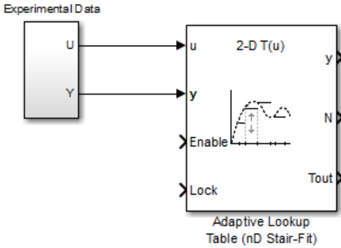


h Click **OK** to close the Function Block Parameters dialog box.

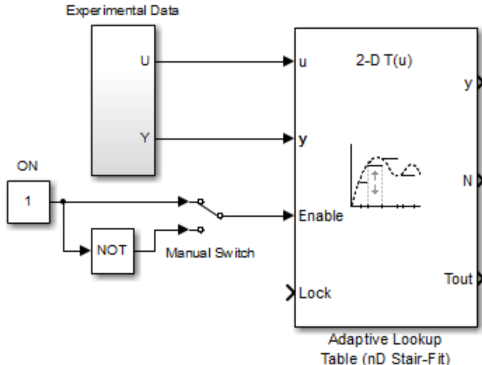
The Simulink model now looks similar to the following figure.



5 Assign the input and output data to the engine model by connecting the U and Y ports of the Experimental Data block to the u and y ports of the Adaptive Lookup Table block, respectively.

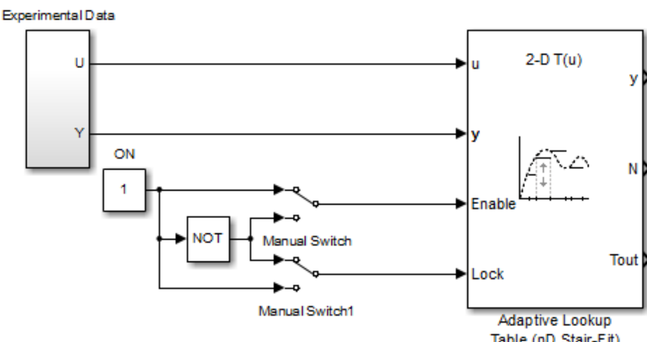


6 Design a logic using Simulink blocks to enable or disable the adaptation process. Connect the logic to the Adaptive Lookup Table block, as shown in the following figure.

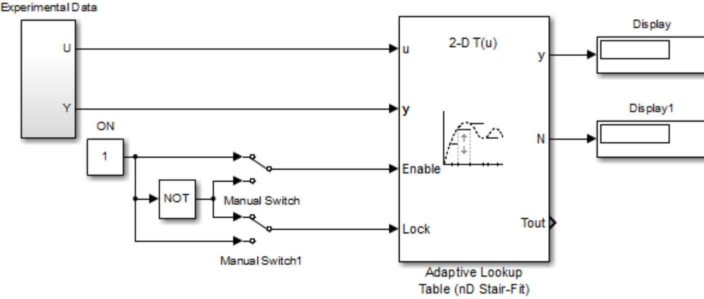


This logic outputs an initial value of 1 which enables the adaptation process.

7 Design a logic to lock a cell during adaptation. Connect the logic to the Adaptive Lookup Table block, as shown in the following figure.



8 In the Simulink Library Browser, select the **Simulink** > **Sinks** library, and drag Display blocks to the model window. Connect the blocks, as shown in the following figure.

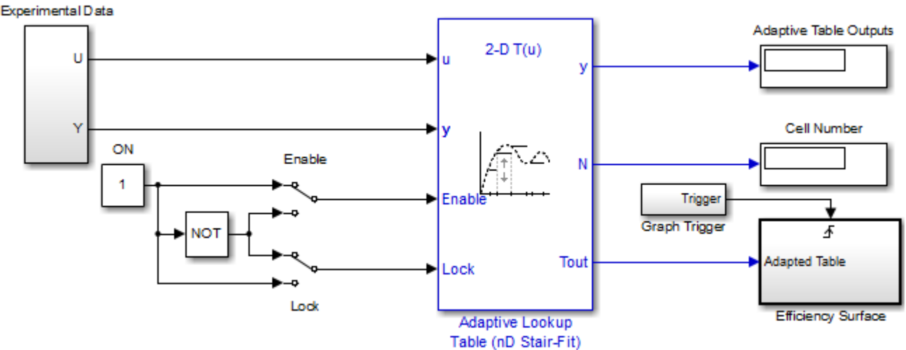


During simulation, the Display blocks show the following:

- `Display` block — Shows the value of the current cell being adapted.
- `Display1` block — Shows the number of the current cell being adapted.

9 Write a MATLAB function to plot the lookup table values as they adapt during simulation.

Alternatively, type `enginetable` at the MATLAB prompt to open a preconfigured Simulink model. The `Efficiency Surface` subsystem contains a function to plot the lookup table values, as shown in the next figure.

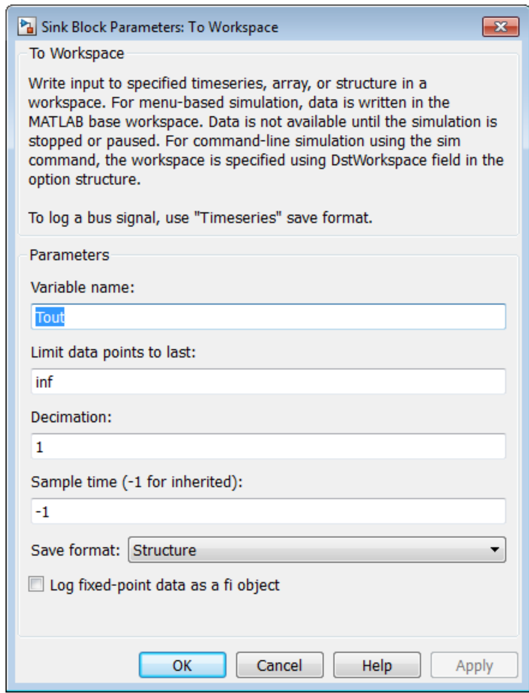


10 Connect a To Workspace block to export the adapted table values:

a In the Simulink Library Browser, select the **Simulink** > **Sinks** library, and drag the To Workspace block to the model window.

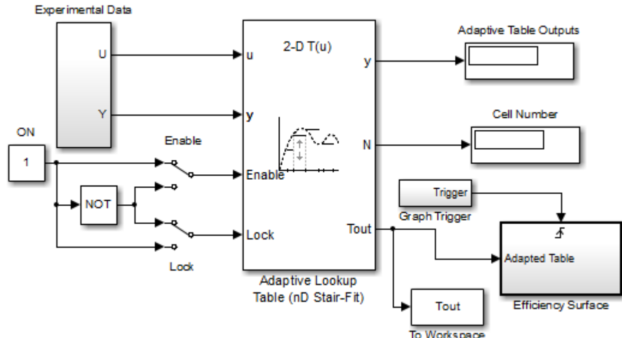
To learn more about this block, see the To Workspace block reference page in the Simulink documentation.

b Double-click the To Workspace block to open the Sink Block Parameters dialog box, and type `Tout` in the **Variable name** field.



c Click **OK**.

d Connect the To Workspace block to the adaptive lookup table output signal `Tout`, as shown in the next figure.



You have now built the model for updating and viewing the adaptive lookup table values. You must now simulate the model to start the adaptation, as described in "Adapting the Lookup Table Values Using Time-Varying I/O Data" on page 6-40.

Adapting the Lookup Table Values Using Time-Varying I/O Data

In this portion of the tutorial, you learn how to update the lookup table values to adapt to the time-varying input and output values.

You must have already built the Simulink model, as described "Building a Model Using Adaptive Lookup Table Blocks" on page 6-33.

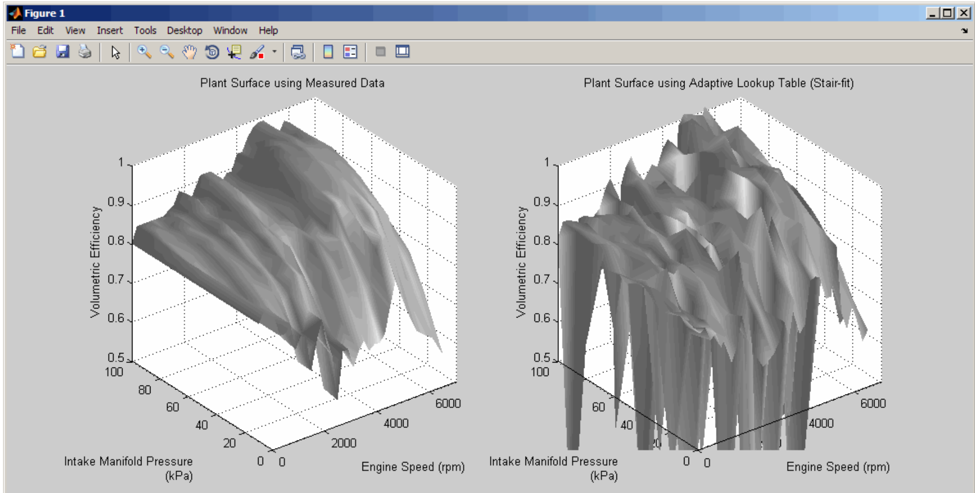
To perform the adaptation:

1. In the Simulink Editor, specify the simulation time as `inf`.

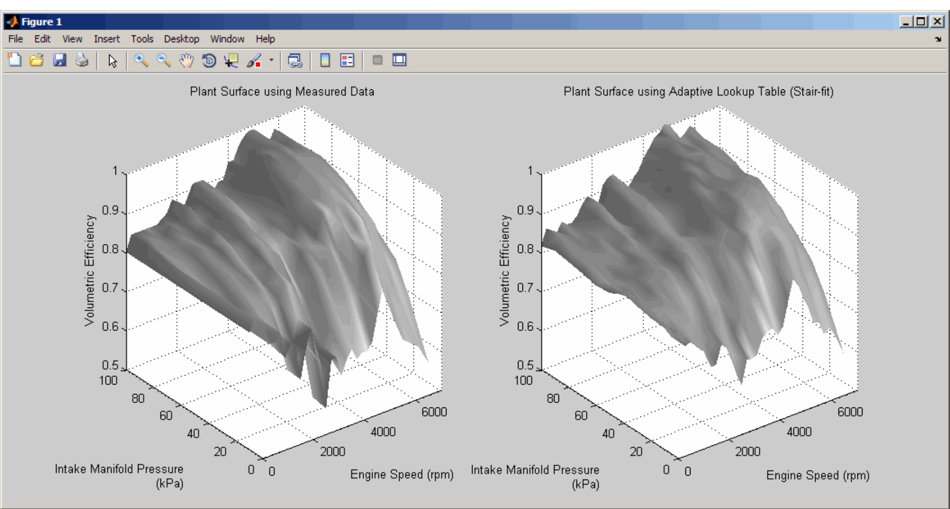
   The simulation time of infinity specifies that the adaptation process continues as long as the input and output values of the engine change.
2. In the Simulink Editor, click **Run** under **Simulation** to start the adaptation process.

   A figure window opens that shows the volumetric efficiency of the engine as a function of the intake manifold pressure and engine speed:

   - The left plot shows the measured volumetric efficiency as a function of intake manifold pressure and engine speed.
   - The right plot shows the volumetric efficiency as it adapts with the time-varying intake manifold pressure and engine speed.



During simulation, the lookup table values displayed on the right plot adapt to the variations in the I/O data. The left and the right plots resemble each other after a few seconds, as shown in the next figure.



Tip During simulation, the `Cell Number` and `Adaptive Table Outputs` blocks in the Simulink model display the cell number, and the adapted lookup table value in the cell, respectively.

---

3. Pause the simulation by clicking **Pause** under **Simulation**.

   This action also exports the adapted table values `Tout` to the MATLAB workspace.

Note After you pause the simulation, the adapted table values are stored in the Adaptive Lookup Table block.

---

4. Examine that the left and the right plots match. This resemblance indicates that the table values have adapted to the time-varying I/O data.
5. Lock a table cell so that only one cell adapts. You may find this feature useful if a portion of the data is highly erratic or otherwise difficult for the algorithm to handle.

a. Click **Run** under **Simulation** to restart the simulation.
b. Double-click the `Lock` block. This action toggles the switch and feeds the output of the `ON` block to the`Lock` input port of the `Adaptive Lookup Table(nD Stair-Fit)` block.

   You can view the number of the locked cell in the `Cell Number` block in the Simulink model.

6. After the table values adapt to the time-varying I/O data, you can continue to use the Adaptive Lookup Table block as a static lookup table:

   a. In the Simulink model window, double-click the `Enable` block. This action toggles the switch, and disables the adaptation.
   b. Click **Run** under **Simulation** to restart the simulation, if it is not already running.

      During simulation, the Adaptive Lookup Table block works like a static lookup table, and continues to estimate the output values as the input values change. You can see the current lookup table value in the `Adaptive Table Outputs` block in the Simulink model window.

Note After you disable the adaptation, the Adaptive Lookup Table block does not update the stored table values, and the figure that displays the table values does not update.

See Also
Adaptive Lookup Table (nD Stair-Fit)

More About
- “What are Adaptive Lookup Tables?” on page 6-2

Using Adaptive Lookup Tables in Real-Time Environment

You can use experimental data from sensor measurements collected by running various tests on a system in real time. The measured data is then sent to the adaptive table block to generate a lookup table describing the relation between the system inputs and output.

You can also use the Adaptive Lookup Table block in a real-time environment, where some time-varying properties of a system need to be captured. To do so, generate C code using Simulink Coder™ code generation software that can then be run in Simulink Real-Time™ or dSPACE® software. Because you can start, stop, or reset the adaptation if you want, use logic to enable the adaptation of the table data only when it is desired. The cell number output `N`, and the `Enable` and `Lock` inputs facilitate this process. Use the `Enable` input to start and stop the adaptation and the `Lock` input to update only one of the table cells. The `Lock` input combined with some logic using the cell number output `N` provide the means for updating only the desired table cells during a simulation run.

See Also

Adaptive Lookup Table (1D Stair-Fit) | Adaptive Lookup Table (2D Stair-Fit) | Adaptive Lookup Table (nD Stair-Fit)

Related Examples

- "Model Engine Using n-D Adaptive Lookup Table" on page 6-33

More About

- "What are Adaptive Lookup Tables?" on page 6-2

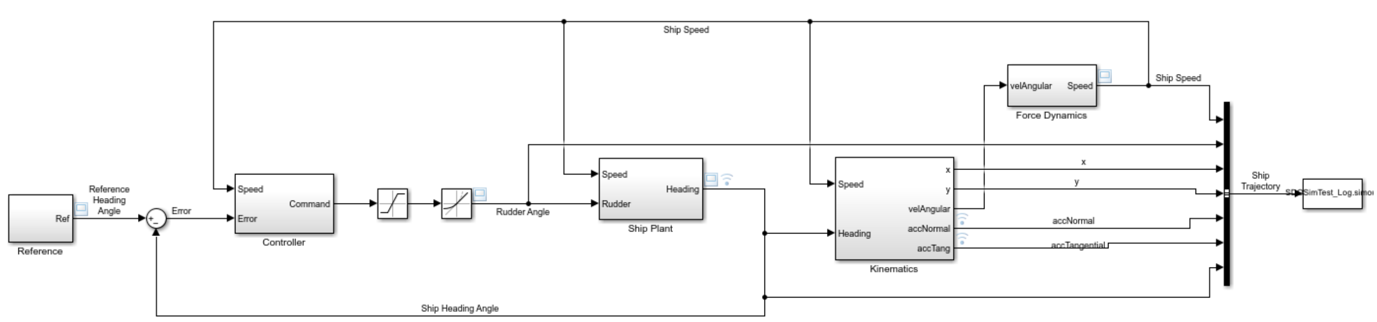
Design Optimization Using Lookup Table Requirements for Gain Scheduling (Code)

This example shows how to tune parameters in a lookup table in a model that uses gain scheduling to adjust the controller's response to a plant that varies. Model tuning uses the `sdo.optimize` command.

Ship Steering Model

Open the Simulink® Model.

```
mdl = 'sdoShipSteering';
open_system(mdl)
```

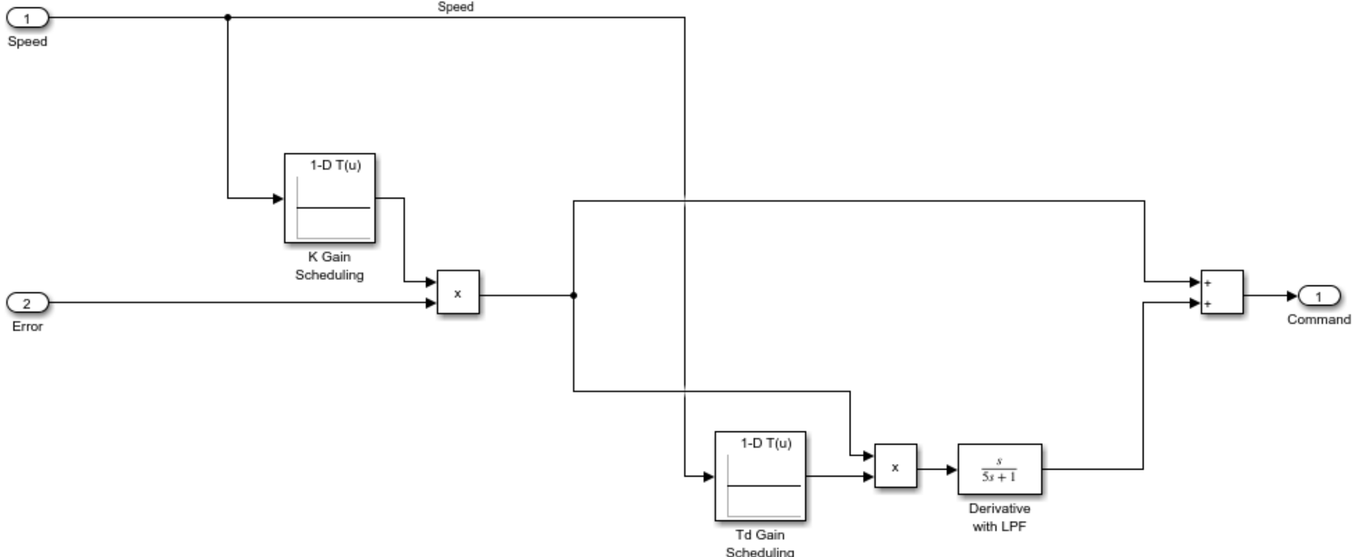


This model implements the Nomoto model which is commonly used for ship steering. The dynamic characteristics of a ship vary significantly with factors such as the ship speed. Therefore the rudder controller should also vary with speed, in order to meet requirements for steering the ship.

To keep the ship on course, a control loop compares the ship's heading angle with the reference heading angle, and a PD controller sends command signals to the rudder. The Ship Plant block implements the Nomoto model, a second order system whose parameters vary with the ship's speed. The ship is initially traveling at its maximum speed of 15 m/s, but it will slow down when the reference trajectory specifies a turn in the water. This turning, along with the force of the engine, is used by the Force Dynamics block to compute the speed of the ship over time. The Kinematics block computes the trajectory of the ship.

Open the Controller block.

```
open_system([mdl  '/Controller'])
```



When the speed changes, the ship plant also changes. Therefore the PD controller gains need to change, and speed is used as the scheduling variable. The controller is in the form `K(1 + sTd)` where `K` is the overall gain and `Td` is the time constant associated with the derivative term. Gain scheduling is implemented via lookup tables, and the table data are specified by `K` and `Td`. These are vectors which specify different values for different speeds. The different speeds are specified in the lookup table breakpoint vectors `bpK` and `bpTd`.

Design Problem

The reference specifies that at 200 seconds, the ship should turn 180 degrees and reverse course. One requirement is that the ship heading angle needs to match the reference heading angle within an envelope. For the safety and comfort of passengers, a second requirement is that the total acceleration of the ship needs to stay within a bound of 0.25 g's, where 1 g is the acceleration of gravity at Earth's surface, 9.8 m/s/s.

The controller parameter vectors `K` and `Td` will be design variables, and will be tuned to try to meet the requirements. If it is not possible to meet both requirements, then the lookup table breakpoints `bpK` and `bpTd` will also be used as design variables. In that case, we will need to specify an additional requirement that `bpK` and `bpTd` must be monotonically strictly increasing, because this is required for breakpoint vectors in Simulink lookup tables.

Specify Design Requirements

Specify the requirements which must be satisfied. First, the ship should follow the reference trajectory. Since the reference is essentially a step change from 0 to 180 degrees, you specify a step response envelope for the ship heading angle.

```
Requirements = struct;
Requirements.StepResponseEnvelope = sdo.requirements.StepResponseEnvelope(...
    'StepTime',        200, ...  (seconds)
    'RiseTime',         75, ...
    'SettlingTime',    200, ...
    'PercentRise',      85, ...  (%)
    'PercentOvershoot',  5, ...
```

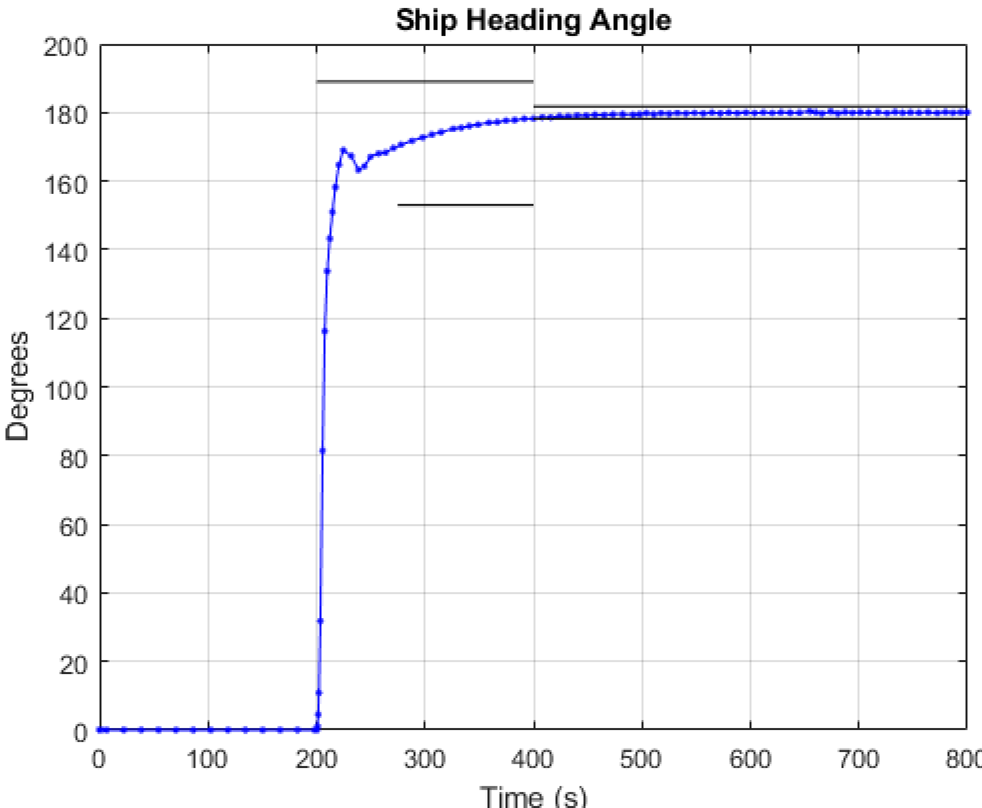
```
    'PercentSettling',   1, ...
    'FinalValue',       pi ...   (radians)
    );
```

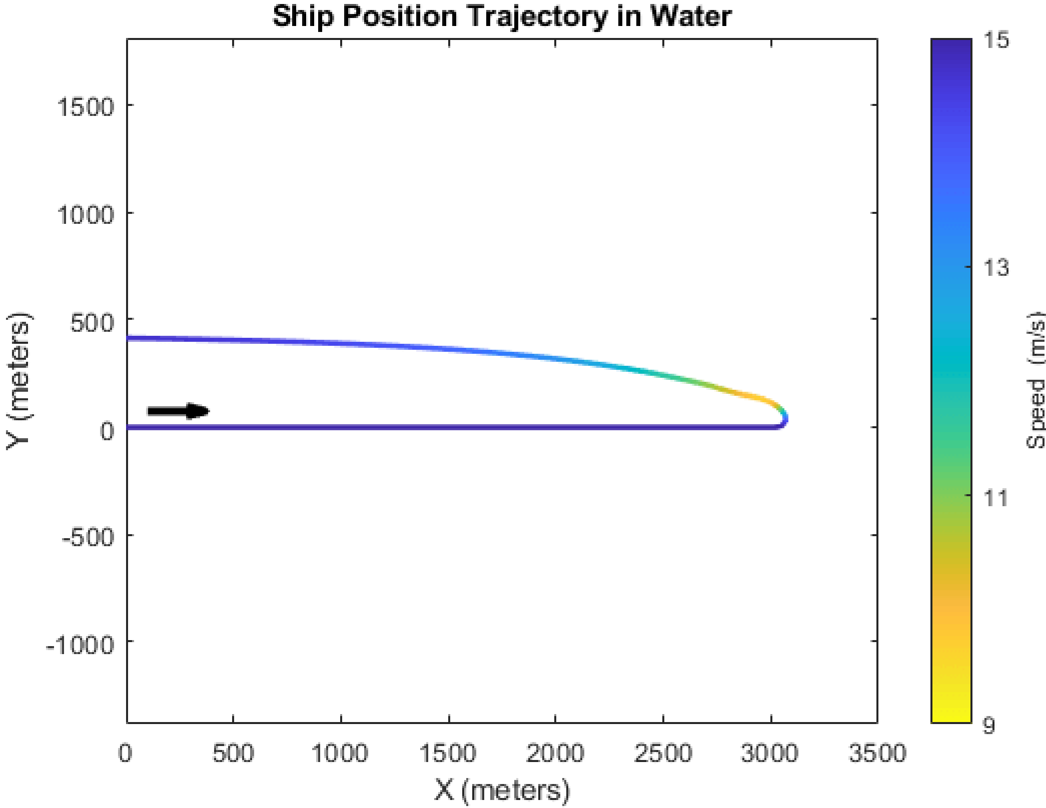
The second requirement is that for the safety and comfort of passengers, the total acceleration should not exceed 0.25 g's at any time. The total acceleration is composed of two components, a tangential component along the direction of the ship's motion, and a normal (horizontal) component. The requirement that total acceleration not exceed 0.25 g's corresponds to requiring that in the phase plane of tangential and normal acceleration, this ship's trajectory remain within a circle of radius 0.25*9.8.

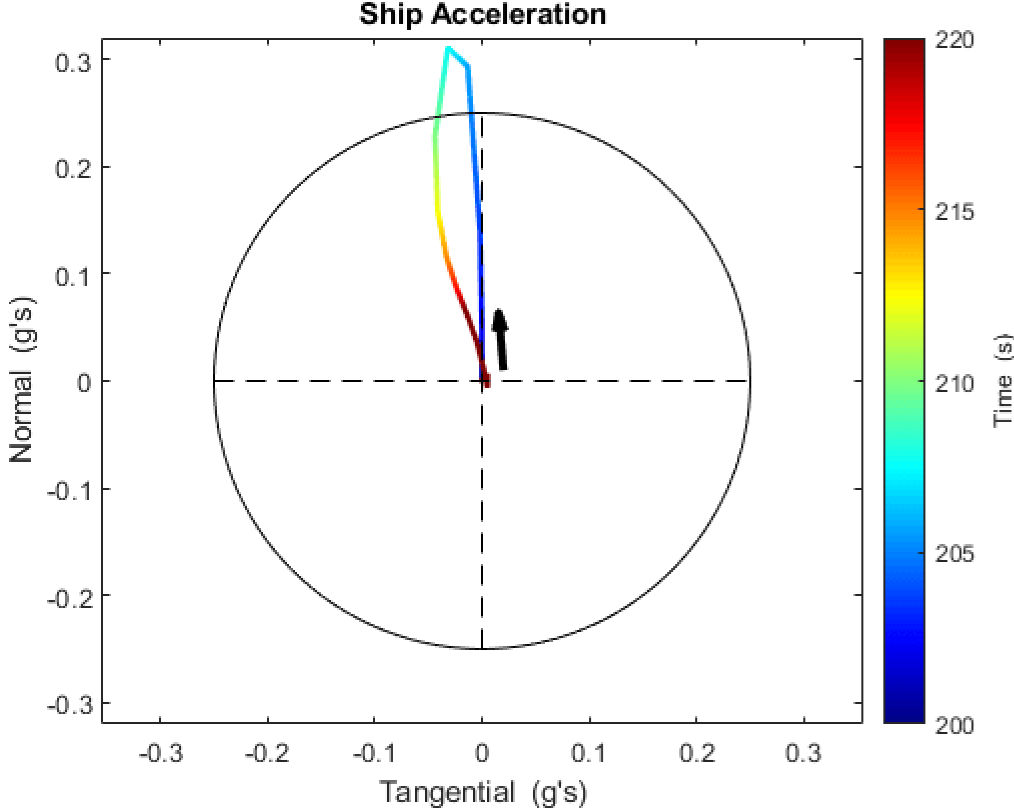
```
accelGravity = 9.8;
Requirements.Comfort = sdo.requirements.PhasePlaneEllipse(...
    'Radius', 0.25*[1 1] * accelGravity );
```

Examine the behavior of the ship with the initial, untuned controller parameters, to see whether the requirements are satisfied. Use the function `sdoShipSteeringPlots` to plot the ship's behavior. The first plot below shows that the ship's heading angle stays within the tolerance bounds of the step response envelope, satisfying the first requirement. The second plot shows the trajectory of the ship in the water. The black arrow indicates the starting position and direction of motion. The ship turns 180 degrees and the diameter is approximately 415 meters. The third plot shows the ship acceleration in the phase plane of tangential and normal acceleration. The black arrow indicates the starting point and direction of evolution over time. The total acceleration exceeds the bound near 208 seconds, so the requirement for passenger safety and comfort is not satisfied.

```
hPlots = sdoShipSteeringPlots(mdl, Requirements);
```




Ship Position Trajectory in Water
Y (meters)
X (meters)
Speed (m/s)
1500
1000
500
0
-500
-1000
0
500
1000
1500
2000
2500
3000
3500
15
13
11
9



Specify Design Variables

Specify the design variables to be tuned by the optimization routine in order to satisfy the requirements. Specify the gains of the PD controller, K and Td, as design variables. For initial values, use -0.1 for all entries in the K vector, and 50 for all entries in the Td vector. If the requirements can't all be satisfied, then later the breakpoint vectors bpK and bpTd can also be design variables.

```
DesignVars = sdo.getParameterFromModel(mdl, {'K','Td'});
DesignVars(1).Value = -0.1*[1 1 1 1];
DesignVars(2).Value =   50*[1 1 1 1];
sdo.setValueInModel(mdl, DesignVars);
```

Create Optimization Objective Function

Create an objective function that will be called at each optimization iteration to evaluate the design requirements as the design variables are tuned. This cost function has input arguments for the model, design variables, simulator (defined below), and design requirements. The cost function uses the maximum of the Comfort requirements at all times when it is computed, in order to consolidate requirement evaluation results to a scalar so the number of elements is the same regardless of time steps taken by the Simulink solver.

```
type sdoShipSteering_Design
```

```
function Vals = sdoShipSteering_Design(mdl, P, Simulator, Requirements)
%SDOSHIPSTEERING_DESIGN Objective function for ship steering
%
```

```
% Function called at each iteration of the optimization problem.
%
% The function is called with the model named mdl, a set of parameter
% values, P, a Simulator, and the design Requirements to evaluate.  It
% returns the objective value and constraint violations, Vals, to the
% optimization solver.
%
% See the sdoExampleCostFunction function and sdo.optimize for a more
% detailed description of the function signature.
%
% See also sdoShipSteering_cmddemo

% Copyright 2016 The MathWorks, Inc.

%% Model Evaluation

% Simulate the model.
Simulator.Parameters = P;
Simulator = sim(Simulator);

% Retrieve logged signal data.
SimLog = find(Simulator.LoggedData,get_param(mdl, 'SignalLoggingName'));
Heading     = find(SimLog, 'Heading');
NormalAccel = find(SimLog, 'NormalAccel');
TangenAccel = find(SimLog, 'TangenAccel');

% Evaluate the step response envelope requirement
Cleq_StepResponseEnvelope = evalRequirement(Requirements.StepResponseEnvelope, Heading.Values);

% Evaluate the safety/comfort requirement on total acceleration.
Cleq_Comfort = evalRequirement(Requirements.Comfort, NormalAccel.Values, TangenAccel.Values);

%% Return Values.

% Collect the evaluated design requirement values in a structure to return
% to the optimization solver.
Vals.Cleq = Cleq_StepResponseEnvelope(:);
Vals.Cleq = [Vals.Cleq  ; Cleq_Comfort];

% Evaluate monotonic variable requirement
if isfield(Requirements, 'Monotonic')
    Cleq_bpK  = evalRequirement(Requirements.Monotonic, P(3).Value);
    Cleq_bpTd = evalRequirement(Requirements.Monotonic, P(4).Value);
    Vals.Cleq = [Vals.Cleq ; Cleq_bpK ; Cleq_bpTd];
end

end
```

The cost function requires a Simulator to run the model. Create the simulator and add model signals to log, so their values are available to the cost function.

```
Simulator = sdo.SimulationTest(mdl);

% Ship Heading Angle
Heading = Simulink.SimulationData.SignalLoggingInfo;
Heading.BlockPath = 'sdoShipSteering/Ship Plant';
Heading.LoggingInfo.LoggingName = 'Heading';
Heading.LoggingInfo.NameMode = 1;
```

```
Heading.OutputPortIndex = 1;

% Normal Acceleration
NormalAccel = Simulink.SimulationData.SignalLoggingInfo;
NormalAccel.BlockPath = 'sdoShipSteering/Kinematics';
NormalAccel.LoggingInfo.LoggingName = 'NormalAccel';
NormalAccel.LoggingInfo.NameMode = 1;
NormalAccel.OutputPortIndex = 4;

% Tangential Acceleration
TangenAccel = Simulink.SimulationData.SignalLoggingInfo;
TangenAccel.BlockPath = 'sdoShipSteering/Kinematics';
TangenAccel.LoggingInfo.LoggingName = 'TangenAccel';
TangenAccel.LoggingInfo.NameMode = 1;
TangenAccel.OutputPortIndex = 5;

% Collect logged signals
Simulator.LoggingInfo.Signals = [...
    Heading ; ...
    NormalAccel ; ...
    TangenAccel ];
```

Optimize Lookup Table Data

Before optimizing, set up the simulator for fast evaluation by enabling Simulink Fast Restart.

```
Simulator = fastRestart(Simulator, 'on');
```

During optimization, the Simulink solver may generate a warning if the size of the time step becomes too small. Temporarily suppress this warning.

```
warnState = warning('query', 'Simulink:Engine:SolverMinStepSizeWarn');
warnState1 = warning('query', 'Simulink:Solver:Warning');
warnState2 = warning('query', 'SimulinkExecution:DE:MinStepSizeWarning');
warning('off', 'Simulink:Engine:SolverMinStepSizeWarn');
warning('off', 'Simulink:Solver:Warning');
warning('off', 'SimulinkExecution:DE:MinStepSizeWarning');
```

To optimize, define a handle to the cost function that uses the Simulator and Requirements defined above. Use an anonymous function that takes one argument (the design variables) and calls the objective function. Finally, call `sdo.optimize` to optimize the design variables to try to meet the requirements.

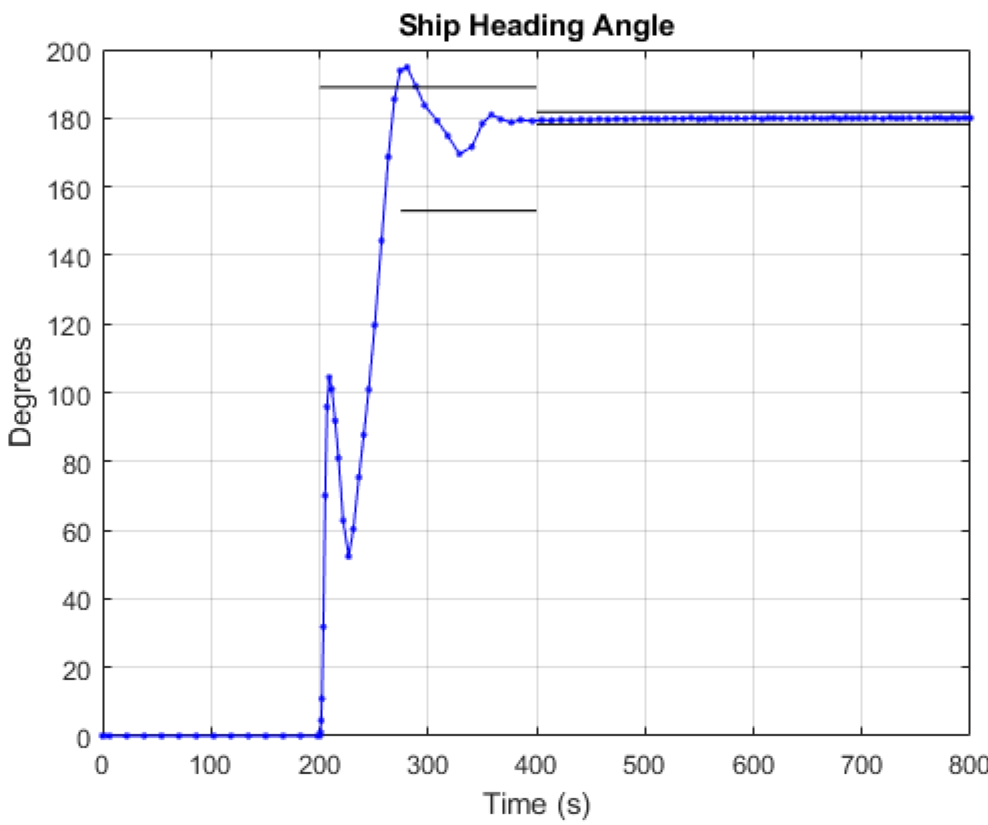
```
optimfcn = @(P) sdoShipSteering_Design(mdl, P, Simulator, Requirements);
[Optimized_DesignVars, Info] = sdo.optimize(optimfcn, DesignVars);
```

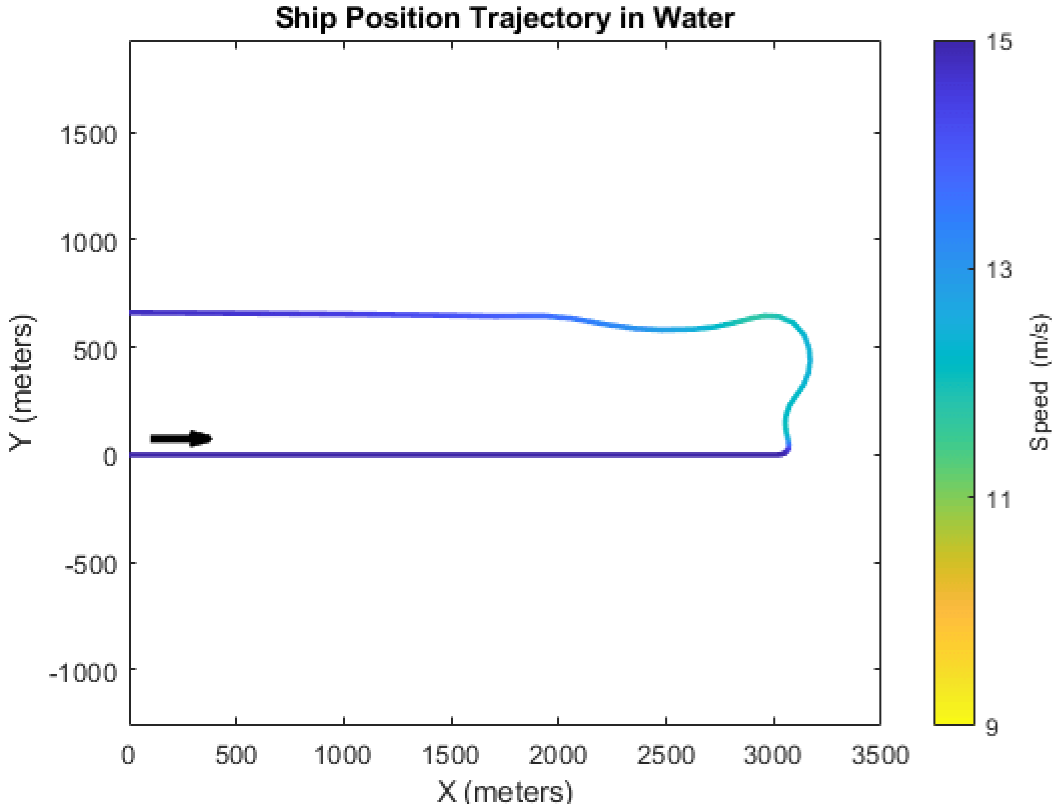
```
 Optimization started 01-Sep-2022 13:51:01

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0      17           0       0.6127
    1      34           0       0.3215        0.865        0.321
    2      57           0       0.3079        0.174        0.308
    3     103           0       0.3079      0.00127        0.308
Converged to an infeasible point.

fmincon stopped because the size of the current step is less than
```

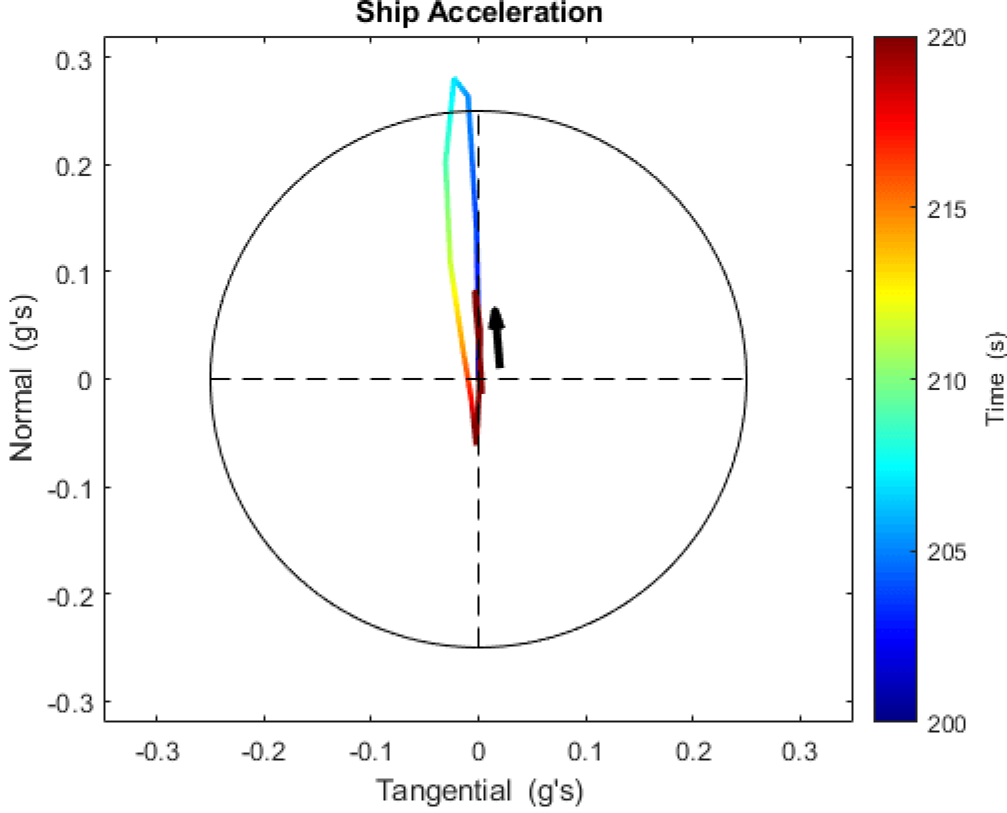
```
the value of the step size tolerance but constraints are not
satisfied to within the value of the constraint tolerance.
```

The display indicates that the optimizer was not able to satisfy all requirements. Try the optimized design variables in the model and plot the results. The heading angle is not within the required step response envelope, and the total acceleration still exceeds the allowable level during part of the turn. In addition, the turning diameter has increased to 660 meters, so the turn is not as tight as with untuned gains.

```
sdo.setValueInModel(mdl, Optimized_DesignVars);
hPlots = sdoShipSteeringPlots(mdl, Requirements, hPlots);
```




Ship Position Trajectory in Water
Y (meters)
X (meters)
Speed (m/s)
1500
1000
500
0
-500
-1000
0
500
1000
1500
2000
2500
3000
3500
15
13
11
9



Optimize Lookup Table Data and Breakpoints

To try to meet the design requirements, use the optimization result from above as the start point, and tune additional variables. Add breakpoints bpK and bpTd as design variables. The ship's maximum speed is 15 m/s, and during turning it may slow to 60% of the maximum speed, or 9 m/s. Set the breakpoint initial values to be equally spaced between 9 and 15 m/s. Constrain the breakpoint minimum values to 9 m/s, and constrain the breakpoint maximum values to 15 m/s.

```
DesignVars = Optimized_DesignVars;
DesignVars(3:4) = sdo.getParameterFromModel(mdl, {'bpK','bpTd'});

% Set initial values
DesignVars(3).Value = [9 11 13 15];
DesignVars(4).Value = [9 11 13 15];

% Constrain min and max values
DesignVars(3).Minimum =  9;
DesignVars(3).Maximum = 15;
DesignVars(4).Minimum =  9;
DesignVars(4).Maximum = 15;

% Set values in the model
sdo.setValueInModel(mdl, DesignVars);
```

Breakpoints in the Simulink lookup table block must be strictly monotonically increasing. Add this to the design requirements.

```
Requirements.Monotonic = sdo.requirements.MonotonicVariable;
optimfcn = @(P) sdoShipSteering_Design(mdl, P, Simulator, Requirements);
```

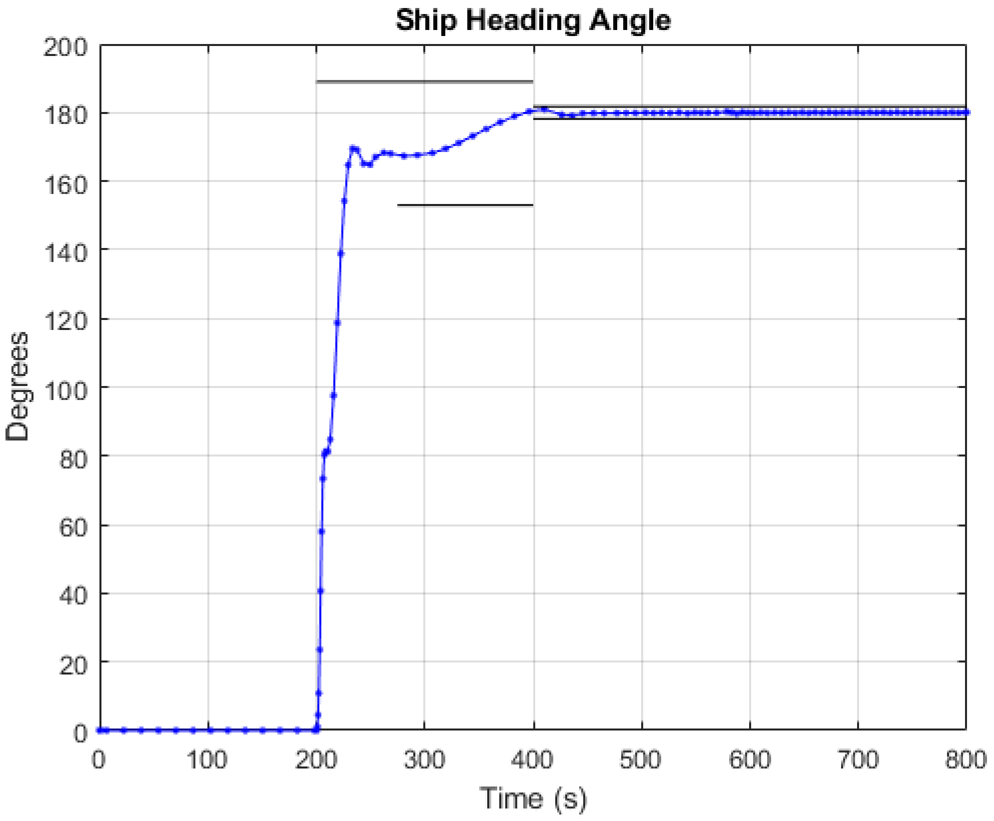
Optimize the model by tuning all four design variables, to see if all requirements can be met.

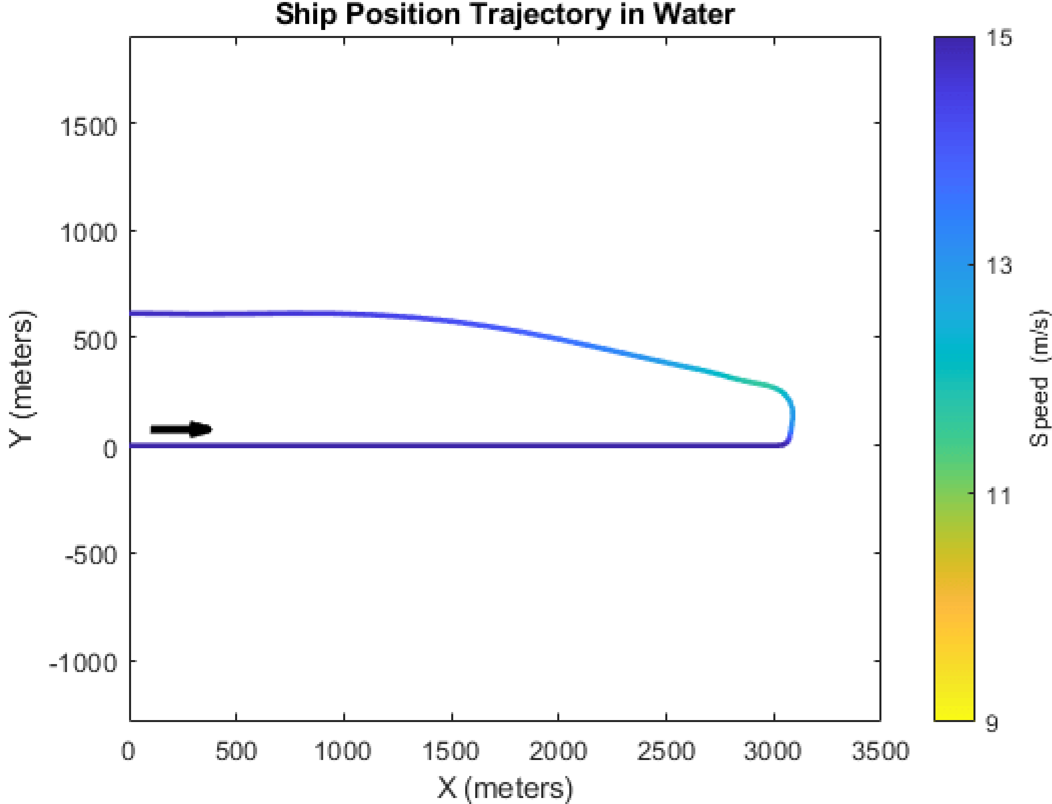
```
[Optimized_DesignVars, Info] = sdo.optimize(optimfcn, DesignVars);
```

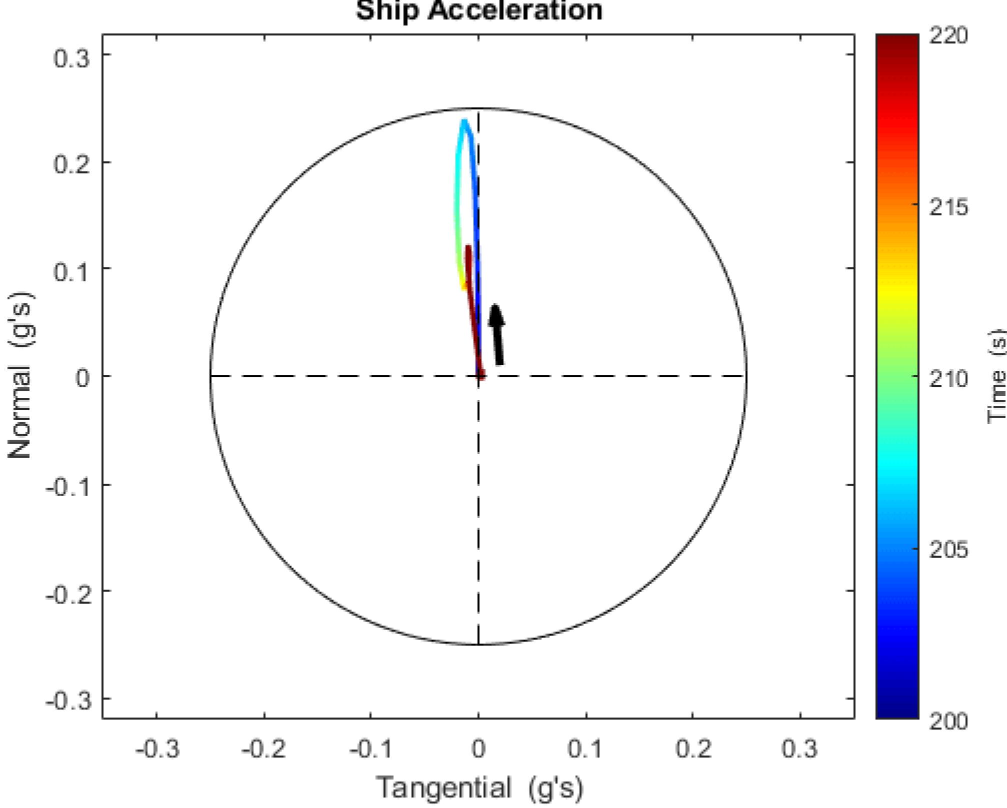
```
 Optimization started 01-Sep-2022 13:51:46

                               max                     First-order
 Iter F-count        f(x)   constraint    Step-size    optimality
    0     29            0       0.3079
    1     61            0       0.1432        0.148         1.01
    2     94            0      0.03626       0.0858        0.597
    3    123            0      0.01911       0.0548       0.0859
    4    153            0     0.007837       0.0341      0.00627
    5    183            0            0       0.0256     0.000903
Local minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the value of the optimality tolerance,
and constraints are satisfied to within the value of the constraint tolerance.
```

The display indicates that the optimizer was able to satisfy all requirements. Try the optimized design variables in the model and plot the results. In the plots below, the heading angle is within the step response envelope, and the total acceleration is within the allowed range of 0.25 g's. In addition, the turning diameter is 615 meters, which is tighter than when breakpoints were not tuned.

```
sdo.setValueInModel(mdl, Optimized_DesignVars);
hPlots = sdoShipSteeringPlots(mdl, Requirements, hPlots);
```


Ship Heading Angle
Degrees
Time (s)
0
20
40
60
80
100
120
140
160
180
200
0
100
200
300
400
500
600
700
800


Ship Position Trajectory in Water
Y (meters)
X (meters)
Speed (m/s)
1500
1000
500
0
-500
-1000
0
500
1000
1500
2000
2500
3000
3500
15
13
11
9



In this example, the ship plant varied with the ship speed, so the controller gains also needed to vary. Gain scheduling was implemented using lookup tables. By tuning the gains and breakpoint values in the controller, the ship was able to follow the reference heading angle, while also constraining total acceleration to ensure a safe and comfortable ride for passengers.

Related Examples

To learn how to optimize the lookup tables in the gain scheduled controller using the **Response Optimizer**, see “Design Optimization Using Lookup Table Requirements for Gain Scheduling (GUI)” on page 6-59.

```
% Close the model and figures, and restore state of warnings.
fastRestart(Simulator, 'off');   % restore fast restart settings
bdclose(mdl)
close(hPlots)
warning(warnState);   % restore state of warning
warning(warnState1);   % restore state of warning
warning(warnState2);   % restore state of warning
```

See Also

sdo.requirements.FunctionMatching | sdo.requirements.MonotonicVariable | sdo.requirements.PhasePlaneEllipse | sdo.requirements.PhasePlaneRegion | sdo.requirements.RelationalConstraint | sdo.requirements.SmoothnessConstraint

Related Examples

- "Design Optimization Using Lookup Table Requirements for Gain Scheduling (GUI)" on page 6-59
- "Estimate Lookup Table Values from Data" on page 6-17

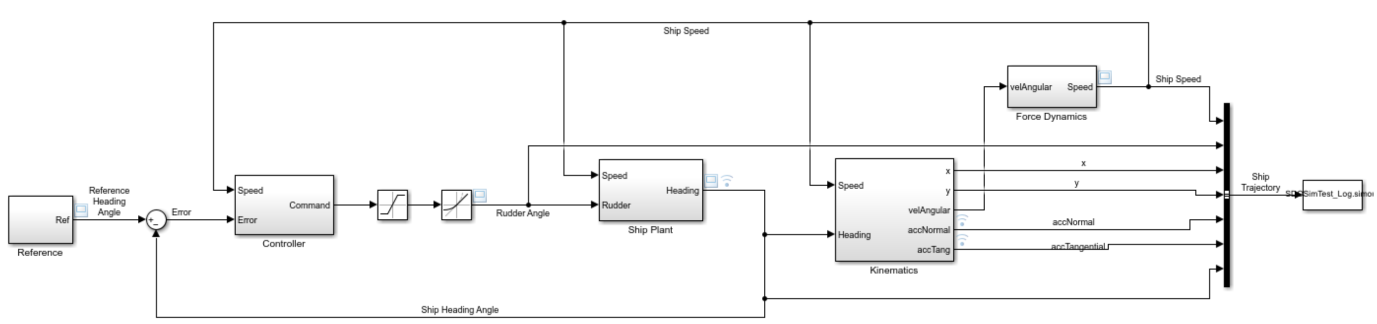
Design Optimization Using Lookup Table Requirements for Gain Scheduling (GUI)

This example shows how to tune parameters in a lookup table in a model that uses gain scheduling to adjust the controller's response to a plant that varies. Model tuning uses the **Response Optimizer** app.

Ship Steering Model

Open the Simulink® model.

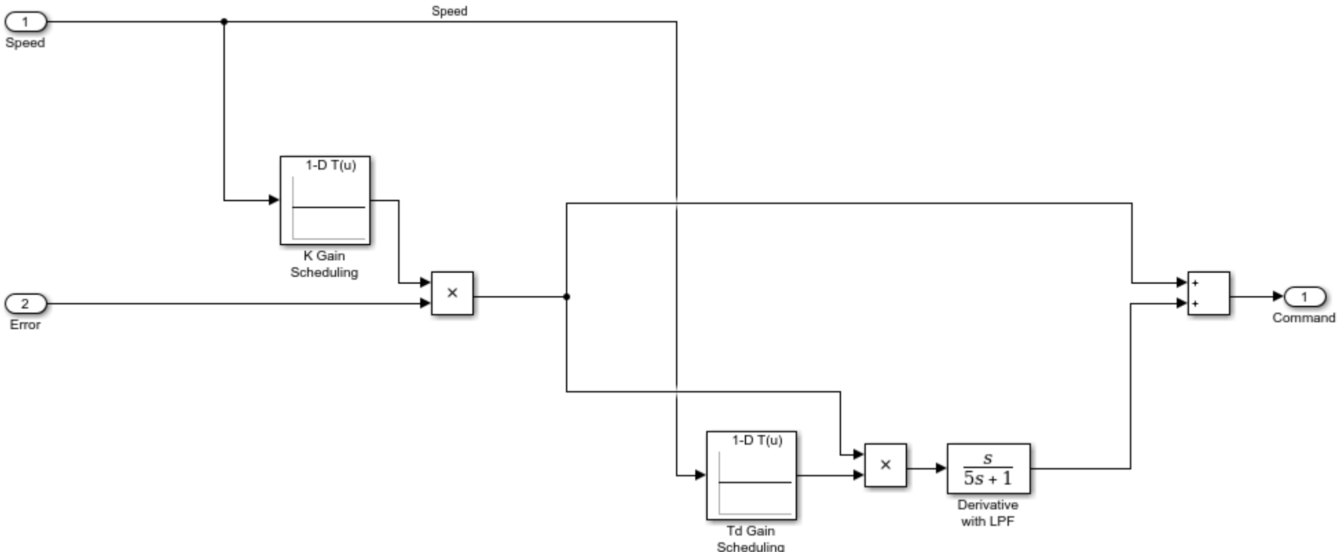
```
open_system('sdoShipSteering')
```



This model implements the Nomoto model which is commonly used for ship steering. The dynamic characteristics of a ship vary significantly with factors such as the ship speed. Therefore the rudder controller should also vary with speed, in order to meet requirements for steering the ship.

To keep the ship on course, a control loop compares the ship's heading angle with the reference heading angle, and a PD controller sends command signals to the rudder. The Ship Plant block implements the Nomoto model, a second order system whose parameters vary with the ship's speed. The ship is initially traveling at its maximum speed of 15 m/s, but it will slow down when the reference trajectory specifies a turn in the water. This turning, along with the force of the engine, is used by the Force Dynamics block to compute the speed of the ship over time. The Kinematics block computes the trajectory of the ship.

Open the Controller block by double clicking it.



When the speed changes, the ship plant also changes. Therefore the PD controller gains need to change, and speed is used as the scheduling variable. The controller is in the form `K(1 + sTd)` where `K` is the overall gain and `Td` is the time constant associated with the derivative term. Gain scheduling is implemented using lookup tables, and the table data are specified by `K` and `Td`. These are vectors which specify different values for different speeds. The different speeds are specified in the lookup table breakpoint vectors `bpK` and `bpTd`.

Design Problem

The reference specifies that at 200 seconds, the ship should turn 180 degrees and reverse course. One requirement is that the ship heading angle needs to match the reference heading angle within an envelope. For the safety and comfort of passengers, a second requirement is that the total acceleration of the ship needs to stay within a bound of 0.25 g's, where 1 g is the acceleration of gravity at Earth's surface, 9.8 m/s^2.

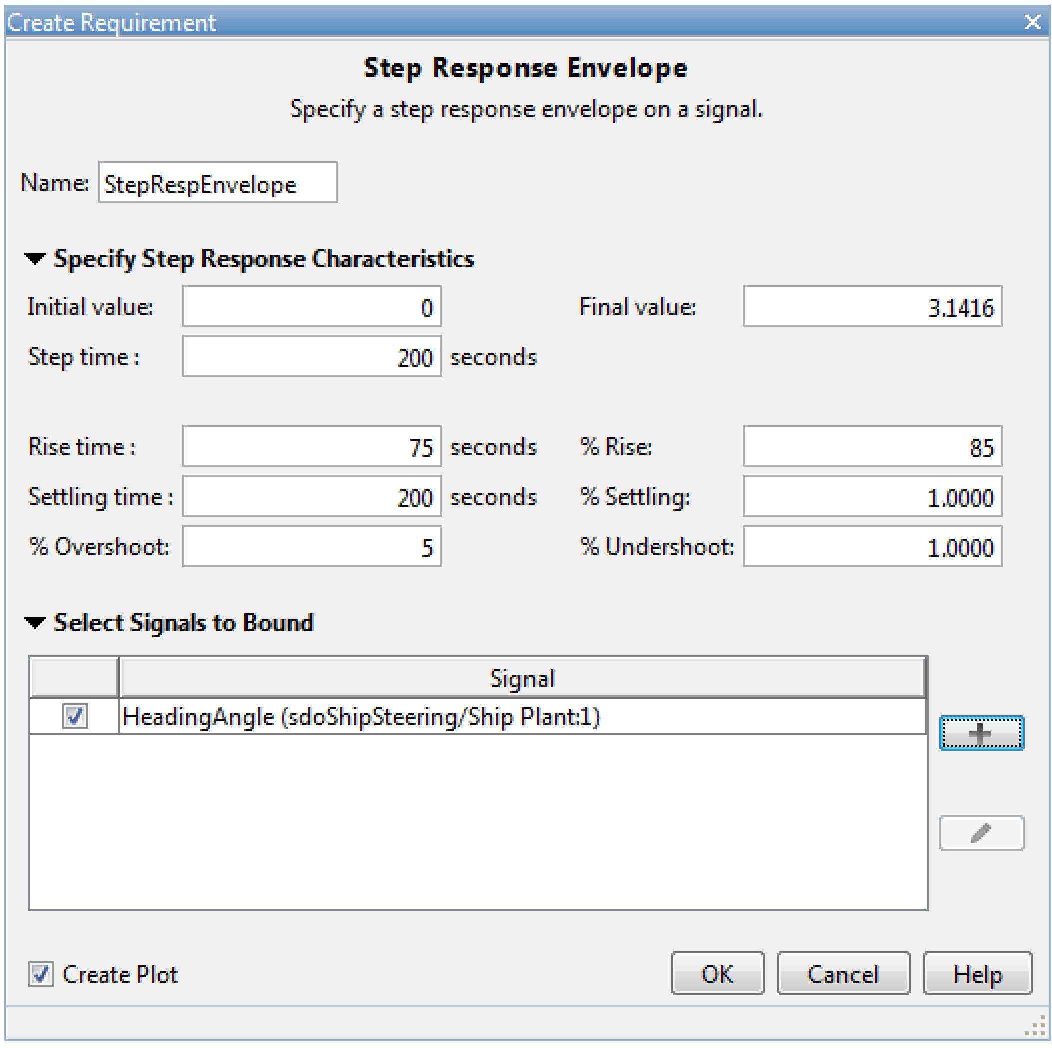
The controller parameter vectors `K` and `Td` will be design variables, and will be tuned to try to meet the requirements. If it is not possible to meet both requirements, then the lookup table breakpoints `bpK` and `bpTd` will also be used as design variables. In that case, we will need to specify an additional requirement that `bpK` and `bpTd` must be monotonically strictly increasing, because this is required for breakpoint vectors in Simulink lookup tables.

Open the Response Optimizer

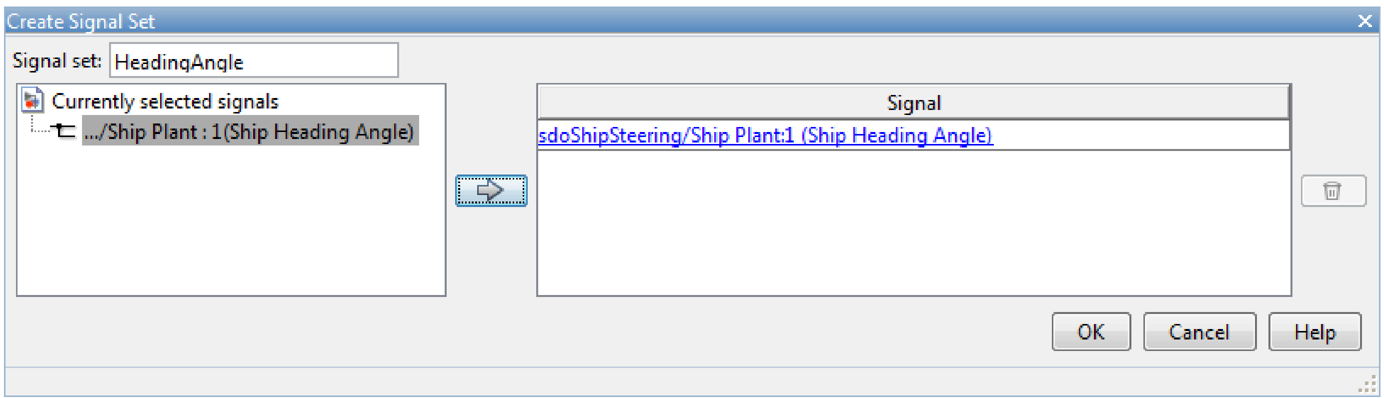
In the **Apps** tab, click **Response Optimizer** under **Control Systems**.

Specify Design Requirements

Specify the requirements which must be satisfied. First, the ship should follow the reference trajectory. Since the reference is essentially a step change from 0 to 180 degrees, you specify a step response envelope for the ship heading angle. In the toolstrip, click **New** and select **Step Response Envelope**. Set the initial value to 0 and the final value to pi radians. Set the step time to 200 seconds. Set the rise time as 75 seconds and the rise percent to 85%. Set the settling time to 200 seconds and the settling percent to 1%. Set the percent overshoot to 5%. To specify that this requirement applies to the ship heading, click +.

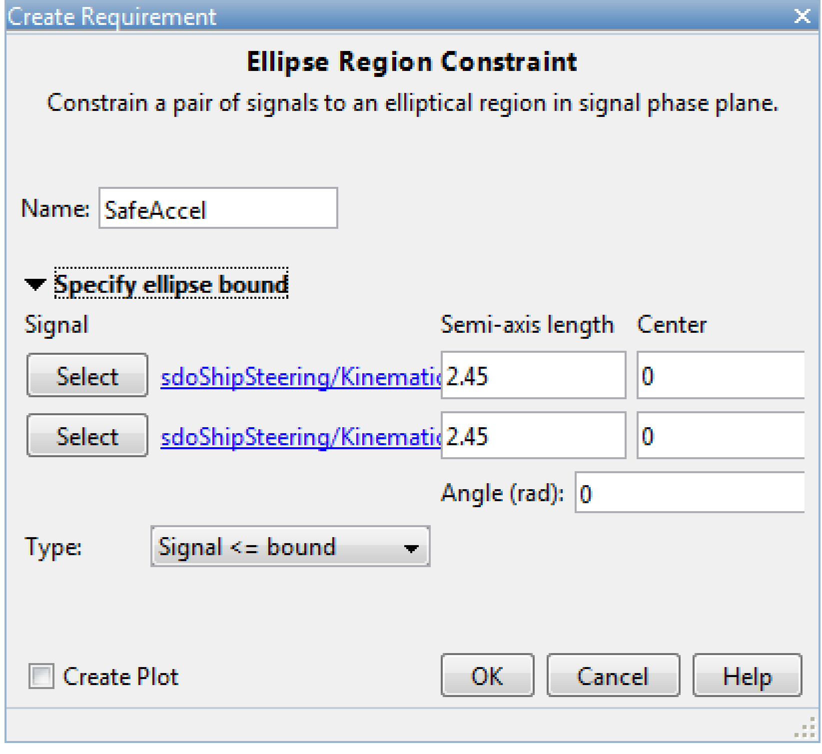


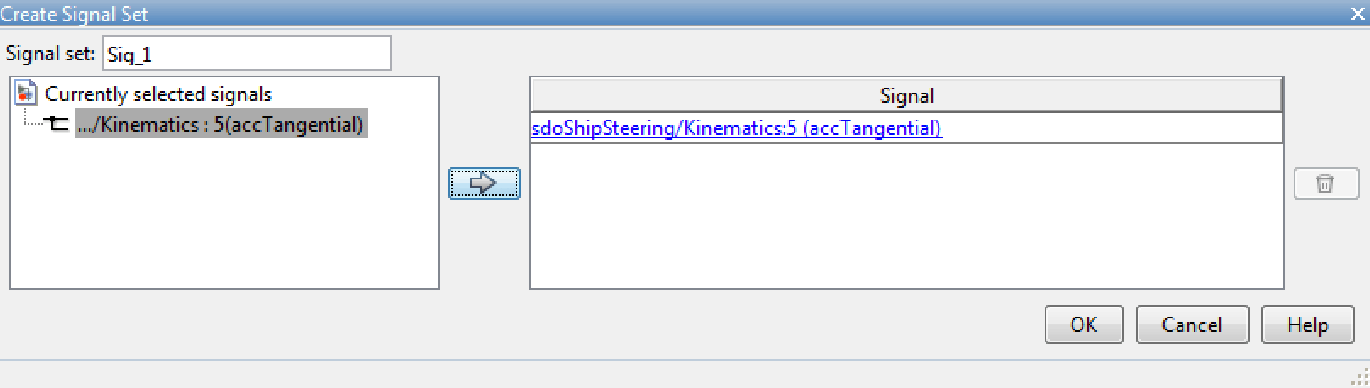
In the Simulink model click the ship heading signal, which is the output of the **Ship Plant** block. Select this signal in the Create Signal Set dialog, and click the arrow button to make it the designated signal, and click OK.

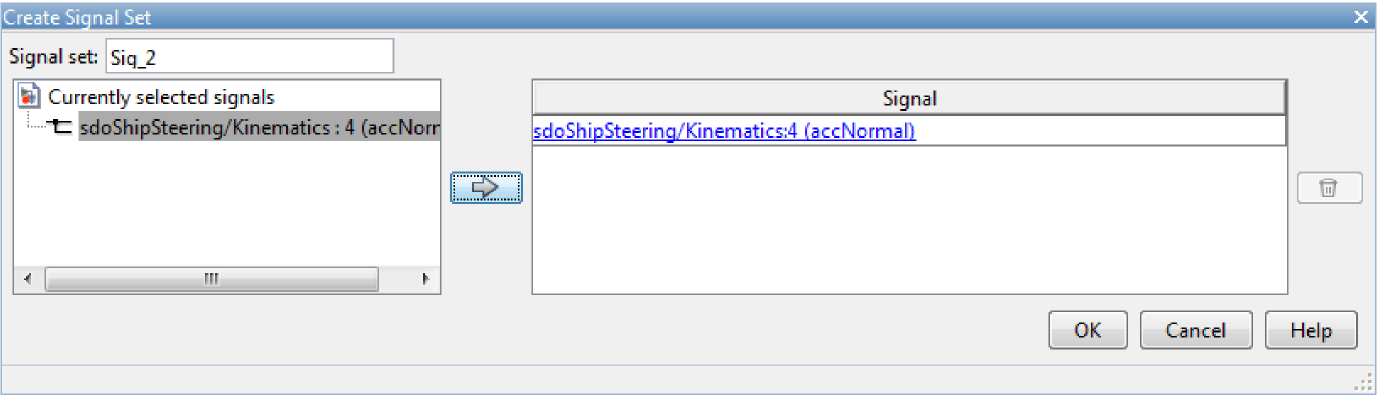


The second requirement is that for the safety and comfort of passengers, the total acceleration should not exceed 0.25 g's at any time. The total acceleration is composed of two components, a tangential component along the direction of the ship's motion, and a normal (horizontal) component. The requirement that total acceleration not exceed 0.25 g's corresponds to requiring that in the phase plane of tangential and normal acceleration, this ship's trajectory remain within a circle of radius 0.25*9.8.

In the toolstrip, click **New** and select **Ellipse Region Constraint**. Specify the name as `SafeAccel`, and the semi-axis length for both signals as 0.25*9.8 = 2.45. To specify that the requirement applies to the tangential acceleration of the ship, click the **Select** button. In the Simulink model click the tangential acceleration signal, which is output from the **Kinematics** block. Select this signal in the Create Signal Set dialog, and click the arrow button to make it the designated signal, and click OK. Similarly, to specify that the requirement applies to the normal acceleration of the ship, in the Ellipse Region Constraint dialog click the other Select button, and use the Create Signal Set dialog to specify the normal acceleration signal.

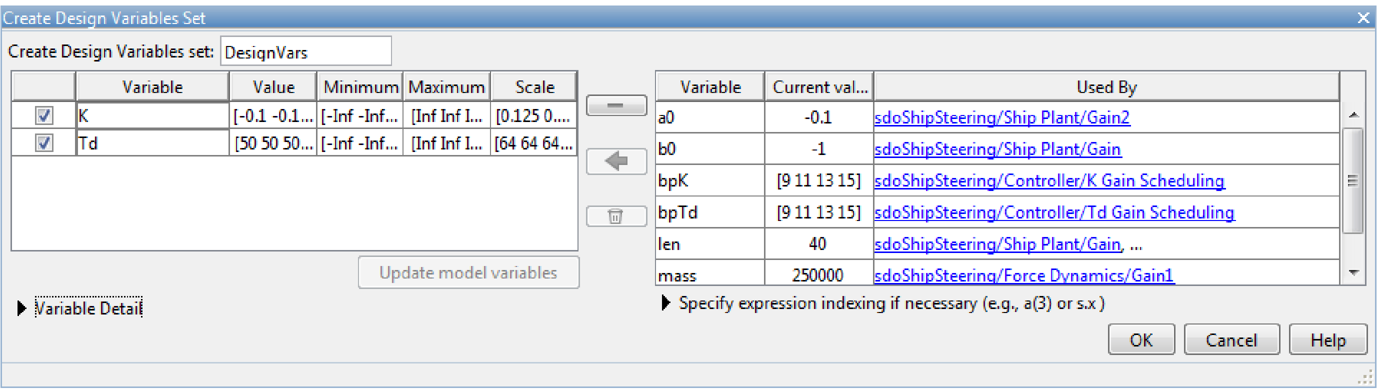






Specify Design Variables

Specify the design variables to be tuned by the optimization in order to satisfy the requirements. In the toolstrip, click the selection box next to **Design Variables Set** and then click **New**. Select the gains of the PD controller, K and `Td`, and click the arrow button to designate them as design variables. Use -0.1 for all entries in the value of the K vector, and use 50 for all entries in the value of the `Td` vector, and click OK. If the requirements can't all be satisfied, then later the breakpoint vectors `bpK` and `bpTd` can also be tried as design variables.

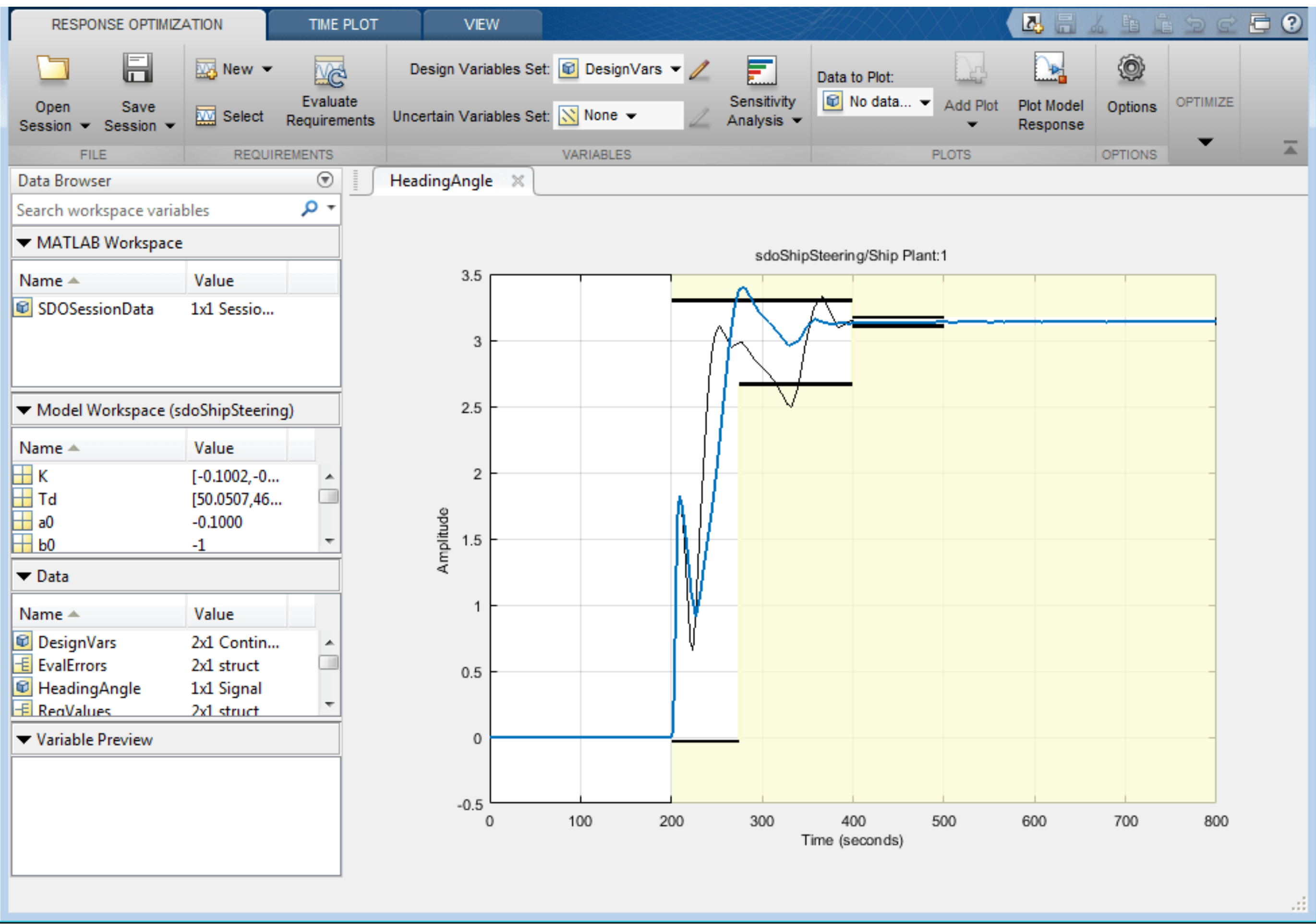


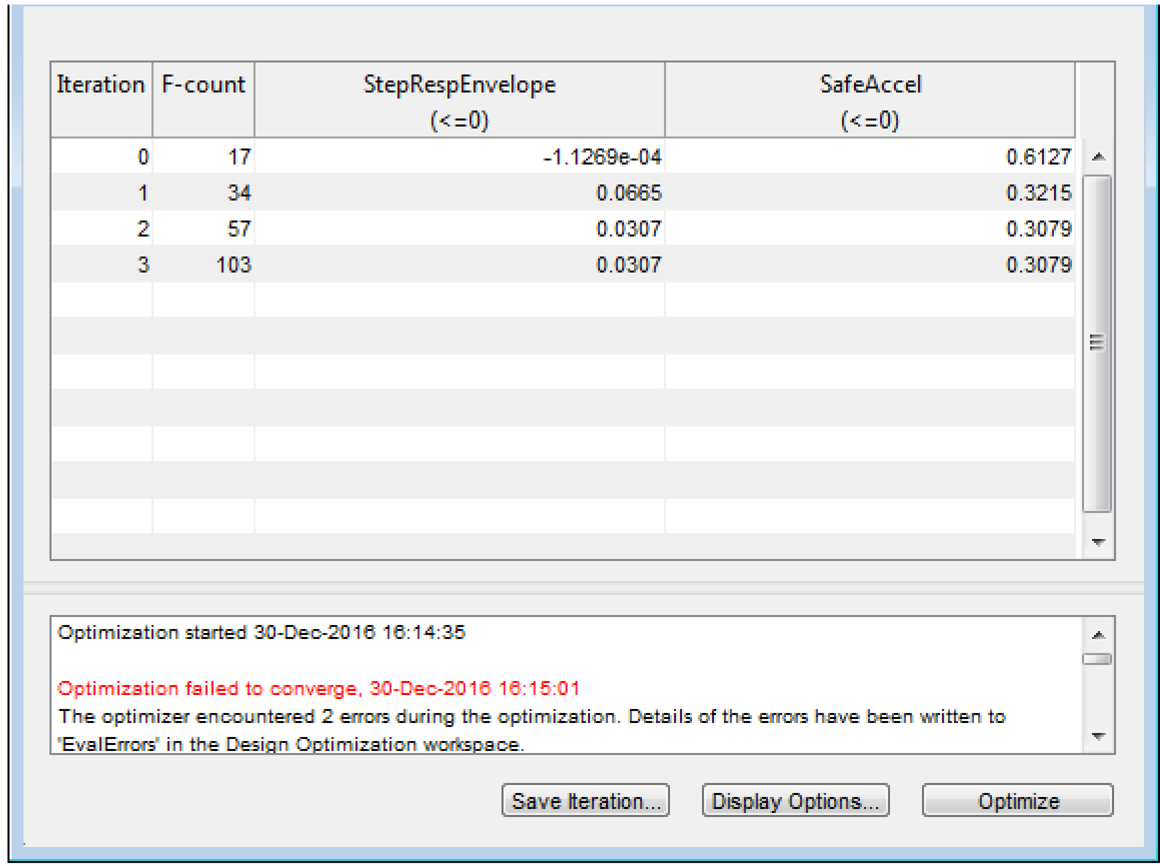
Optimize Lookup Table Data

During optimization, the Simulink solver may generate a warning if the size of the time step becomes too small. Temporarily suppress this warning.

```
warnState = warning('query', 'Simulink:Engine:SolverMinStepSizeWarn');
warning('off', 'Simulink:Engine:SolverMinStepSizeWarn');
```

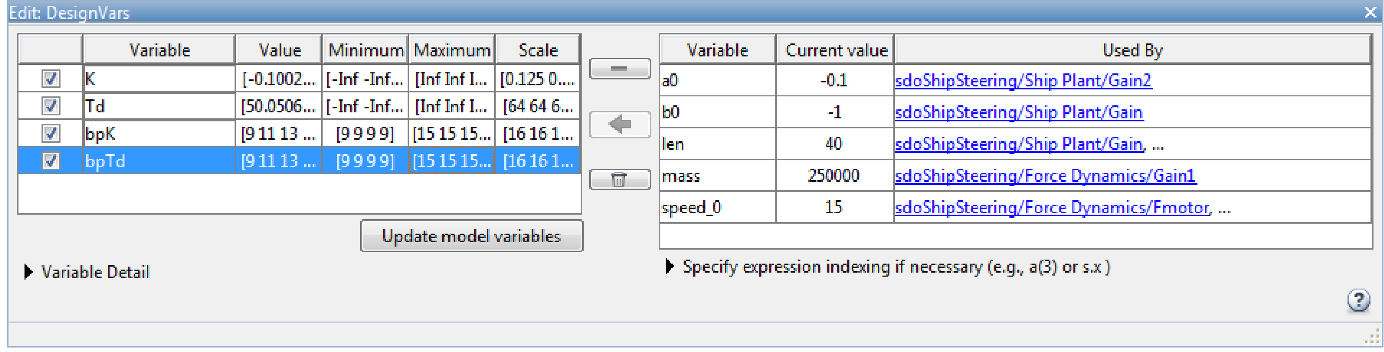
In the **Response Optimizer**, click **Optimize**. The ship heading angle does not meet the required step response envelope, as can be seen in the step response plot in the **Response Optimizer** app and in the Optimization Progress dialog, where the value at the last iteration is still positive, which indicates violation of the requirement. The requirement for safe acceleration is also not met, as seen in the Optimization Progress dialog, where the value at the last iteration is also positive.


RESPONSE OPTIMIZATION
TIME PLOT
VIEW
Open Session
Save Session
FILE
New
Select
Evaluate Requirements
REQUIREMENTS
Design Variables Set:
DesignVars
Uncertain Variables Set:
None
VARIABLES
Sensitivity Analysis
Data to Plot:
No data...
Add Plot
Plot Model Response
PLOTS
Options
OPTIONS
OPTIMIZE
Data Browser
Search workspace variables
MATLAB Workspace
Name
Value
SDOSessionData
1x1 Sessio...
Model Workspace (sdoShipSteering)
K
[-0.1002,-0...
Td
[50.0507,46...
a0
-0.1000
b0
-1
Data
DesignVars
2x1 Contin...
EvalErrors
2x1 struct
HeadingAngle
1x1 Signal
ReqValues
2x1 struct
Variable Preview
HeadingAngle
sdoShipSteering/Ship Plant:1
Amplitude
Time (seconds)
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
0
100
200
300
400
500
600
700
800

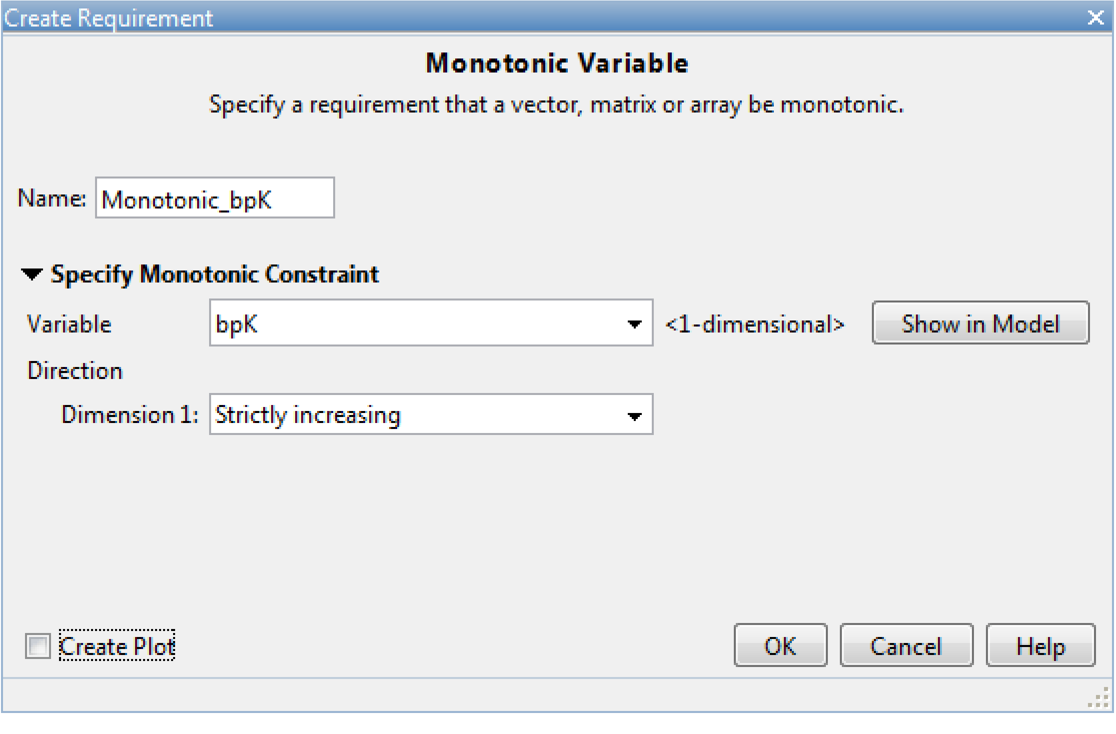


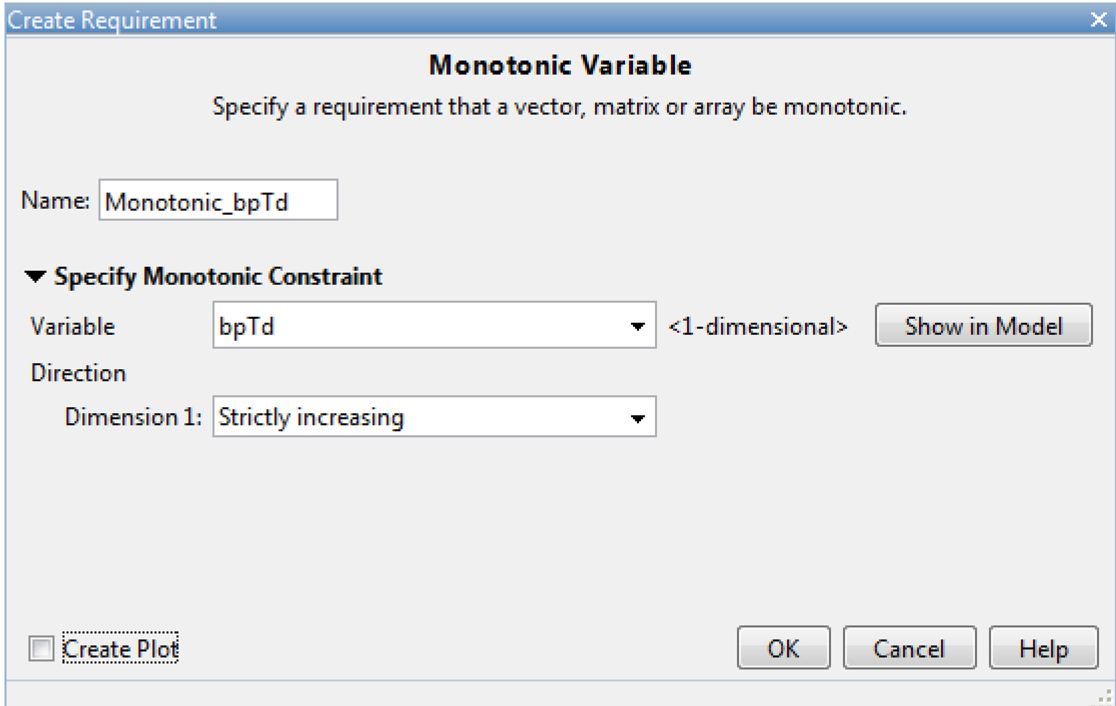
Optimize Lookup Table Data and Breakpoints

To try to meet the design requirements, use the optimization result from above as the start point, and tune additional variables. Add breakpoints `bpK` and `bpTd` as design variables. The ship's maximum speed is 15 m/s, and during turning it may slow to 60% of the maximum speed, or 9 m/s. Set the breakpoint initial values to be equally spaced between 9 and 15 m/s. Constrain the breakpoint minimum values to 9 m/s, and constrain the breakpoint maximum values to 15 m/s.



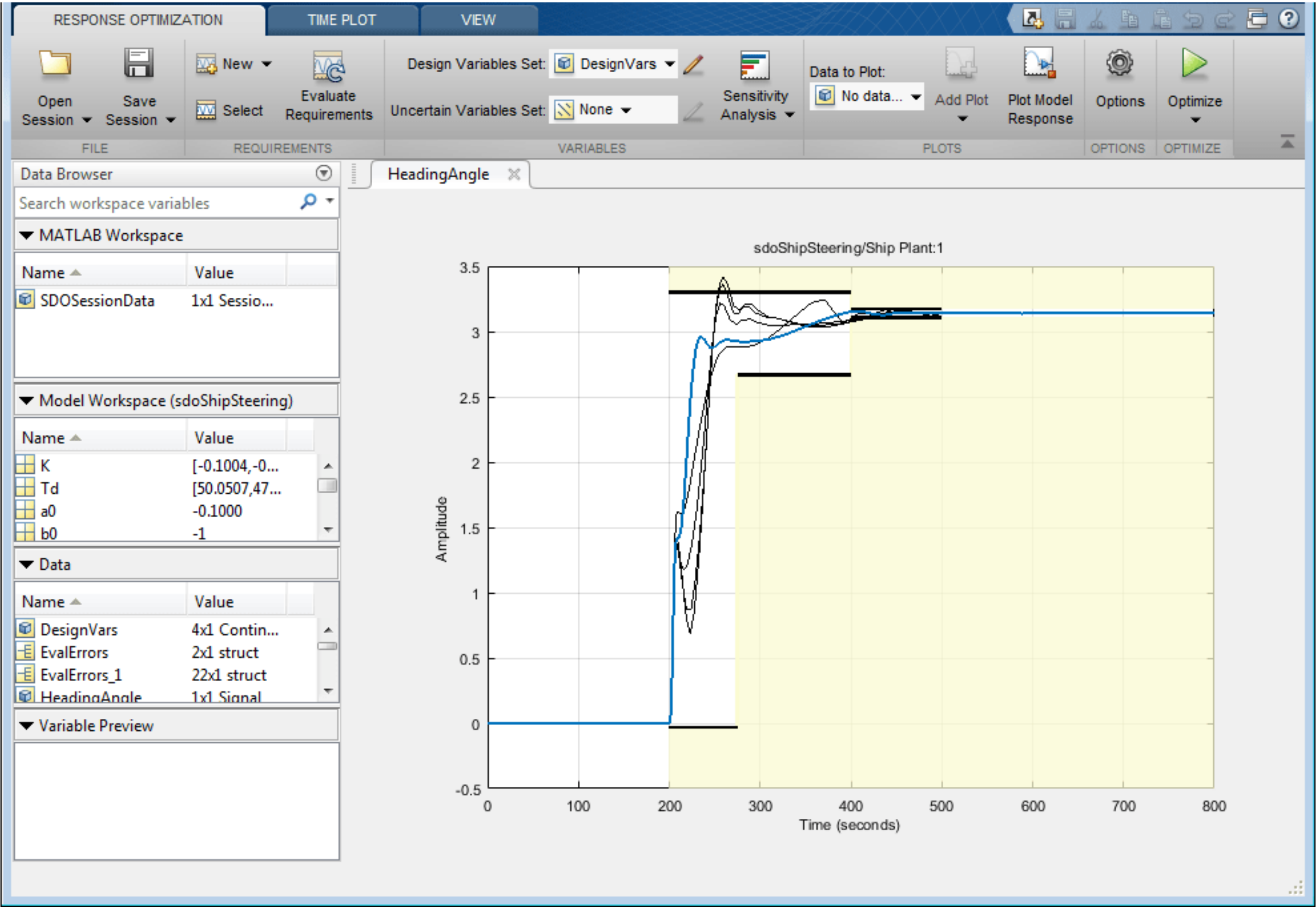
Breakpoints in the Simulink lookup table block must be strictly monotonically increasing. Add this to the design requirements.

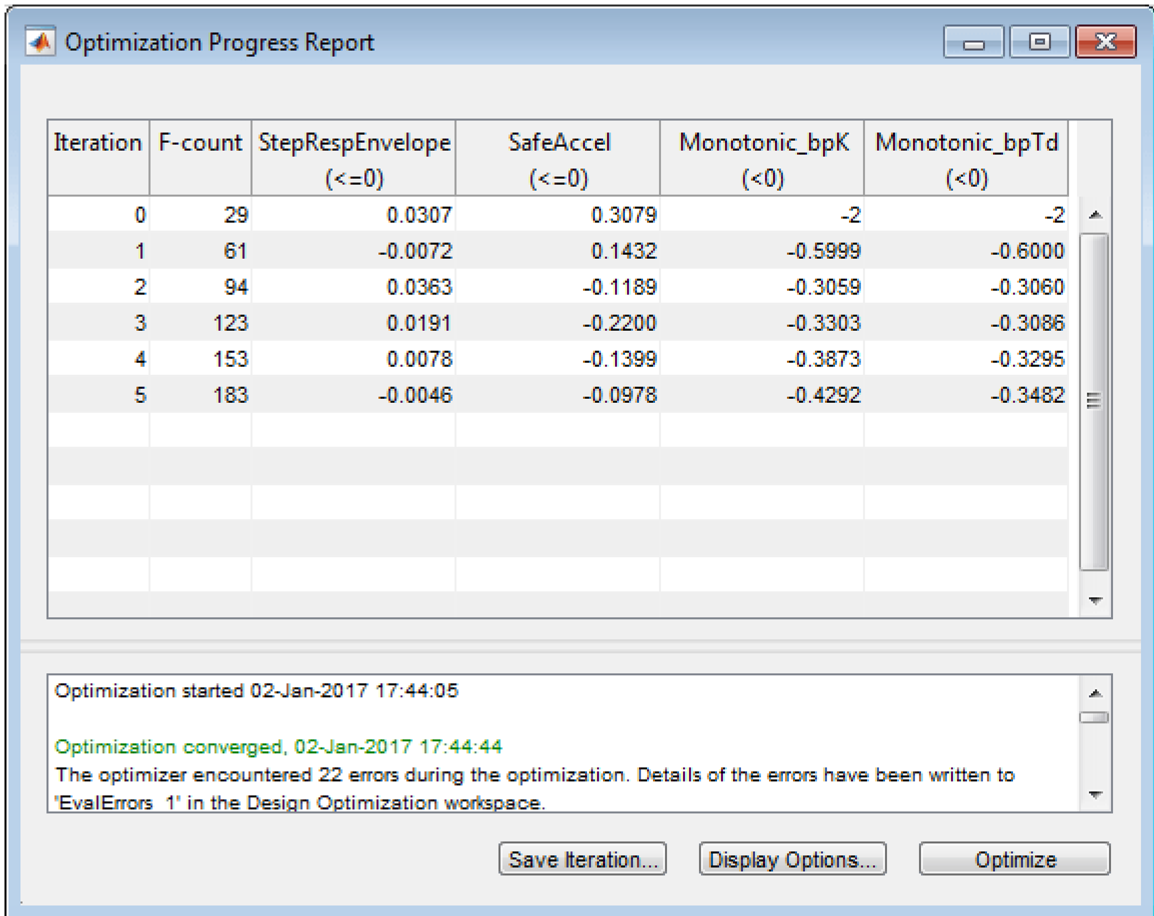




In the **Response Optimizer**, click **Optimize**. This time the ship heading angle meets the required step response envelope, as can be seen in the step response plot in **Response Optimizer** app and in the Optimization Progress dialog, where the value at the last iteration is negative, which indicates the requirement is satisfied. The requirement for safe acceleration is also satisfied, as seen in the

Optimization Progress dialog, where the value at the last iteration is also negative. Similarly, the lookup table breakpoints satisfy the monotonic requirements.





Iteration	F-count	StepRespEnvelope (<=0)	SafeAccel (<=0)	Monotonic_bpK (<0)	Monotonic_bpTd (<0)
0	29	0.0307	0.3079	-2	-2
1	61	-0.0072	0.1432	-0.5999	-0.6000
2	94	0.0363	-0.1189	-0.3059	-0.3060
3	123	0.0191	-0.2200	-0.3303	-0.3086
4	153	0.0078	-0.1399	-0.3873	-0.3295
5	183	-0.0046	-0.0978	-0.4292	-0.3482

In this example, the ship plant varied with the ship speed, so the controller gains also needed to vary. Gain scheduling was implemented using lookup tables. By tuning the gains and breakpoint values in the controller, the ship was able to follow the reference heading angle, while also constraining total acceleration to ensure a safe and comfortable ride for passengers.

Related Examples

To learn how to optimize the lookup tables in the gain scheduled controller using the `sdo.optimize` command, see "Design Optimization Using Lookup Table Requirements for Gain Scheduling (Code)" on page 6-44.

```
% Close the model and restore state of warnings.
bdclose('sdoShipSteering')
warning(warnState);    % restore state of warning
```

See Also

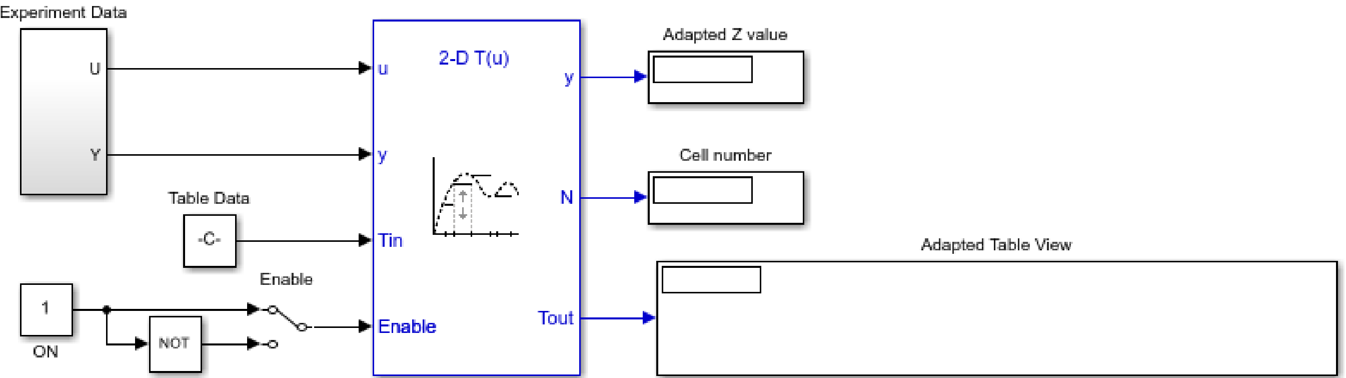
Related Examples

- "Design Optimization Using Lookup Table Requirements for Gain Scheduling (Code)" on page 6-44
- "Estimate Lookup Table Values from Data" on page 6-17

- “Specify Time-Domain Design Requirements in the App” on page 3-16
- “Specify Variable Requirements in the App” on page 3-31

2-D Adaptive Lookup Table Generation

This example shows how to create a 2-D lookup table from experimental data.



Click here to open the Adaptive Lookup Tables library.

See Also

Adaptive Lookup Table (2D Stair-Fit)

Related Examples

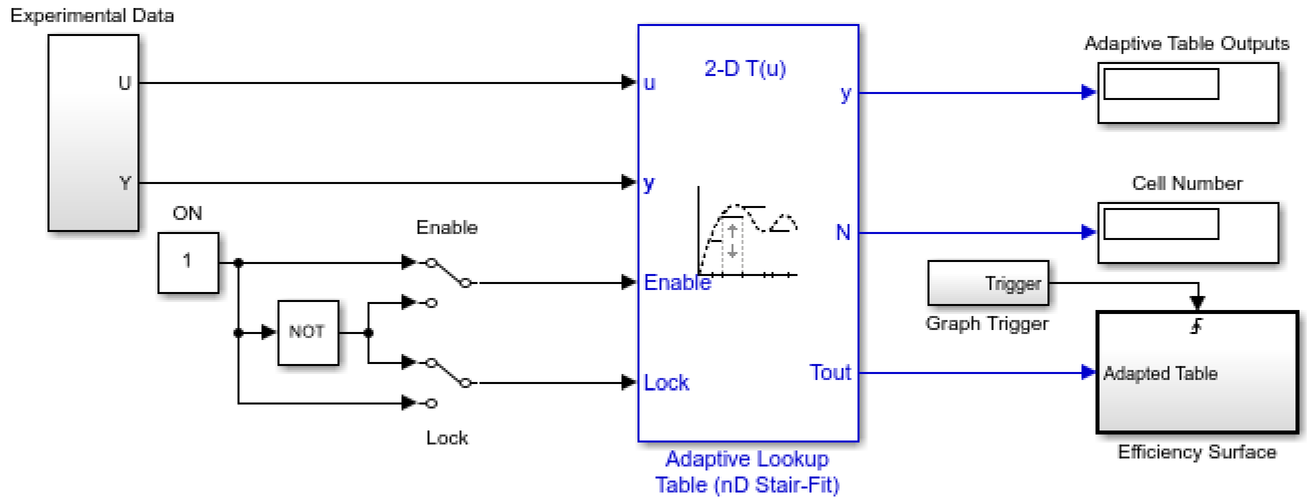
- "Model Engine Using n-D Adaptive Lookup Table" on page 6-33

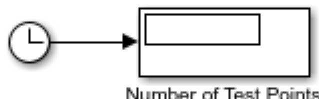
More About

- "What are Adaptive Lookup Tables?" on page 6-2

Engine Volumetric Efficiency Surface Matching

This example shows how to generate a lookup table to approximate an engine volumetric efficiency surface using experimental data.





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Click here to open the Adaptive Lookup Tables library.

See Also

Adaptive Lookup Table (2D Stair-Fit)

Related Examples

- “Model Engine Using n-D Adaptive Lookup Table” on page 6-33

More About

- “What are Adaptive Lookup Tables?” on page 6-2