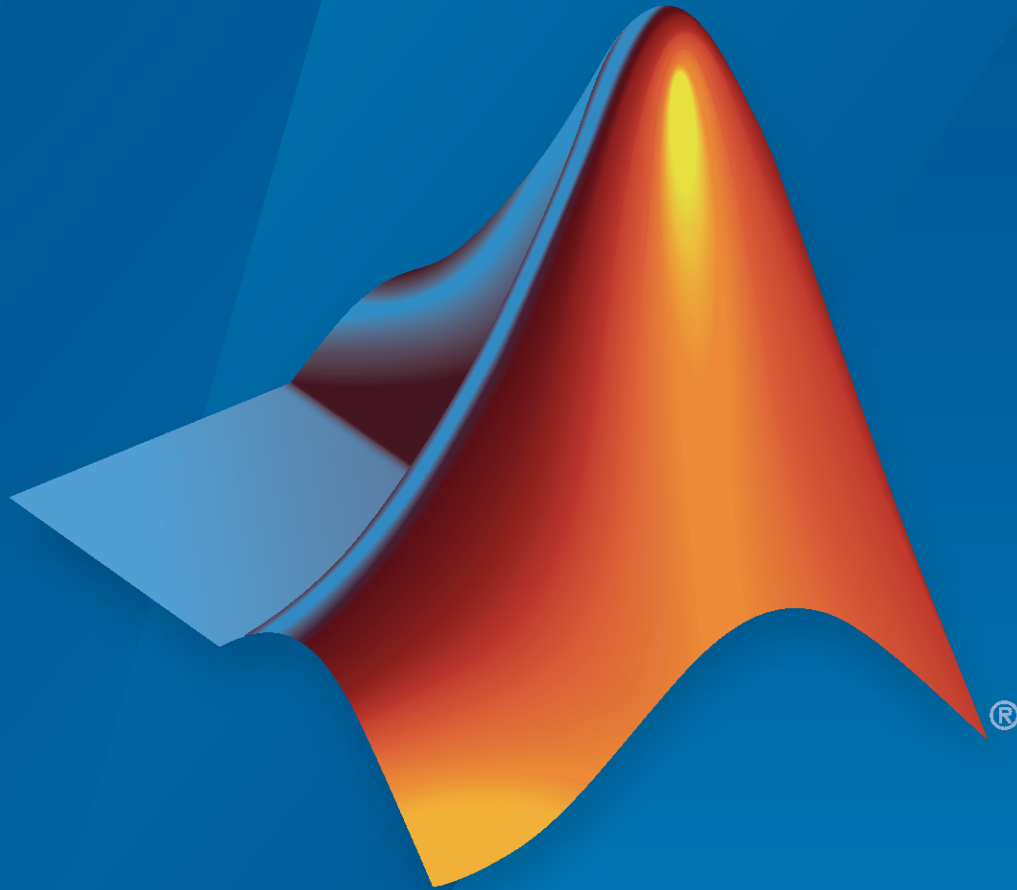


Model Predictive Control Toolbox™

Reference

*Alberto Bemporad
N. Lawrence Ricker
Manfred Morari*



MATLAB®

R2020a



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The MathWorks, Inc.
1 Apple Hill Drive
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Model Predictive Control Toolbox™ Reference

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Apps

MPC Designer

Design and simulate model predictive controllers

Description

The **MPC Designer** app lets you design and simulate model predictive controllers in MATLAB® and Simulink®.

Using this app, you can:

- Interactively design model predictive controllers and validate their performance using simulation scenarios
- Obtain linear plant models by linearizing Simulink models (requires Simulink Control Design™)
- Review controller designs for potential run-time stability or numerical issues
- Compare response plots for multiple model predictive controllers
- Generate Simulink models with an MPC controller and plant model
- Generate MATLAB scripts to automate MPC controller design and simulation tasks

Limitations

The following advanced MPC features are not available in the **MPC Designer** app:

- Explicit MPC design
- Adaptive MPC design
- Nonlinear MPC design
- Mixed input/output constraints (`setconstraint`)
- Terminal weight specification (`setterminal`)
- Custom state estimation (`setEstimator`)
- Sensitivity analysis (`sensitivity`)
- Alternative cost functions with off-diagonal weights
- Specification of initial plant and controller states for simulation
- Specification of nominal state values using `mpcObj.Model.Nominal.X` and `mpcObj.Model.Nominal.DX`
- Updating weights, constraints, MV targets, and external MV online during simulations

If your application requires any of these features, design and simulate your controller at the command line. You can also run simulations in Simulink when using these features.

When using **MPC Designer** in MATLAB Online™, the following features are not available:

- Designing controllers in Simulink
- Generating Simulink models for your controller and plant

Open the MPC Designer App

- MATLAB Toolstrip: On the **Apps** tab, under **Control System Design and Analysis**, click the app icon.
- MATLAB command prompt: Enter `mpcDesigner`.
- Simulink model editor: In the MPC Controller Block Parameters dialog box, click **Design**.

Examples

- “Design Controller Using MPC Designer”
- “Design MPC Controller in Simulink”
- “Compare Multiple Controller Responses Using MPC Designer”
- “Generate MATLAB Code from MPC Designer”
- “Generate Simulink Model from MPC Designer”

Programmatic Use

`mpcDesigner` opens the **MPC Designer** app. You can then import a plant or controller to start the design process, or open a saved design session.

`mpcDesigner(plant)` opens the app and creates a default MPC controller using `plant` as the internal prediction model. Specify `plant` as an `ss`, `tf`, or `zpk` LTI model.

If `plant` is a stable, continuous-time LTI system, **MPC Designer** sets the controller sample time to $0.1 T_r$, where T_r is the average rise time of the plant. If `plant` is an unstable, continuous-time system, **MPC Designer** sets the controller sample time to 1.

By default, plant input and output signals are treated as manipulated variables and measured outputs respectively. To specify a different input/output channel configuration, use `setmpcsignals` before opening **MPC Designer**.


You can also specify `plant` as a linear System Identification Toolbox™ model, such as an `idss` or `idtf` system. The app converts the identified model to a state-space system, discarding any noise channels. To convert noise channels to unmeasured disturbances, convert the identified model to a state-space model using the `'augmented'` option. For more information on identifying plant models, see “Identify Plant from Data”.

`mpcDesigner(MPCobj)` opens the app and imports the model predictive controller `MPCobj` from the MATLAB workspace. To create an MPC controller, use `mpc`.

`mpcDesigner(MPCobjs)` opens the app and imports multiple MPC controllers specified in the cell array `MPCobjs`. All of the controllers in `MPCobjs` must have the same input/output channel configuration.

`mpcDesigner(MPCobjs, names)` additionally specifies controller names when opening the app with multiple MPC controllers. Specify `names` as a cell array of character vectors or string array with the same length as `MPCobjs`. Specify a unique name for each controller.

`mpcDesigner(sessionFile)` opens the app and loads a previously saved session. Specify `sessionFile` as one of the following:

- The name of a session data file in the current working directory or on the MATLAB path, specified as a character vector or string. To save session data to disk, in the **MPC Designer** app, on the **MPC Designer** tab, click  **Save Session**. The saved session data includes all plants, controllers, and scenarios in the **Data Browser**, the current MPC structure, and the current plot configuration.
- A previously loaded `SessionData` object in the MATLAB workspace. To load a `SessionData` object from a session data file, at the command line, enter:

```
load sessionFile
```

See Also

Functions

`mpc` | `sim`

Topics

“Design Controller Using MPC Designer”

“Design MPC Controller in Simulink”

“Compare Multiple Controller Responses Using MPC Designer”

“Generate MATLAB Code from MPC Designer”

“Generate Simulink Model from MPC Designer”

Introduced in R2015b

Functions

buildMEX

Build MEX file that solves nonlinear MPC control problem

Syntax

```
mexFcn = buildMEX(nlmpcobj,mexName,coreData,onlineData)
mexFcn = buildMEX(nlmpcobj,mexName,coreData,onlineData,mexConfig)
```

Description

`mexFcn = buildMEX(nlmpcobj,mexName,coreData,onlineData)` builds a MEX file that solves the nonlinear MPC control problem faster than using `nlmpcmove`. The MEX file is created in the current working folder.

`mexFcn = buildMEX(nlmpcobj,mexName,coreData,onlineData,mexConfig)` generates a MEX function using the code generation configuration object `mexConfig`. Use this syntax to customize your MEX code generation.

Examples

Simulate Nonlinear MPC Controller Using MEX File

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nlobj = nlmpc(4,2,1);
```

In standard cost function, zero weights are applied by default to one or more OVs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The prediction model uses an optional parameter, `Ts`, to represent the sample time. Specify the number of parameters and create a parameter vector.

```
nlobj.Model.NumberOfParameters = 1;
params = {Ts};
```

Specify the output function of the model, passing the sample time parameter as an input argument.

```
nlobj.Model.OutputFcn = "pendulumOutputFcn";
```

Define standard constraints for the controller.

```
nlobj.Weights.OutputVariables = [3 3];
nlobj.Weights.ManipulatedVariablesRate = 0.1;
nlobj.OV(1).Min = -10;
nlobj.OV(1).Max = 10;
nlobj.MV.Min = -100;
nlobj.MV.Max = 100;
```

Validate the prediction model functions.

```
x0 = [0.1;0.2;-pi/2;0.3];
u0 = 0.4;
validateFcns(nlobj,x0,u0,[],params);
```

```
Model.StateFcn is OK.
Model.OutputFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Only two of the plant states are measurable. Therefore, create an extended Kalman filter for estimating the four plant states. Its state transition function is defined in `pendulumStateFcn.m` and its measurement function is defined in `pendulumMeasurementFcn.m`.

```
EKF = extendedKalmanFilter(@pendulumStateFcn,@pendulumMeasurementFcn);
```

Define initial conditions for the simulation, initialize the extended Kalman filter state, and specify a zero initial manipulated variable value.

```
x0 = [0;0;-pi;0];
y0 = [x0(1);x0(3)];
EKF.State = x0;
mv0 = 0;
```

Create code generation data structures for the controller, specifying the initial conditions and parameters.

```
[coreData,onlineData] = getCodeGenerationData(nlobj,x0,mv0,params);
```

Specify the output reference value in the online data structure.

```
onlineData.ref = [0 0];
```

Build a MEX function for solving the nonlinear MPC control problem. The MEX function is created in the current working directory.

```
mexFcn = buildMEX(nlobj,"myController",coreData,onlineData);
```

```
Generating MEX function "myController" from nonlinear MPC to speed up simulation.
MEX function "myController" successfully generated.
```

Run the simulation for 10 seconds. During each control interval:

- 1 Correct the previous prediction using the current measurement.
- 2 Compute optimal control moves using the MEX function This function returns the computed optimal sequences in `onlineData`. Passing the updated data structure to the MEX function in the next control interval provides initial guesses for the optimal sequences.
- 3 Predict the model states.

- 4 Apply the first computed optimal control move to the plant, updating the plant states.
- 5 Generate sensor data with white noise.
- 6 Save the plant states.

```

mv = mv0;
y = y0;
x = x0;
Duration = 10;
xHistory = x0;
for ct = 1:(Duration/Ts)
    % Correct previous prediction
    xk = correct(EKF,y);
    % Compute optimal control move
    [mv,onlineData] = myController(xk,mv,onlineData);
    % Predict prediction model states for the next iteration
    predict(EKF,[mv; Ts]);
    % Implement first optimal control move
    x = pendulumDT0(x,mv,Ts);
    % Generate sensor data
    y = x([1 3]) + randn(2,1)*0.01;
    % Save plant states
    xHistory = [xHistory x];
end

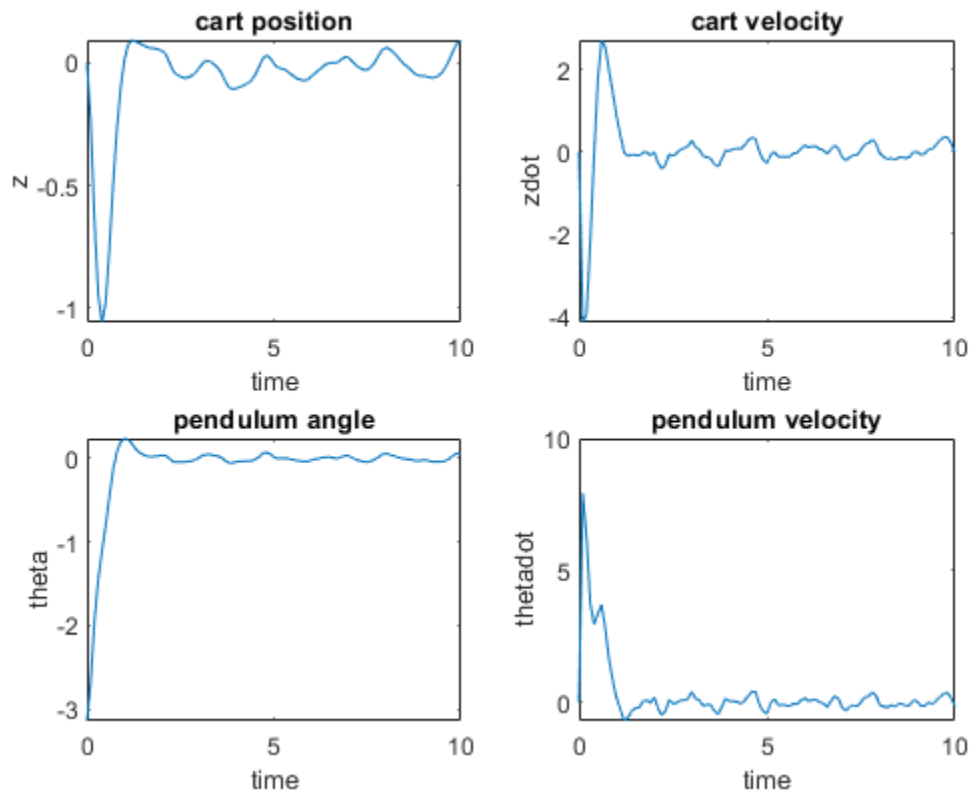
```

Plot the resulting state trajectories.

```

figure
subplot(2,2,1)
plot(0:Ts:Duration,xHistory(1,:))
xlabel('time')
ylabel('z')
title('cart position')
subplot(2,2,2)
plot(0:Ts:Duration,xHistory(2,:))
xlabel('time')
ylabel('zdot')
title('cart velocity')
subplot(2,2,3)
plot(0:Ts:Duration,xHistory(3,:))
xlabel('time')
ylabel('theta')
title('pendulum angle')
subplot(2,2,4)
plot(0:Ts:Duration,xHistory(4,:))
xlabel('time')
ylabel('thetadot')
title('pendulum velocity')

```



Input Arguments

n_{lmpcobj} — Nonlinear model predictive controller

n_{lmpc} object

Nonlinear model predictive controller, specified as an n_{lmpc} object.

Your controller must use the default `fmincon` solver with the SQP algorithm. Also, your controller must not use anonymous functions for its prediction model, custom cost function, or custom constraint functions.

mexName — MEX function name

string | character vector

MEX function name, specified as a string or character vector.

coreData — Nonlinear MPC configuration parameters

structure

Nonlinear MPC configuration parameters that are constant at run time, specified as a structure generated using `getCodeGenerationData`.

onlineData — Initial online controller data

structure

Initial online controller data, specified as a structure generated using `getCodeGenerationData`. For more information on settings the fields on `onlineData`, see `nlpmoveCodeGeneration`.

mexConfig — Code generation configuration object

MexCodeConfig object

Code generation configuration object, specified as a MexCodeConfig object.

To create the configuration object, use the following code.

```
mexConfig = coder.config('mex');
```

To customize your MEX code generation, modify the settings of this object. For example, to detect run-time memory access violations during debugging, set `IntegrityChecks` to `true`.

```
mexConfig.IntegrityChecks = true;
```

By default, to improve the performance of the generated code, checks such as `IntegrityChecks` and `ResponsivenessChecks` are disabled by `buildMEX`.

`buildMEX` overwrites the following configuration settings with the values indicated.

Configuration Setting	Value
<code>cfg.DynamicMemoryAllocation</code>	'AllVariableSizeArrays'
<code>cfg.ConstantInputs</code>	'Remove'

Output Arguments

mexFcn — Generated MEX function

function handle

Generated MEX function, returned as a function handle. This MEX function has the following signature.

```
[mv,newOnlineData,info] = mexFcn(x,lastMV,onlineData)
```

The MEX function has the following input arguments, which are the same as the corresponding input arguments of `nlpmoveCodeGeneration`.

Input Argument	Description
<code>x</code>	Current prediction model states, specified as a vector of length N_x , where N_x is the number of prediction model states.
<code>lastMV</code>	Control signals used in plant at previous control interval, specified as a vector of length N_{mv} , where N_{mv} is the number of manipulated variables.
<code>onlineData</code>	Online controller data that you must update at run time, specified as a structure with the following fields. Generate the initial structure using <code>getCodeGenerationData</code> .

The MEX function has the following output arguments, which are the same as the output arguments of `nlpmoveCodeGeneration`.

Output Argument	Description
mv	Optimal manipulated variable control action, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.
newOnlineData	Updated online controller data, returned as a structure. This structure is the same as <code>onlineData</code> , except that the decision variable initial guesses are updated.
info	Solution details, returned as a structure.

To simulate a controller using the generated MEX function, use the initial online data structure `onlineData` for the first control interval. For subsequent control intervals, modify the online data in `newOnlineData` and pass the updated structure to the MEX function as `onlineData`.

See Also

`getCodeGenerationData` | `nmpc` | `nmpcmove` | `nmpcmoveCodeGeneration`

Topics

“Parallel Parking Using Nonlinear Model Predictive Control”

Introduced in R2020a

cloffset

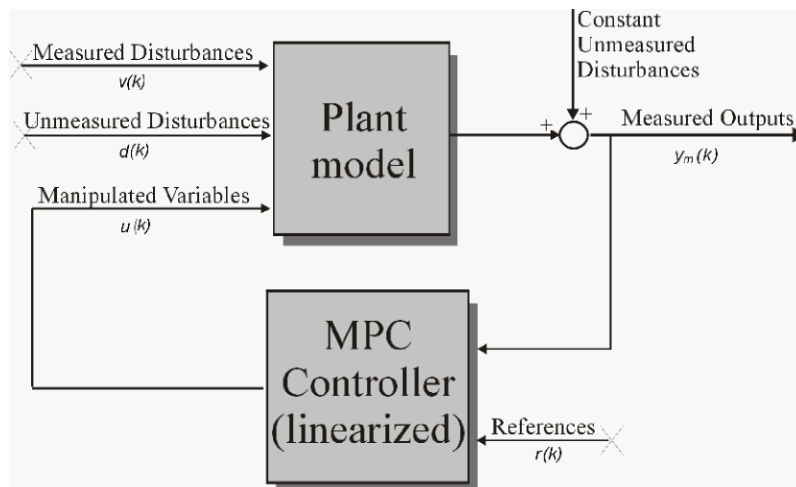
Compute MPC closed-loop DC gain from output disturbances to measured outputs assuming constraints are inactive at steady state

Syntax

```
DCgain = cloffset(MPCobj)
```

Description

The `cloff` function computes the DC gain from output disturbances to measured outputs, assuming constraints are not active, based on the feedback connection between `Model.Plant` and the linearized MPC controller, as depicted below.



Computing the Effect of Output Disturbances

By superposition of effects, the gain is computed by zeroing references, measured disturbances, and unmeasured input disturbances.

`DCgain = cloffset(MPCobj)` returns an n_{ym} -by- n_{ym} DC gain matrix `DCgain`, where n_{ym} is the number of measured plant outputs. `MPCobj` is the MPC object specifying the controller for which the closed-loop gain is calculated. `DCgain(i, j)` represents the gain from an additive (constant) disturbance on output j to measured output i . If row i contains all zeros, there will be no steady-state offset on output i .

See Also

`mpc` | `ss`

Topics

“Compute Steady-State Gain”

Introduced before R2006a

compare

Compare two MPC objects

Syntax

```
yesno = compare(MPC1,MPC2)
```

Description

The compare function compares the contents of two MPC objects MPC1, MPC2. If the design specifications (models, weights, horizons, etc.) are identical, then `yesno` is equal to 1.

Note compare may return `yesno = 1` even if the two objects are not identical. For instance, MPC1 may have been initialized while MPC2 may have not, so that they may have different sizes in memory. In any case, if `yesno = 1`, the behavior of the two controllers will be identical.

See Also

mpc

Introduced before R2006a

convertToMPC

Convert `nlmpc` object into one or more `mpc` objects

Syntax

```
mpcobj = convertToMPC(nlmpcobj,states,inputs)
mpcobj = convertToMPC(nlmpcobj,states,inputs,M0Index)
mpcobj = convertToMPC(nlmpcobj,states,inputs,M0Index,parameters)
```

Description

In practice, when producing comparable performance, linear MPC is preferred over nonlinear MPC due to its higher computational efficiency. Using the `convertToMPC` function, you can convert a nonlinear MPC controller into one or more linear MPC controllers at specific operating points. You can then implement gain-scheduled or adaptive MPC using the linear controllers and compare their performance to the benchmark nonlinear MPC controller. For an example, see “Nonlinear and Gain-Scheduled MPC Control of an Ethylene Oxidation Plant”.

To use `convertToMPC`, your nonlinear controller must not have custom cost or constraint functions, since these custom functions are not supported for linear MPC controllers.

`mpcobj = convertToMPC(nlmpcobj,states,inputs)` converts the nonlinear MPC controller object `nlmpcobj` into one or more linear MPC controller objects at the nominal conditions specified in `states` and `inputs`. The number of linear MPC controllers, N , is equal to the number of rows in `states` and `inputs`.

`mpcobj = convertToMPC(nlmpcobj,states,inputs,M0Index)` specifies the indices of the measured outputs. Use this syntax when your controller has unmeasured output signals.

`mpcobj = convertToMPC(nlmpcobj,states,inputs,M0Index,parameters)` specifies the values of prediction model parameters for each nominal condition. Use this syntax when your controller prediction model has optional parameters.

Examples

Create Linear MPC Controllers from Nonlinear MPC Controller

Create a nonlinear MPC controller with four states, one output variable, one manipulated variable, and one measured disturbance.

```
nlobj = nlmpc(4,1,'MV',1,'MD',2);
```

Specify the controller sample time and horizons.

```
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 3;
```

Specify the state function of the prediction model.

```
nlobj.Model.StateFcn = 'oxidationStateFcn';
```

Specify the prediction model output function and the output variable scale factor.

```
nlobj.Model.OutputFcn = @(x,u) x(3);
nlobj.OutputVariables.ScaleFactor = 0.03;
```

Specify the manipulated variable constraints and scale factor.

```
nlobj.ManipulatedVariables.Min = 0.0704;
nlobj.ManipulatedVariables.Max = 0.7042;
nlobj.ManipulatedVariables.ScaleFactor = 0.6;
```

Specify the measured disturbance scale factor.

```
nlobj.MeasuredDisturbances.ScaleFactor = 0.5;
```

Compute the state and input operating conditions for three linear MPC controllers using the `fsolve` function.

```
options = optimoptions('fsolve','Display','none');

uLow = [0.38 0.5];
xLow = fsolve(@(x) oxidationStateFcn(x,uLow),[1 0.3 0.03 1],options);

uMedium = [0.24 0.5];
xMedium = fsolve(@(x) oxidationStateFcn(x,uMedium),[1 0.3 0.03 1],options);

uHigh = [0.15 0.5];
xHigh = fsolve(@(x) oxidationStateFcn(x,uHigh),[1 0.3 0.03 1],options);
```

Create linear MPC controllers for each of these nominal conditions.

```
mpcobjLow = convertToMPC(nlobj,xLow,uLow);
mpcobjMedium = convertToMPC(nlobj,xMedium,uMedium);
mpcobjHigh = convertToMPC(nlobj,xHigh,uHigh);
```

You can also create multiple controllers using arrays of nominal conditions. The number of rows in the arrays specifies the number controllers to create. The linear controllers are returned as cell array of `mpc` objects.

```
u = [uLow; uMedium; uHigh];
x = [xLow; xMedium; xHigh];
mpcobjs = convertToMPC(nlobj,x,u);
```

View the properties of the `mpcobjLow` controller.

```
mpcobjLow
```

```
MPC object (created on 29-Feb-2020 02:55:58):
```

```
-----
Sampling time:      1 (seconds)
Prediction Horizon: 10
Control Horizon:   3
```

```
Plant Model:
```

```

1 manipulated variable(s)  -->| 4 states |
                             |         | --> 1 measured output(s)
                             |         |
1 measured disturbance(s)  -->| 2 inputs |
```

```

      0 unmeasured disturbance(s) --> | 1 outputs | --> 0 unmeasured output(s)
      |-----|-----|
Indices:
  (input vector)   Manipulated variables: [1 ]
                   Measured disturbances: [2 ]
  (output vector)   Measured outputs: [1 ]

Disturbance and Noise Models:
  Output disturbance model: default (type "getoutdist(mpcobjLow)" for details)
  Measurement noise model: default (unity gain after scaling)

Weights:
  ManipulatedVariables: 0
  ManipulatedVariablesRate: 0.1000
  OutputVariables: 1
  ECR: 100000

State Estimation: Default Kalman Filter (type "getEstimator(mpcobjLow)" for details)

Constraints:
  0.0704 <= u1 <= 0.7042, u1/rate is unconstrained, y1 is unconstrained

```

Input Arguments

n_{lmpcobj} — Nonlinear MPC controller

n_{lmpc} object

Nonlinear MPC controller, specified as an n_{lmpc} object.

Note Your n_{lmpc} controller object must not have custom cost or constraint functions.

states — Nominal state values

array

Nominal state values, specified as an N -by- N_x array, where N_x is equal to `nlmpcobj.Dimensions.NumberOfStates`. Each row of `States` specifies a nominal set of states to be used in conversion.

The number of rows in `states` and `inputs` must match.

inputs — Nominal input values

array

Nominal input values, specified as an N -by- N_u array, where N_u is equal to `nlmpcobj.Dimensions.NumberOfInputs`. Each row of `Inputs` specifies a nominal set of inputs to be used in conversion.

The number of rows in `states` and `inputs` must match.

M0Index — Measured output indices

[] (default) | vector

Measured output indices, specified as a vector of length N_y , where N_y is the number of outputs. If `M0Index` is `[]`, every output is measured. Otherwise, any outputs not listed in `M0Index` are unmeasured.

`convertToMPC` uses `M0Index` to configure the default state estimators in `mpcobj`.

parameters — Prediction model parameter values

`{}` (default) | cell array

Prediction model parameter values, specified as an N -by- N_p cell array, where N_p is equal to `nmpcobj.Model.NumberOfParameters`. Each row of `parameters` specifies the model parameter values for a given nominal condition. In each row, the order of the parameters must match the order specified in the model functions. Each parameter must be a numeric parameter with the correct dimensions; that is, the dimensions expected by the prediction model functions.

For each nominal condition, these parameters are passed to the state function (`nmpcobj.Model.StateFcn`) and output function (`nmpcobj.Model.OutputFcn`) of the nonlinear MPC controller.

The number of rows in `parameters` must match the number of rows in `states` and `inputs`.

If your controller prediction model has optional parameters, you must specify `parameters`.

Output Arguments

mpcobj — Linear MPC controllers

mpc object | cell array of mpc objects

Linear MPC controllers created for each nominal condition, returned as one of the following:

- Single mpc object when $N = 1$.
- Cell array of mpc objects of length N when $N > 1$. Each object corresponds to one nominal condition.

`convertToMPC` copies the following controller properties from `nmpcobj` to the controllers in `mpcobj`:

- Sample time
- Prediction and control horizons
- Tuning weights
- Bounds on output variables, manipulated variables, and manipulated variable rates
- Scale factors, names, and units for variables and disturbances

If `nmpcobj`:

- Has unmeasured disturbance channels, then the controllers in `mpcobj` have unity gains for their input and output disturbance models.
- Does not have unmeasured disturbance channels, then the controllers in `mpcobj` have default output disturbance models.

Any state bounds in `nmpcobj` are dropped during conversion.

See Also

nlpmpc

Topics

“Nonlinear MPC”

“Nonlinear and Gain-Scheduled MPC Control of an Ethylene Oxidation Plant”

Introduced in R2018b

createParameterBus

Create Simulink bus object and configure Bus Creator block for passing model parameters to Nonlinear MPC Controller block

Syntax

```
createParameterBus(nlmpcobj, nlmpcblk, busName, parameters)
```

Description

`createParameterBus(nlmpcobj, nlmpcblk, busName, parameters)` creates a `Simulink.Bus` object, `busName`, in the MATLAB workspace for passing model parameters to a Nonlinear MPC Controller block, `nlmpcblk`. `createParameterBus` requires you to connect a Bus Creator block to the Nonlinear MPC Controller block in advance so that it can configure the Bus Creator block to use the bus object.

Examples

Create Parameter Bus for Nonlinear MPC Controller Block

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nlobj = nlmpc(4,2,1);
```

In standard cost function, zero weights are applied by default to one or more 0Vs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous-time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The prediction model uses an optional parameter, `Ts`, to represent the sample time. Specify the number of parameters.

```
nlobj.Model.NumberOfParameters = 1;
```

Specify the output function of the model, passing the sample-time parameter as an input argument.

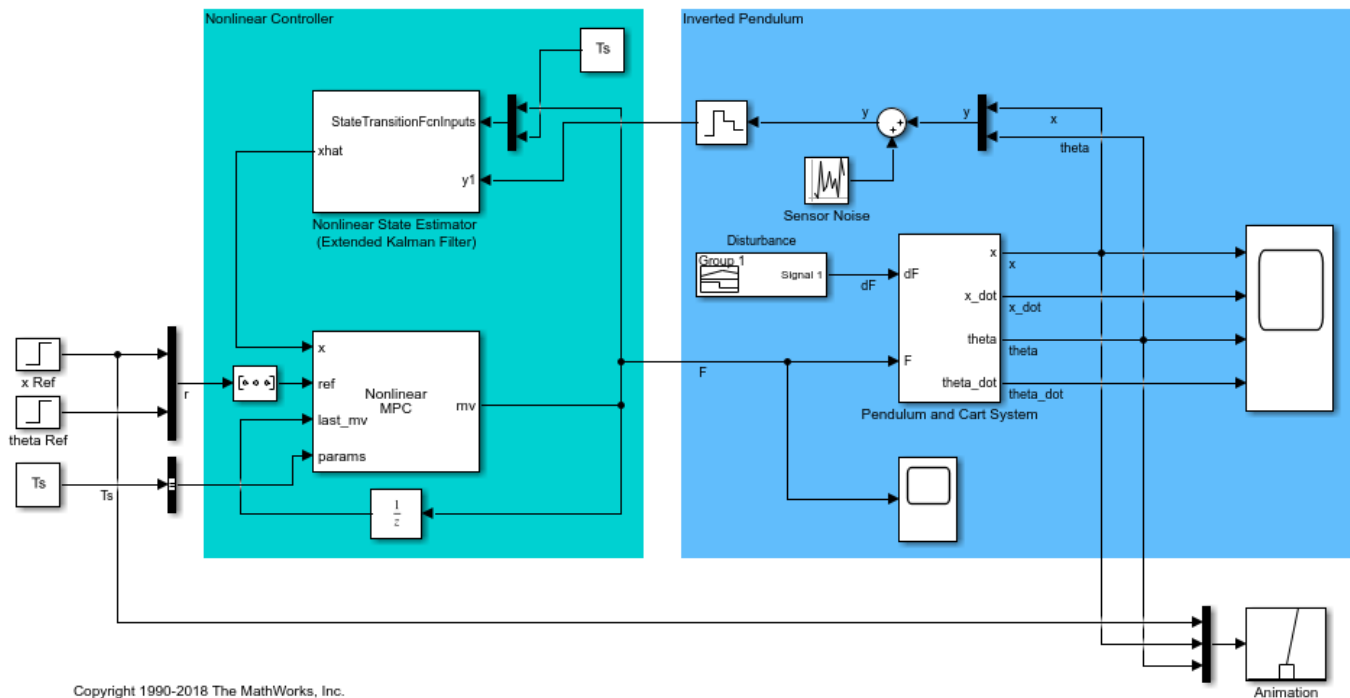
```
nlobj.Model.OutputFcn = @(x,u,Ts) [x(1); x(3)];
```

Define standard constraints for the controller.

```
nlobj.Weights.OutputVariables = [3 3];
nlobj.Weights.ManipulatedVariablesRate = 0.1;
nlobj.OV(1).Min = -10;
nlobj.OV(1).Max = 10;
nlobj.MV.Min = -100;
nlobj.MV.Max = 100;
```

Open Simulink model.

```
mdl = 'mpc_pendcartNMPC';
open_system(mdl)
```



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In this model, the Nonlinear MPC Controller block is configured to use the controller `nlobj`.

To use the optional parameter in the prediction model, the model has a Simulink Bus block connected to the `params` input port of the Nonlinear MPC Controller block. To configure this bus block to use the `Ts` parameter, create a Bus object in the MATLAB® workspace, and configure the Bus Creator block to use this object. Name the Bus object `'myBusObject'`.

```
createParameterBus(nlobj, [mdl '/Nonlinear MPC Controller'], 'myBusObject', {Ts});
```

```
bdclose(mdl)
```

A Simulink Bus object "myBusObject" created in the MATLAB Workspace, and Bus Creator block "mpc_

Input Arguments

`nlmpcobj` — Nonlinear MPC controller

`nlmpc` object

Nonlinear MPC controller, specified as an `nlmpc` object.

nLmpcblk — Block path of Nonlinear MPC Controller block

string | string | character vector

Block path of Nonlinear MPC Controller block, specified as a string or character vector.

busName — Name of Simulink bus object

string | string | character vector

Name of Simulink bus object to be created in the MATLAB workspace and set in the Bus Creator block, specified as a string or character vector.

The corresponding Bus Creator block must already be connected to the `params` input port of the Nonlinear MPC Controller block specified by `nLmpcblk`. Also, the Bus Creator block must have the correct number of input ports, and these ports must already be properly connected.

parameters — Nominal prediction model parameter values

cell array

Nominal prediction model parameter values, specified as a cell array of length N_p , where N_p is equal to `nLmpcobj.Model.NumberOfParameters`. The order of the parameters must match the order specified in the model functions, and each parameter must be a numeric parameter with the correct dimensions.

See Also**Functions**`nLmpc` | `nLmpcmove` | `nLmpcmoveopt`**Blocks**

Nonlinear MPC Controller

Topics

"Specify Prediction Model for Nonlinear MPC"

Introduced in R2018b

d2d

Change MPC controller sample

Syntax

```
MPCobj = d2d(MPCobj,Ts)
```

Description

The `d2d` function changes the sample time of the MPC controller `MPCobj` to `Ts`. All models are sampled or resampled as soon as the QP matrices must be computed, for example when `sim` or `mpcmove` are called.

See Also

`mpc` | `set`

Introduced before R2006a

generateExplicitMPC

Convert implicit MPC controller to explicit MPC controller

Syntax

```
EMPCobj = generateExplicitMPC(MPCobj, range)
EMPCobj = generateExplicitMPC(MPCobj, range, opt)
```

Description

Given a traditional Model Predictive Controller design in the implicit form, convert it to the explicit form for real-time applications requiring fast sample time.

`EMPCobj = generateExplicitMPC(MPCobj, range)` converts a traditional (implicit) MPC controller to the equivalent explicit MPC controller, using the specified parameter bounds. This calculation usually requires significant computational effort because a multi-parametric quadratic programming problem is solved during the conversion.

`EMPCobj = generateExplicitMPC(MPCobj, range, opt)` converts the MPC controller using additional optimization options.

Examples

Generate Explicit MPC Controller

Generate an explicit MPC controller based upon a traditional MPC controller for a double-integrator plant.

Define the double-integrator plant.

```
plant = tf(1,[1 0 0]);
```

Create a traditional (implicit) MPC controller for this plant, with sample time 0.1, a prediction horizon of 10, and a control horizon of 3.

```
Ts = 0.1;
p = 10;
m = 3;
MPCobj = mpc(plant, Ts, p, m);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

To generate an explicit MPC controller, you must specify the ranges of parameters such as state values and manipulated variables. To do so, generate a range structure. Then, modify values within the structure to the desired parameter ranges.

```
range = generateExplicitRange(MPCobj);
```

```
-->Converting the "Model.Plant" property of "mpc" object to state-space.
-->Converting model to discrete time.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
range.State.Min(:) = [-10;-10];
range.State.Max(:) = [10;10];
range.Reference.Min = -2;
range.Reference.Max = 2;
range.ManipulatedVariable.Min = -1.1;
range.ManipulatedVariable.Max = 1.1;
```

Use the more robust reduction method for the computation. Use `generateExplicitOptions` to create a default options set, and then modify the `polyreduction` option.

```
opt = generateExplicitOptions(MPCobj);
opt.polyreduction = 1;
```

Generate the explicit MPC controller.

```
EMPCobj = generateExplicitMPC(MPCobj,range,opt)
```

Explicit MPC Controller

```
-----
Controller sample time:    0.1 (seconds)
Polyhedral regions:       1
Number of parameters:     4
Is solution simplified:    No
State Estimation:         Default Kalman gain
-----
```

```
Type 'EMPCobj.MPC' for the original implicit MPC design.
Type 'EMPCobj.Range' for the valid range of parameters.
Type 'EMPCobj.OptimizationOptions' for the options used in multi-parametric QP computation.
Type 'EMPCobj.PiecewiseAffineSolution' for regions and gain in each solution.
```

Input Arguments

MPCobj — Traditional MPC controller

MPC controller object

Traditional MPC controller, specified as an `mpc` object

range — Parameter bounds

structure

Parameter bounds, specified as a structure that you create with the `generateExplicitRange` command. This structure specifies the bounds on the parameters upon which the explicit MPC control law depends, such as state values, measured disturbances, and manipulated variables. For detailed descriptions of the range parameters, see `generateExplicitRange`.

opt — optimization options

structure

Optimization options for the conversion computation, specified as a structure that you create with the `generateExplicitOptions` function. For detailed descriptions of these options, see `generateExplicitOptions`.

Output Arguments

EMPCobj — Explicit MPC controller

`explicitMPC` object

Explicit MPC controller that is equivalent to the input traditional controller, returned as an `explicitMPC` object.

Property	Description
MPC	Traditional (implicit) controller object used to generate the explicit MPC controller. You create this MPC controller using is the <code>mpc</code> command. It is the first argument to <code>generateExplicitMPC</code> when you create the explicit MPC controller.
Range	1-D structure containing the parameter bounds used to generate the explicit MPC controller. These determine the resulting controller's valid operating range. This property is automatically populated by the <code>range</code> input argument to <code>generateExplicitMPC</code> when you create the explicit MPC controller. See <code>generateExplicitRange</code> for details about this structure.
OptimizationOptions	1-D structure containing user-modifiable options used to generate the explicit MPC controller. This property is automatically populated by the <code>opt</code> argument to <code>generateExplicitMPC</code> when you create the explicit MPC controller. See <code>generateExplicitOptions</code> for details about this structure.
PiecewiseAffineSolution	n_r -dimensional structure, where n_r is the number of piecewise affine (PWA) regions required to represent the control law. The i th element contains the details needed to compute the optimal manipulated variables when the solution lies within the i th region. See "Implementation".
IsSimplified	Logical switch indicating whether the explicit control law has been modified using the <code>simplify</code> command such that the explicit control law approximates the base (implicit) MPC controller. If the control law has not been modified, the explicit controller should reproduce the base controller's behavior exactly, provided both operate within the bounds described by the <code>Range</code> property.

Tips

- Using Explicit MPC, you will most likely achieve best performance in small control problems, which involve small numbers of plant inputs/outputs/states as well as the number of constraints.
- Test the implicit controller thoroughly before attempting a conversion. This helps to determine the range of controller states and other parameters needed to generate the explicit controller.
- Simulate the explicit controller's performance using the `sim` or `mpcmoveExplicit` commands, or the Explicit MPC Controller block in Simulink.
- `generateExplicitMPC` displays progress messages in the command window. Use `mpcverbosity` to turn off the display.

See Also

`generateExplicitOptions` | `generateExplicitRange` | `mpc` | `simplify`

Topics

"Explicit MPC Control of a Single-Input-Single-Output Plant"

"Explicit MPC Control of an Aircraft with Unstable Poles"

"Explicit MPC Control of DC Servomotor with Constraint on Unmeasured Output"

"Explicit MPC"

"Design Workflow for Explicit MPC"

Introduced in R2014b

generateExplicitOptions

Optimization options for explicit MPC generation

Syntax

```
opt = generateExplicitOptions(MPCobj)
```

Description

`opt = generateExplicitOptions(MPCobj)` creates a set of options to use when converting a traditional MPC controller, `MPCobj`, to explicit form using `generateExplicitMPC`. The options set is returned with all options set to default values. Use dot notation to modify the options.

Examples

Generate Explicit MPC Controller

Generate an explicit MPC controller based upon a traditional MPC controller for a double-integrator plant.

Define the double-integrator plant.

```
plant = tf(1,[1 0 0]);
```

Create a traditional (implicit) MPC controller for this plant, with sample time 0.1, a prediction horizon of 10, and a control horizon of 3.

```
Ts = 0.1;
p = 10;
m = 3;
MPCobj = mpc(plant,Ts,p,m);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

To generate an explicit MPC controller, you must specify the ranges of parameters such as state values and manipulated variables. To do so, generate a range structure. Then, modify values within the structure to the desired parameter ranges.

```
range = generateExplicitRange(MPCobj);
```

```
-->Converting the "Model.Plant" property of "mpc" object to state-space.
-->Converting model to discrete time.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
range.State.Min(:) = [-10;-10];
range.State.Max(:) = [10;10];
range.Reference.Min = -2;
range.Reference.Max = 2;
```

```
range.ManipulatedVariable.Min = -1.1;
range.ManipulatedVariable.Max = 1.1;
```

Use the more robust reduction method for the computation. Use `generateExplicitOptions` to create a default options set, and then modify the `polyreduction` option.

```
opt = generateExplicitOptions(MPCobj);
opt.polyreduction = 1;
```

Generate the explicit MPC controller.

```
EMPCobj = generateExplicitMPC(MPCobj,range,opt)
```

```
Explicit MPC Controller
```

```
-----
Controller sample time:    0.1 (seconds)
Polyhedral regions:       1
Number of parameters:     4
Is solution simplified:    No
State Estimation:         Default Kalman gain
-----
```

Type 'EMPCobj.MPC' for the original implicit MPC design.

Type 'EMPCobj.Range' for the valid range of parameters.

Type 'EMPCobj.OptimizationOptions' for the options used in multi-parametric QP computation.

Type 'EMPCobj.PiecewiseAffineSolution' for regions and gain in each solution.

Input Arguments

MPCobj — Traditional MPC controller

MPC controller object

Traditional MPC controller, specified as an MPC controller object. Use the `mpc` command to create a traditional MPC controller.

Output Arguments

opt — Options for generating explicit MPC controller

structure

Options for generating explicit MPC controller, returned as a structure. When you create the structure, all the options are set to default values. Use dot notation to modify any options you want to change. The fields and their default values are as follows.

zerotol — Zero-detection tolerance

1e-8 (default) | positive scalar value

Zero-detection tolerance used by the NNLS solver, specified as a positive scalar value.

removetol — Redundant-inequality-constraint detection tolerance

1e-4 (default) | positive scalar value

Redundant-inequality-constraint detection tolerance, specified as a positive scalar value.

flattol – Flat region detection tolerance

1e-5 (default) | positive scalar value

Flat region detection tolerance, specified as a positive scalar value.

normalizetol – Constraint normalization tolerance

0.01 (default) | positive scalar value

Constraint normalization tolerance, specified as a positive scalar value.

maxiterNNLS – Maximum number of NNLS solver iterations

500 (default) | positive integer

Maximum number of NNLS solver iterations, specified as a positive integer.

maxiterQP – Maximum number of QP solver iterations

200 (default) | positive integer

Maximum number of QP solver iterations, specified as a positive integer.

maxiterBS – Maximum number of bisection method iterations

100 (default) | positive integer

Maximum number of bisection method iterations used to detect region flatness, specified as a positive integer.

polyreduction – Method for removing redundant inequalities

2 (default) | 1

Method used to remove redundant inequalities, specified as either 1 (robust) or 2 (fast).

See Also

generateExplicitMPC

Introduced in R2014b

generateExplicitRange

Bounds on explicit MPC control law parameters

Syntax

```
Range = generateExplicitRange(MPCobj)
```

Description

`Range = generateExplicitRange(MPCobj)` creates a structure of parameter bounds based upon a traditional (implicit) MPC controller object. The range structure is intended for use as an input argument to `generateExplicitMPC`. Usually, the initial range values returned by `generateExplicitRange` are not suitable for generating an explicit MPC controller. Therefore, use dot notation to set the values of the range structure before calling `generateExplicitMPC`.

Examples

Generate Explicit MPC Controller

Generate an explicit MPC controller based upon a traditional MPC controller for a double-integrator plant.

Define the double-integrator plant.

```
plant = tf(1,[1 0 0]);
```

Create a traditional (implicit) MPC controller for this plant, with sample time 0.1, a prediction horizon of 10, and a control horizon of 3.

```
Ts = 0.1;
p = 10;
m = 3;
MPCobj = mpc(plant,Ts,p,m);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

To generate an explicit MPC controller, you must specify the ranges of parameters such as state values and manipulated variables. To do so, generate a range structure. Then, modify values within the structure to the desired parameter ranges.

```
range = generateExplicitRange(MPCobj);
```

```
-->Converting the "Model.Plant" property of "mpc" object to state-space.
-->Converting model to discrete time.
```

```
Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
range.State.Min(:) = [-10;-10];
range.State.Max(:) = [10;10];
```

```
range.Reference.Min = -2;
range.Reference.Max = 2;
range.ManipulatedVariable.Min = -1.1;
range.ManipulatedVariable.Max = 1.1;
```

Use the more robust reduction method for the computation. Use `generateExplicitOptions` to create a default options set, and then modify the `polyreduction` option.

```
opt = generateExplicitOptions(MPCObj);
opt.polyreduction = 1;
```

Generate the explicit MPC controller.

```
EMPCObj = generateExplicitMPC(MPCObj,range,opt)
```

```
Explicit MPC Controller
```

```
-----
Controller sample time:    0.1 (seconds)
Polyhedral regions:       1
Number of parameters:     4
Is solution simplified:    No
State Estimation:         Default Kalman gain
-----
```

```
Type 'EMPCObj.MPC' for the original implicit MPC design.
Type 'EMPCObj.Range' for the valid range of parameters.
Type 'EMPCObj.OptimizationOptions' for the options used in multi-parametric QP computation.
Type 'EMPCObj.PiecewiseAffineSolution' for regions and gain in each solution.
```

Input Arguments

MPCObj — Traditional MPC controller

MPC controller object

Traditional MPC controller, specified as an MPC controller object. Use the `mpc` command to create a traditional MPC controller.

Output Arguments

Range — Parameter bounds

structure

Parameter bounds for generating an explicit MPC controller from `MPCObj`, returned as a structure.

Initially, each parameter's minimum and maximum bounds are identical. All such parameters are considered fixed. When you generate an explicit controller, any fixed parameters must be constant when the controller operates. This is unlikely to happen in general. Thus, you must specify valid bounds for all parameters. Use dot notation to set the values of the range structure as appropriate for your system.

The fields of the range structure are as follows.

State — Bounds on controller state values

structure

Bounds on controller state values, specified as a structure containing fields `Min` and `Max`. Each of `Min` and `Max` is a vector of length n_x , where n_x is the number of controller states. `Range.State.Min` and `Range.State.Max` contain the minimum and maximum values, respectively, of all controller states. For example, suppose you are designing a two-state controller. You have determined that the range of the first controller state is `[-1000,1000]`, and that of the second controller state is `[0,2*pi]`. Set these bounds as follows:

```
Range.State.Min(:) = [-1000,0];
Range.State.Max(:) = [1000,2*pi];
```

MPC controller states include states from plant model, disturbance model, and noise model, in that order. Setting the range of a state variable is sometimes difficult when a state does not correspond to a physical parameter. In that case, multiple runs of open-loop plant simulation with typical reference and disturbance signals are recommended in order to collect data that reflect the ranges of states.

Reference — Bounds on controller reference signal values

structure

Bounds on controller reference signal values, specified as a structure containing fields `Min` and `Max`. Each of `Min` and `Max` is a vector of length n_y , where n_y is the number of plant outputs. `Range.Reference.Min` and `Range.Reference.Max` contain the minimum and maximum values, respectively, of all reference signal values. For example, suppose you are designing a controller for a two-output plant. You have determined that the range of the first plant output is `[-1000,1000]`, and that of the second plant output is `[0,2*pi]`. Set these bounds as follows:

```
Range.Reference.Min(:) = [-1000,0];
Range.Reference.Max(:) = [1000,2*pi];
```

Usually you know the practical range of the reference signals being used at the nominal operating point in the plant. The ranges used to generate the explicit MPC controller must be at least as large as the practical range.

MeasuredDisturbance — Bounds on measured disturbance values

structure

Bounds on measured disturbance values, specified as a structure containing fields `Min` and `Max`. Each of `Min` and `Max` is a vector of length n_{md} , where n_{md} is the number of measured disturbances. If your system has no measured disturbances, leave the generated values of this field unchanged.

`Range.MeasuredDisturbance.Min` and `Range.MeasuredDisturbance.Max` contain the minimum and maximum values, respectively, of all measured disturbance signals. For example, suppose you are designing a controller for a system with two measured disturbances. You have determined that the range of the first disturbance is `[-1,1]`, and that of the second disturbance is `[0,0.1]`. Set these bounds as follows:

```
Range.MeasuredDisturbance.Min(:) = [-1,0];
Range.MeasuredDisturbance.Max(:) = [1,0.1];
```

Usually you know the practical range of the measured disturbance signals being used at the nominal operating point in the plant. The ranges used to generate the explicit MPC controller must be at least as large as the practical range.

ManipulatedVariable — Bounds on manipulated variable values

structure

Bounds on manipulated variable values, specified as a structure containing fields `Min` and `Max`. Each of `Min` and `Max` is a vector of length n_u , where n_u is the number of manipulated variables. `Range.ManipulatedVariable.Min` and `Range.ManipulatedVariable.Max` contain the minimum and maximum values, respectively, of all manipulated variables. For example, suppose your system has two manipulated variables. The range of the first manipulated variable is $[-1, 1]$, and that of the second variable is $[0, 0.1]$. Set these bounds as follows:

```
Range.ManipulatedVariable.Min(:) = [-1,0];  
Range.ManipulatedVariable.Max(:) = [1,0.1];
```

If manipulated variables are constrained, the ranges used to generate the explicit MPC controller must be at least as large as these limits.

See Also

[generateExplicitMPC](#) | [generateExplicitOptions](#) | [mpc](#)

Introduced in R2014b

generatePlotParameters

Parameters for plotSection

Syntax

```
plotParams = generatePlotParameters(EMPCobj)
```

Description

`plotParams = generatePlotParameters(EMPCobj)` creates a structure of parameters for a 2-D sectional plot of the explicit MPC control law of the explicit MPC controller, `EMPCobj`. You set the fields of this structure and use it to generate the plot using the `plotSection` command.

Examples

Specify Fixed Parameters for 2-D Plot of Explicit Control Law

Define a double integrator plant model and create a traditional implicit MPC controller for this plant. Constrain the manipulated variable to have an absolute value less than 1.

```
plant = tf(1,[1 0 0]);
MPCobj = mpc(plant,0.1,10,3);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
```

```
MPCobj.MV = struct('Min',-1,'Max',1);
```

Define the parameter bounds for generating an explicit MPC controller.

```
range = generateExplicitRange(MPCobj);
```

```
-->Converting the "Model.Plant" property of "mpc" object to state-space.
-->Converting model to discrete time.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
range.State.Min(:) = [-10;-10];
range.State.Max(:) = [10;10];
range.Reference.Min(:) = -2;
range.Reference.Max(:) = 2;
range.ManipulatedVariable.Min(:) = -1.1;
range.ManipulatedVariable.Max(:) = 1.1;
```

Create an explicit MPC controller.

```
EMPCobj = generateExplicitMPC(MPCobj,range);
```

```
Regions found / unexplored:      19/      0
```


Create a default plot parameter structure, which specifies that all of the controller parameters are fixed at their nominal values for plotting.

```
plotParams = generatePlotParameters(EMPCobj);
```

Allow the controller states to vary when creating a plot.

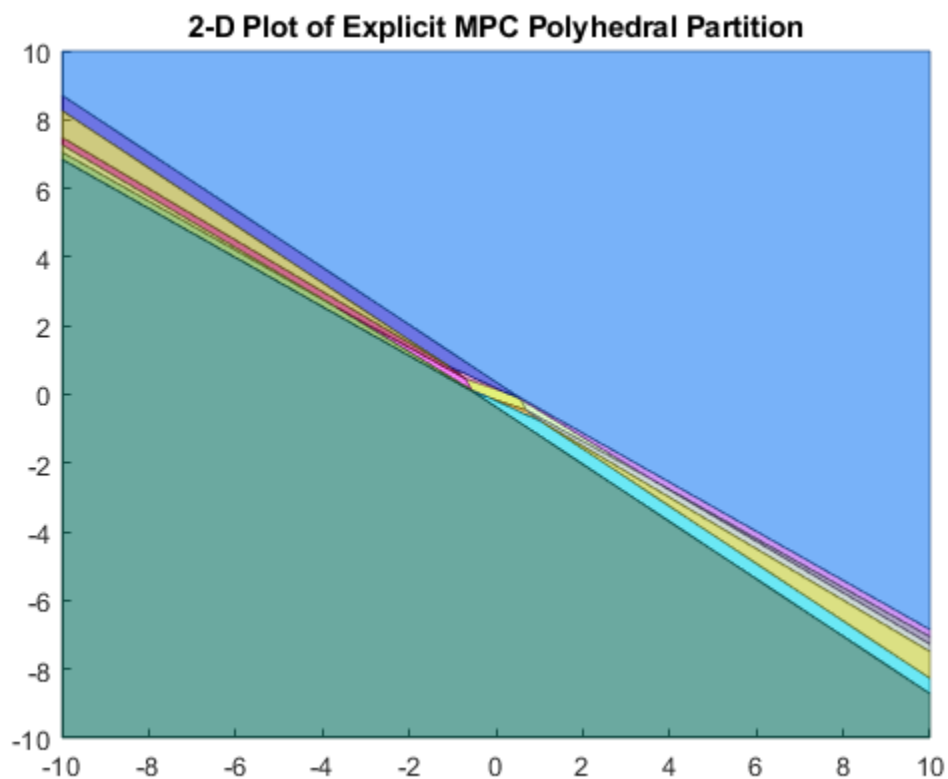
```
plotParams.State.Index = [];
plotParams.State.Value = [];
```

Fix the manipulated variable and reference signal to θ for plotting.

```
plotParams.ManipulatedVariable.Index(1) = 1;
plotParams.ManipulatedVariable.Value(1) = 0;
plotParams.Reference.Index(1) = 1;
plotParams.Reference.Value(1) = 0;
```

Generate the 2-D section plot for the explicit MPC controller.

```
plotSection(EMPCobj,plotParams)
```



ans =

Figure (1: PiecewiseAffineSectionPlot) with properties:

```
Number: 1
Name: 'PiecewiseAffineSectionPlot'
Color: [0.9400 0.9400 0.9400]
Position: [360 502 560 420]
```

Units: 'pixels'

Show all properties

Input Arguments

EMPCobj — Explicit MPC controller

explicit MPC controller object

Explicit MPC controller for which you want to create a 2-D sectional plot, specified as an Explicit MPC controller object. Use `generateExplicitMPC` to create an explicit MPC controller.

Output Arguments

plotParams — Parameters for sectional plot

structure

Parameters for sectional plot of explicit MPC control law, returned as a structure.

As returned by `generatePlotParameters`, the `plotParams` structure command fixes all the control law's parameters at their nominal values. To obtain the desired plot, eliminate the `Index` and `Value` entries of the two parameters forming the plot axes, and modify fixed values as necessary. Then, use the `plotSection` command to display the 2-D sectional plot of the explicit control law's PWA regions with the remaining free parameters as the *x* and *y* axes.

The fields of the plot-parameters structure are as follows.

State — Fixed controller states

structure

Fixed controller states, specified as a structure having an `Index` field and a `Value` field. The field `plotParams.State.Index` is a vector that contains the indices of the controller states to fix for the plot, and `plotParams.State.Value` contains the corresponding constant state values.

Modify the default value of `plotParams.State` to generate the desired plot. See “Specify Fixed Parameters for 2-D Plot of Explicit Control Law” on page 2-30.

Reference — Fixed reference signal values

structure

Fixed reference signal values, specified as a structure having an `Index` field and a `Value` field. The field `plotParams.Reference.Index` is a vector that contains the indices of the reference signals to fix for the plot, and `plotParams.Reference.Value` contains the corresponding constant reference signal values.

Modify the default value of `plotParams.Reference` to generate the desired plot. See “Specify Fixed Parameters for 2-D Plot of Explicit Control Law” on page 2-30.

MeasuredDisturbance — Fixed measured disturbance values

structure

Fixed measured disturbance values, specified as a structure having an `Index` field and a `Value` field. The field `plotParams.MeasuredDisturbance.Index` is a vector that contains the indices of the

measured disturbances to fix for the plot, and `plotParams.MeasuredDisturbance.Value` contains the corresponding constant measured disturbance values.

Modify the default value of `plotParams.MeasuredDisturbance` to generate the desired plot. See “Specify Fixed Parameters for 2-D Plot of Explicit Control Law” on page 2-30.

ManipulatedVariable — Fixed manipulated variable values

structure

Fixed manipulated variable values, specified as a structure having an `Index` field and a `Value` field. The field `plotParams.ManipulatedVariable.Index` is a vector that contains the indices of the manipulated variables to fix for the plot, and `plotParams.ManipulatedVariable.Value` contains the corresponding constant manipulated variable values.

Modify the default value of `plotParams.ManipulatedVariable` to generate the desired plot. See “Specify Fixed Parameters for 2-D Plot of Explicit Control Law” on page 2-30.

See Also

`generateExplicitMPC` | `plotSection`

Introduced in R2014b

get

MPC property values

Syntax

```
Value = get(MPCobj,PropertyName)  
Struct = get(MPCobj)  
get(MPCobj)
```

Description

`Value = get(MPCobj,PropertyName)` returns the current value of the property `PropertyName` of the MPC controller `MPCobj`. Specify `PropertyName` as a character vector or string that contains the full property name (for example, `'UserData'`) or any unambiguous case-insensitive abbreviation (for example, `'user'`). You can specify any generic MPC property.

`Struct = get(MPCobj)` converts the MPC controller `MPCobj` into a standard MATLAB structure with the property names as field names and the property values as field values.

`get(MPCobj)` without a left-side argument displays all properties of `MPCobj` and their values.

Tips

An alternative to the syntax

```
Value = get(MPCobj, 'PropertyName')
```

is the structure-like referencing

```
Value = MPCobj.PropertyName
```

For example,

```
MPCobj.Ts  
MPCobj.p
```

return the values of the sampling time and prediction horizon of the MPC controller `MPCobj`.

See Also

[mpc](#) | [set](#)

Introduced before R2006a

getCodeGenerationData

Create data structures for `mpcmoveCodeGeneration`

Syntax

```
[configData, stateData, onlineData] = getCodeGenerationData(mpcobj)
[ ___ ] = getCodeGenerationData( ___ , Name, Value)
```

Description

Use this function to create data structures for the `mpcmoveCodeGeneration` function, which computes optimal control moves for implicit and explicit linear MPC controllers.

For information on generating data structures for `nlmpcmoveCodeGeneration`, see `getCodeGenerationData`.

`[configData, stateData, onlineData] = getCodeGenerationData(mpcobj)` creates data structures for use with `mpcmoveCodeGeneration`.

`[___] = getCodeGenerationData(___ , Name, Value)` specifies additional options using one or more `Name, Value` pair arguments.

Examples

Create MPC Code Generation Data Structures

Create a plant model, and define the MPC signal types.

```
plant = rss(3,2,2);
plant.D = 0;
plant = setmpcsignals(plant, 'mv', 1, 'ud', 2, 'mo', 1, 'uo', 2);
```

Create an MPC controller.

```
mpcObj = mpc(plant, 0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
    for output(s) y1 and zero weight for output(s) y2
```

Configure your controller parameters. For example, define bounds for the manipulated variable.

```
mpcObj.ManipulatedVariables.Min = -1;
mpcObj.ManipulatedVariables.Max = 1;
```

Create code generation data structures.

```
[configData, stateData, onlineData] = getCodeGenerationData(mpcObj);
```

```
-->Converting model to discrete time.
-->The "Model.Disturbance" property of "mpc" object is empty:
    Assuming unmeasured input disturbance #2 is integrated white noise.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
-->Converting model to discrete time.
-->The "Model.Disturbance" property of "mpc" object is empty:
    Assuming unmeasured input disturbance #2 is integrated white noise.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Specify Options for Creating MPC Code Generation Structures

Create a plant model, and define the MPC signal types.

```
plant = rss(3,2,2);
plant.D = 0;
```

Create an MPC controller.

```
mpcObj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Create code generation data structures. Configure options to:

- Use single-precision floating-point values in the generated code.
- Improve computational efficiency by not computing optimal sequence data.
- Run your MPC controller in adaptive mode.

```
[configData,stateData,onlineData] = getCodeGenerationData(mpcObj,...
    'DataType','single','OnlyComputeCost',true,'IsAdaptive',true);
```

```
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->Assuming output disturbance added to measured output channel #2 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->Assuming output disturbance added to measured output channel #2 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Input Arguments

mpcobj — Model predictive controller

mpc object | explicitMPC object

Model predictive controller, specified as one of the following:

- `mpc` object — Implicit MPC controller
- `explicitMPC` object — Explicit MPC controller created using `generateExplicitMPC`.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `'DataType', 'single'` specifies that the generated code uses single-precision floating point values.

InitialState — Initial controller state

`mpcstate` object

Initial controller state when using `mpcmoveCodeGeneration`, specified as the comma-separated pair consisting of `'InitialState'` and an `mpcstate` object. This state is used in place of the default state information from `mpcobj`.

DataType — Data type used in generated code

`'double'` (default) | `'single'`

Data type used in generated code when using `mpcmoveCodeGeneration`, specified as specified as the comma-separated pair consisting of `'DataType'` and one of the following:

- `'double'` — Use double-precision floating point values.
- `'single'` — Use single-precision floating point values.

OnlyComputeCost — Toggle for computing only optimal cost

`false` (default) | `true`

Toggle for computing only optimal cost during simulation when using `mpcmoveCodeGeneration`, specified as specified as the comma-separated pair consisting of `'OnlyComputeCost'` and either `true` or `false`. To reduce computational load by not calculating optimal sequence data, set `OnlyComputeCost` to `true`.

IsAdaptive — Adaptive MPC indicator

`false` (default) | `true`

Adaptive MPC indicator when using `mpcmoveCodeGeneration`, specified as specified as the comma-separated pair consisting of `'IsAdaptive'` and either `true` or `false`. Set `IsAdaptive` to `true` if your controller is running in adaptive mode.

For more information on adaptive MPC, see “Adaptive MPC”.

Note `IsAdaptive` and `IsLTV` cannot be `true` at the same time.

IsLTV — Time-varying MPC indicator

`false` (default) | `true`

Time-varying MPC indicator when using `mpcmoveCodeGeneration`, specified as the comma-separated pair consisting of `'IsLTV'` and either `true` or `false`. Set `IsLTV` to `true` if your controller is running in time-varying mode.

For more information on time-varying MPC, see “Time-Varying MPC”.

Note `IsAdaptive` and `IsLTV` cannot be `true` at the same time.

UseVariableHorizon — Variable horizon indicator

`false` (default) | `true`

Variable horizon indicator when using `mpcmoveCodeGeneration`, specified as the comma-separated pair consisting of 'UseVariableHorizon' and either `true` or `false`. To vary your prediction and control horizons at run time, set `UseVariableHorizons` to `true`.

When you use variable horizons, `mpcmoveCodeGeneration` ignores the horizons specified in `configData` and instead uses the prediction and control horizon specified in `onlineData.horizons`.

For more information, see “Adjust Horizons at Run Time”.

Output Arguments

configData — MPC configuration parameters

structure

MPC configuration parameters that are constant at run time, returned as a structure. These parameters are derived from the controller settings in `mpcobj`. When simulating your controller, pass `configData` to `mpcmoveCodeGeneration` without changing any parameters.

For more information on how generated MPC code uses constant matrices in `configData` to solve the QP problem, see “QP Problem Construction for Generated C Code”.

stateData — Initial controller states

structure

Initial controller states, returned as a structure. To initialize your simulation with the initial states defined in `mpcobj`, pass `stateData` to `mpcmoveCodeGeneration`. To use different initial conditions, modify `stateData`. You can specify nondefault controller states using `InitialState`.

For more information on the `stateData` fields, see `mpcmoveCodeGeneration`.

`stateData` has the following fields.

Field	Description
Plant	Plant model state estimates
Disturbance	Unmeasured disturbance model state estimates
Noise	Output measurement noise model state estimates
LastMove	Manipulated variable control moves from previous control interval
Covariance	Covariance matrix for controller state estimates
iA	Active inequality constraints

onlineData — Online MPC controller data

structure

Online MPC controller data that you must update at each control interval, returned as a structure with the following fields.

Field	Description	
signals	Input and output signals, returned as a structure with the following fields.	
	Field	Description
	ym	Measured outputs
	ref	Output references
	md	Measured disturbances
	mvTarget	Targets for manipulated variables
	externalMV	Manipulated variables externally applied to the plant
limits	Input and output constraints, returned as a structure with the following fields:	
	Field	Description
	ymin	Lower bounds on output signals
	ymax	Upper bounds on output signals
	umin	Lower bounds on input signals
	umax	Upper bounds on input signals
	When <code>mpcobj</code> is an explicit MPC controller, <code>mpcmoveCodeGeneration</code> ignores the <code>limits</code> field.	
weights	Updated QP optimization weights, returned as a structure with the following fields:	
	Field	Description
	ywt	Output weights
	uwt	Manipulated variable weights
	duwt	Manipulated variable rate weights
	ecr	Weight on slack variable used for constraint softening
	When <code>mpcobj</code> is an explicit MPC controller, <code>mpcmoveCodeGeneration</code> ignores the <code>weights</code> field.	

Field	Description	
customconstraints	Updated custom mixed input/output constraints, returned as a structure with the following fields:	
	Field	Description
	E	Manipulated variable constraint constant
	F	Controlled output constraint constant
	G	Mixed input/output constraint constant
	S	Measured disturbance constraint constant
When <code>mpcobj</code> is an explicit MPC controller, <code>mpcmoveCodeGeneration</code> ignores the <code>customconstraints</code> field.		
horizons	Updated controller horizon values, returned as a structure with the following fields:	
	Field	Description
	p	Prediction horizon
	m	Control horizon
	The <code>horizons</code> field is returned only when the <code>UseVariableHorizon</code> name-value pair is <code>true</code> .	
When <code>mpcobj</code> is an explicit MPC controller, <code>mpcmoveCodeGeneration</code> ignores the <code>horizons</code> field.		
model	Updated plant and nominal values for adaptive MPC and time-varying MPC, returned as a structure with the following fields:	
	Field	Description
	A, B, C, D	State-space matrices of discrete-time state-space model.
	X	Nominal plant states
	U	Nominal plant inputs
	Y	Nominal plant outputs
	DX	Nominal plant state derivatives
The <code>model</code> field is returned only when either the <code>IsAdaptive</code> or <code>IsLTV</code> name-value pair is <code>true</code> .		

`getCodeGenerationData` returns `onlineData` with empty matrices for all structure fields, except `signals.ref`, `signals.ym`, and `signals.md`. These fields contain the corresponding nominal signal values from `mpcobj`. If your controller does not have measured disturbances, `signals.md` is returned as an empty matrix.

For more information on configuring `onlineData` fields, see `mpcmoveCodeGeneration`.

See Also

`mpcmoveCodeGeneration`

Topics

“Generate Code To Compute Optimal MPC Moves in MATLAB”

“Generate Code and Deploy Controller to Real-Time Targets”

Introduced in R2016a

getCodeGenerationData

Create data structures for `nLmpcmoveCodeGeneration`

Syntax

```
[coreData,onlineData] = getCodeGenerationData(nLmpcobj,x,lastMV,params)
[ ___ ] = getCodeGenerationData( ___ ,field)
[ ___ ] = getCodeGenerationData( ___ ,field1,...,fieldn)
```

Description

Use this function to create data structures for the `nLmpcmoveCodeGeneration` function, which computes optimal control moves for nonlinear MPC controllers.

For information on generating data structures for `mpcmoveCodeGeneration`, see `getCodeGenerationData`.

`[coreData,onlineData] = getCodeGenerationData(nLmpcobj,x,lastMV,params)` creates data structures for use with `nLmpcmoveCodeGeneration`.

`[___] = getCodeGenerationData(___ ,field)` adds the specified online weight and constraint field to the `nLOnlineData` structure.

`[___] = getCodeGenerationData(___ ,field1,...,fieldn)` adds multiple online weight and constraint fields to the `nLOnlineData` structure.

Examples

Create Nonlinear MPC Code Generation Structures

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nlobj = nLmpc(4,2,1);
```

In standard cost function, zero weights are applied by default to one or more 0Vs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The prediction model uses an optional parameter, T_s , to represent the sample time. Specify the number of parameters and create a parameter vector.

```
nlobj.Model.NumberOfParameters = 1;
params = {Ts};
```

Specify the output function of the model, passing the sample time parameter as an input argument.

```
nlobj.Model.OutputFcn = "pendulumOutputFcn";
```

Define standard constraints for the controller.

```
nlobj.Weights.OutputVariables = [3 3];
nlobj.Weights.ManipulatedVariablesRate = 0.1;
nlobj.OV(1).Min = -10;
nlobj.OV(1).Max = 10;
nlobj.MV.Min = -100;
nlobj.MV.Max = 100;
```

Validate the prediction model functions.

```
x0 = [0.1;0.2;-pi/2;0.3];
u0 = 0.4;
validateFcns(nlobj,x0,u0,[],params);
```

```
Model.StateFcn is OK.
Model.OutputFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Only two of the plant states are measurable. Therefore, create an extended Kalman filter for estimating the four plant states. Its state transition function is defined in `pendulumStateFcn.m` and its measurement function is defined in `pendulumMeasurementFcn.m`.

```
EKF = extendedKalmanFilter(@pendulumStateFcn,@pendulumMeasurementFcn);
```

Define initial conditions for the simulation, initialize the extended Kalman filter state, and specify a zero initial manipulated variable value.

```
x0 = [0;0;-pi;0];
y0 = [x0(1);x0(3)];
EKF.State = x0;
mv0 = 0;
```

Create code generation data structures for the controller, specifying the initial conditions and parameters.

```
[coreData,onlineData] = getCodeGenerationData(nlobj,x0,mv0,params);
```

View the online data structure.

```
onlineData
```

```
onlineData = struct with fields:
    ref: [0 0]
    MVTarget: 0
    Parameters: {[0.1000]}
        X0: [10x4 double]
        MV0: [10x1 double]
```

```
Slack0: 0
```

If your application uses online weights or constraints, you must add corresponding fields to the code generation data structures. For example, create data structures that include fields for output and manipulated variable tuning weights and manipulated variable bounds.

```
[coreData2,onlineData2] = getCodeGenerationData(nlobj,x0,mv0,params,...
    'OutputWeights','MVWeights','MVMin','MVMax');
```

View the online data structure. At run time, specify the online weights and constraints in the added structure fields.

```
onlineData2
```

```
onlineData2 = struct with fields:
    ref: [0 0]
    MVTarget: 0
    Parameters: {[0.1000]}
    X0: [10x4 double]
    MV0: [10x1 double]
    Slack0: 0
    OutputWeights: [3 3]
    MVWeights: 0
    MVMin: [10x1 double]
    MVMax: [10x1 double]
```

Input Arguments

nlpmpcobj — Nonlinear model predictive controller

nlpmpc object

Nonlinear model predictive controller, specified as an nlpmpc object.

x — Initial states of the nonlinear prediction model

column vector of length N_x

Initial states of the nonlinear prediction model, specified as a column vector of length N_x , where N_x is the number of prediction model states.

lastMV — Initial manipulated variable control signals

column vector of length N_{mv}

Initial manipulated variable control signals, specified as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

params — Initial parameter values

cell vector

Initial parameter values, specified as a cell vector with length equal to `nlobj.Model.NumberOfParameters`, which is the number of optional parameters in the controller prediction model. If the controller has no optional parameters, specify `params` as `{}`.

For more information on optional prediction model parameters, see “Specify Prediction Model for Nonlinear MPC”.

field — Online weight or constraint field name

string | character vector

Online weight or constraint field name, specified as a string or character vector. When creating data structures for `nlpmoveCodeGeneration`, you can add any of the following fields to the `onlineData` output structure. Add a given field to the online data structure only if you expect the corresponding weight or constraint to vary at run time.

Online Tuning Weights

- "OutputWeights" — Output variable weights
- "MVWeights" — Manipulated variable weights
- "MVRateWeights" — Manipulated variable rate weights
- "ECRWeight" — Slack variable weight

Online Constraints

- "OutputMin" — Output variable lower bounds
- "OutputMax" — Output variable upper bounds
- "StateMin" — State lower bounds
- "StateMax" — State upper bounds
- "MVMin" — Manipulated variable lower bounds
- "MVMax" — Manipulated variable upper bounds
- "MVRateMin" — Manipulated variable rate of change lower bound
- "MVRateMax" — Manipulated variable rate of change upper bound

Output Arguments**coreData — Nonlinear MPC configuration parameters**

structure

Nonlinear MPC configuration parameters that are constant at run time, returned as a structure. These parameters are derived from the controller settings in `nlpmoveObj`. When simulating your controller, pass `coreData` to `nlpmoveCodeGeneration` without changing any parameters.

onlineData — Online nonlinear MPC controller data

structure

Online nonlinear MPC controller data that you must update at each control interval, returned as a structure. The structure always contains the following fields.

Field	Description
ref	Output reference values, returned as a column vector of zeros with length N_y , where N_y is the number of prediction model outputs.
mvTarget	Manipulated variable reference values, returned as a column vector of zeros with length N_{mv} , where N_{mv} is the number of manipulated variables
X0	Initial guess for the state trajectory, returned as a column vector equal to <code>x0</code> .

Field	Description
MV0	Initial guess for the manipulated variable trajectory, returned as a column vector equal to <code>lastMV</code> .
Slack0	Initial guess for the slack variable, returned as zero.

`onlineData` can also contain the following fields, depending on the controller configuration and argument values.

Field	Description
<code>md</code>	Measured disturbance values — This field is returned only when the controller has measured disturbance inputs, that is, when <code>nlpcoobj.Dimensions.MDIndex</code> is nonzero. <code>md</code> is returned as a column vector of zeros with length N_{md} , where N_{md} is the number of measured disturbances.
<code>Parameters</code>	Parameter values — This field is returned only when the controller uses optional model parameters. <code>Parameters</code> is returned as a cell vector equal to <code>params</code> .
<ul style="list-style-type: none"> • <code>OutputWeights</code> • <code>MVWeights</code> • <code>MVRateWeights</code> • <code>ECRWeight</code> • <code>OutputMin</code> • <code>OutputMax</code> • <code>StateMin</code> • <code>StateMax</code> • <code>MVMin</code> • <code>MVMax</code> • <code>MVRateMin</code> • <code>MVRateMax</code> 	Weight and constraint values — Each field is returned only when the corresponding field name is specified using the <code>field</code> argument. The value of each field is equal to the corresponding default value defined in the controller, as returned in <code>coreData</code> .

For more information on configuring `onlineData` fields, see `nlpmoveCodeGeneration`.

See Also

`nlpmoveCodeGeneration`

Topics

“Generate Code To Compute Optimal MPC Moves in MATLAB”
 “Generate Code and Deploy Controller to Real-Time Targets”

Introduced in R2020a

getconstraint

Obtain mixed input/output constraints from model predictive controller

Syntax

```
[E,F,G,V,S] = getconstraint(MPCobj)
```

Description

`[E,F,G,V,S] = getconstraint(MPCobj)` returns the mixed-input/output constraints previously defined for the MPC controller, `MPCobj`. For more information, see “Mixed Input/Output Constraints” on page 2-49.

Examples

Retrieve Custom Constraints from MPC Controller

Create a third-order plant model with two manipulated variables, one measured disturbance, and two measured outputs.

```
plant = rss(3,2,3);
plant.D = 0;
plant = setmpcsignals(plant, 'mv', [1 2], 'md', 3);
```

Create an MPC controller for this plant.

```
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
```

Assume that you have two soft constraints.

$$u_1 + u_2 \leq 5$$

$$y_2 + v \leq 10$$

Set the constraints for the MPC controller.

```
E = [1 1; 0 0];
F = [0 0; 0 1];
G = [5;10];
V = [1;1];
S = [0;1];
setconstraint(MPCobj,E,F,G,V,S)
```

Retrieve the constraints from the controller.

```
[E,F,G,V,S] = getconstraint(MPCobj)
```

$$E = 2 \times 2$$

$$\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$$

$$F = 2 \times 2$$

$$\begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

$$G = 2 \times 1$$

$$\begin{bmatrix} 5 \\ 10 \end{bmatrix}$$

$$V = 2 \times 1$$

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$S = 2 \times 1$$

$$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Input Arguments

MPCobj — Model predictive controller

MPC controller object

Model predictive controller, specified as an MPC controller object. To create an MPC controller, use `mpc`.

Output Arguments

E — Manipulated variable constraint constant

N_c -by- N_{mv} array | []

Manipulated variable constraint constant, returned as an N_c -by- N_{mv} array, where N_c is the number of constraints, and N_{mv} is the number of manipulated variables.

If MPCobj has no mixed input/output constraints, then E is [].

F — Controlled output constraint constant

N_c -by- N_y array | []

Controlled output constraint constant, returned as an N_c -by- N_y array, where N_y is the number of controlled outputs (measured and unmeasured).

If MPCobj has no mixed input/output constraints, then F is [].

G – Mixed input/output constraint constantcolumn vector of length N_c | []

Mixed input/output constraint constant, returned as a column vector of length N_c , where N_c is the number of constraints.

If MPCobj has no mixed input/output constraints, then G is [].

V – Constraint softening constantcolumn vector of length N_c | []

Constraint softening constant representing the equal concern for the relaxation (ECR), returned as a column vector of length N_c , where N_c is the number of constraints. If MPCobj has no mixed input/output constraints, then V is [].

If V is not specified, a default value of 1 is applied to all constraint inequalities and all constraints are soft. This behavior is the same as the default behavior for output bounds, as described in “Standard Cost Function”.

To make the i^{th} constraint hard, specify $V(i) = 0$.

To make the i^{th} constraint soft, specify $V(i) > 0$ in keeping with the constraint violation magnitude you can tolerate. The magnitude violation depends on the numerical scale of the variables involved in the constraint.

In general, as $V(i)$ decreases, the controller hardens the constraints by decreasing the constraint violation that is allowed.

S – Measured disturbance constraint constant N_c -by- N_v array | []

Measured disturbance constraint constant, returned as an N_c -by- N_v array, where N_v is the number of measured disturbances.

If there are no measured disturbances in the mixed input/output constraints, or MPCobj has no mixed input/output constraints, then S is [].

Algorithms**Mixed Input/Output Constraints**

The general form of the mixed input/output constraints is:

$$Eu(k + j) + Fy(k + j) + Sv(k + j) \leq G + \varepsilon V$$

Here, $j = 0, \dots, p$, and:

- p is the prediction horizon.
- k is the current time index.
- u is a column vector manipulated variables.
- y is a column vector of all plant output variables.
- v is a column vector of measured disturbance variables.
- ε is a scalar slack variable used for constraint softening (as in “Standard Cost Function”).

- E , F , G , V , and S are constant matrices.

Since the MPC controller does not optimize $u(k+p)$, `getconstraint` calculates the last constraint at time $k+p$ assuming that $u(k+p) = u(k+p-1)$.

See Also

`setconstraint`

Topics

“Constraints on Linear Combinations of Inputs and Outputs”

Introduced in R2011a

getEstimator

Obtain Kalman gains and model for estimator design

Syntax

```
[L,M] = getEstimator(MPCobj)
[L,M,A,Cm,Bu,Bv,Dvm] = getEstimator(MPCobj)
[L,M,model,index] = getEstimator(MPCobj,'sys')
```

Description

`[L,M] = getEstimator(MPCobj)` extracts the Kalman gains used by the state estimator in a model predictive controller. The estimator updates the states of internal plant, disturbance, and noise models at the beginning of each controller interval.

`[L,M,A,Cm,Bu,Bv,Dvm] = getEstimator(MPCobj)` also returns the system matrices used to calculate the estimator gains.

`[L,M,model,index] = getEstimator(MPCobj,'sys')` returns an LTI state-space representation of the system used for state-estimator design and a structure summarizing the I/O signal types of the system.

Examples

Extract Parameters for State Estimation

The plant is a stable, discrete LTI state-space model with four states, three inputs, and three outputs. The manipulated variables are inputs 1 and 2. Input 3 is an unmeasured disturbance. Outputs 1 and 3 are measured. Output 2 is unmeasured.

Create a model of the plant and specify the signals for MPC.

```
rng(1253) % For repeatable results
Plant = drss(4,3,3);
Plant.Ts = 0.25;
Plant = setmpcsignals(Plant,'MV',[1,2],'UD',3,'MO',[1 3],'UO',2);
Plant.d(:,[1,2]) = 0;
```

The last command forces the plant to satisfy the assumption of no direct feedthrough.

Calculate the default model predictive controller for this plant.

```
MPCobj = mpc(Plant);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
    for output(s) y1 y3 and zero weight for output(s) y2
```

Obtain the parameters to be used in state estimation.

```
[L,M,A,Cm,Bu,Bv,Dvm] = getEstimator(MPCobj);
```

```
-->The "Model.Disturbance" property of "mpc" object is empty:
    Assuming unmeasured input disturbance #3 is integrated white noise.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
    Assuming no disturbance added to measured output channel #3.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Based on the estimator state equation, the estimator poles are given by the eigenvalues of $A - L \cdot C_m$. Calculate and display the poles.

```
Poles = eig(A - L*Cm)
```

```
Poles = 6×1
```

```
-0.7467
-0.5019
 0.0769
 0.4850
 0.8825
 0.8291
```

Confirm that the default estimator is asymptotically stable.

```
max(abs(Poles))
```

```
ans = 0.8825
```

This value is less than 1, so the estimator is asymptotically stable.

Verify that in this case, $L = A \cdot M$.

```
L - A*M
```

```
ans = 6×2
10-15 ×
```

```
 0.2776    0.2359
 0.0416         0
-0.0971   -0.1527
         0   -0.0278
-0.1318   -0.0833
 0.0694    0.0278
```

Input Arguments

MPCobj — MPC controller

MPC controller object

MPC controller, specified as an MPC controller object. Use the `mpc` command to create the MPC controller.

Output Arguments

L — Kalman gain matrix for time update

matrix

Kalman gain matrix for the time update, returned as a matrix. The dimensions of L are n_x -by- n_{ym} , where n_x is the total number of controller states, and n_{ym} is the number of measured outputs.

M — Kalman gain matrix for measurement update

matrix

Kalman gain matrix for the measurement update, returned as a matrix. The dimensions of L are n_x -by- n_{ym} , where n_x is the total number of controller states, and n_{ym} is the number of measured outputs.

A, Cm, Bu, Bv, Dvm — System matrices

matrices

System matrices used to calculate the estimator gains, returned as matrices of various dimensions. For definitions of these system matrices, see “State Estimator Equations” on page 2-54.

model — System used for state-estimator design

state-space model

System used for state-estimator design, returned as a state-space (ss) model. The input to model is a vector signal comprising the following components, concatenated in the following order:

- Manipulated variables
- Measured disturbance variables
- 1
- Noise inputs to disturbance models
- Noise inputs to measurement noise model

The number of noise inputs depends on the disturbance and measurement noise models within MPCobj. For the category noise inputs to disturbance models, inputs to the input disturbance model (if any) precede those entering the output disturbance model (if any). The constant input, 1, accounts for nonequilibrium nominal values (see “MPC Modeling”).

To make the calculation of gains L and M more robust, additive white noise inputs are assumed to affect the manipulated variables and measured disturbances (see “Controller State Estimation”). These white noise inputs are not included in model.

index — Locations of variables within model

structure

Locations of variables within the inputs and outputs of model. The structure summarizes these locations with the following fields and values.

Field Name	Value
ManipulatedVariables	Indices of manipulated variables within the input vector of model.
MeasuredDisturbances	Indices of measured input disturbances within the input vector of model.

Field Name	Value
Offset	Index of the constant input 1 within the input vector of model.
WhiteNoise	Indices of unmeasured disturbance inputs within the input vector of model.
MeasuredOutputs	Indices of measured outputs within the output vector of model.
UmeasuredOutputs	Indices of unmeasured outputs within the output vector of model.

Algorithms

State Estimator Equations

In general, the controller states are unmeasured and must be estimated. By default, the controller uses a steady-state Kalman filter that derives from the state observer. For more information, see “Controller State Estimation”.

At the beginning of the k th control interval, the controller state is estimated with the following steps:

1 Obtain the following data:

- $x_c(k|k-1)$ — Controller state estimate from previous control interval, $k-1$
- $u^{act}(k-1)$ — Manipulated variable (MV) actually used in the plant from $k-1$ to k (assumed constant)
- $u^{opt}(k-1)$ — Optimal MV recommended by MPC and assumed to be used in the plant from $k-1$ to k
- $v(k)$ — Current measured disturbances
- $y_m(k)$ — Current measured plant outputs
- B_u, B_v — Columns of observer parameter B corresponding to $u(k)$ and $v(k)$ inputs
- C_m — Rows of observer parameter C corresponding to measured plant outputs
- D_{mv} — Rows and columns of observer parameter D corresponding to measured plant outputs and measured disturbance inputs
- L, M — Constant Kalman gain matrices

Plant input and output signals are scaled to be dimensionless prior to use in calculations.

2 Revise $x_c(k|k-1)$ when $u^{act}(k-1)$ and $u^{opt}(k-1)$ are different.

$$x_c^{rev}(k|k-1) = x_c(k|k-1) + B_u[u^{act}(k-1) - u^{opt}(k-1)]$$

3 Compute the innovation.

$$e(k) = y_m(k) - [C_m x_c^{rev}(k|k-1) + D_{mv} v(k)]$$

4 Update the controller state estimate to account for the latest measurements.

$$x_c(k|k) = x_c^{rev}(k|k-1) + M e(k)$$

Then, the software uses the current state estimate $x_c(k|k)$ to solve the quadratic program at interval k . The solution is $u^{opt}(k)$, the MPC-recommended manipulated-variable value to be used between control intervals k and $k+1$.

Finally, the software prepares for the next control interval assuming that the unknown inputs, $w_{id}(k)$, $w_{od}(k)$, and $w_n(k)$ assume their mean value (zero) between times k and $k+1$. The software predicts the impact of the known inputs and the innovation as follows:

$$x_c(k+1|k) = Ax_c^{rev}(k|k-1) + B_u u^{opt}(k) + B_v v(k) + Le(k)$$

See Also

`getindist` | `getoutdist` | `mpc` | `mpcstate` | `setEstimator`

Topics

“Controller State Estimation”

“MPC Modeling”

Introduced in R2014b

getindist

Retrieve unmeasured input disturbance model

Syntax

```
indist = getindist(MPCobj)
[indist,channels] = getindist(MPCobj)
```

Description

`indist = getindist(MPCobj)` returns the input disturbance model, `indist`, used by the model predictive controller, `MPCobj`.

`[indist,channels] = getindist(MPCobj)` also returns the input channels to which integrated white noise has been added by default. For more information on the default model, see “MPC Modeling”.

Examples

Retrieve Input Disturbance Model

Define a plant model with no direct feedthrough.

```
plant = rss(3,1,2);
plant.D = 0;
```

Set the first input signal as a manipulated variable and the second input as an unmeasured disturbance.

```
plant = setmpcsignals(plant, 'MV', [1], 'UD', [2]);
```

Create an MPC controller for the defined plant.

```
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
```

Extract the input disturbance model.

```
indist = getindist(MPCobj);
```

```
-->Converting model to discrete time.
-->The "Model.Disturbance" property of "mpc" object is empty:
    Assuming unmeasured input disturbance #2 is integrated white noise.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Retrieve Input Disturbance Model Channels with Default Integrated White Noise

Define a plant model with no direct feedthrough.

```
plant = rss(3,1,3);
plant.D = 0;
```

Set the first input signal as a manipulated variable and the other two inputs as unmeasured disturbances.

```
plant = setmpcsignals(plant, 'MV', [1], 'UD', [2 3]);
```

Create an MPC controller for the defined plant.

```
MPCobj = mpc(plant, 0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
```

Extract the default output disturbance model.

```
[indist, channels] = getindist(MPCobj);
```

```
-->Converting model to discrete time.
-->The "Model.Disturbance" property of "mpc" object is empty:
    Assuming unmeasured input disturbance #2 is integrated white noise.
    Assuming unmeasured input disturbance #3 is white noise.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Check which input disturbance channels have integrated white noise added by default.

```
channels
```

```
channels = 1
```

An integrator has been added only to the first unmeasured input disturbance. The other input disturbance uses a static unity gain to preserve state observability.

Input Arguments

MPCobj — Model predictive controller

MPC controller object

Model predictive controller, specified as an MPC controller object. To create an MPC controller, use `mpc`.

Output Arguments

indist — Input disturbance model

discrete-time, delay-free, state-space model

Input disturbance model used by the model predictive controller, `MPCobj`, returned as a discrete-time, delay-free, state-space model.

The input disturbance model has:

- Unit-variance white noise input signals. By default, the number of inputs depends upon the number of unmeasured input disturbances and the need to maintain controller state observability. For custom input disturbance models, the number of inputs is your choice.
- n_d outputs, where n_d is the number of unmeasured disturbance inputs defined in `MPCobj.Model.Plant`. Each disturbance model output is sent to the corresponding plant unmeasured disturbance input.

If `MPCobj` does not have any unmeasured disturbance, `indist` is returned as an empty state-space model.

This model, in combination with the output disturbance model (if any), governs how well the controller compensates for unmeasured disturbances and modeling errors. For more information on the disturbance modeling in MPC and about the model used during state estimation, see “MPC Modeling” and “Controller State Estimation”.

channels — Input channels with integrated white noise

vector of input indices

Input channels with integrated white noise added by default, returned as a vector of input indices. If you set `indist` to a custom input disturbance model using `setindist`, `channels` is empty.

Tips

- To specify a custom input disturbance model, use the `setindist` command.

See Also

`getEstimator` | `getoutdist` | `mpc` | `setEstimator` | `setindist`

Topics

“MPC Modeling”

“Controller State Estimation”

Introduced in R2006a

getname

Retrieve I/O signal names in MPC prediction model

Syntax

```
name = getname(MPCobj, 'input', I)
name = getname(MPCobj, 'output', I)
```

Description

`name = getname(MPCobj, 'input', I)` returns the name of the Ith input signal in variable `name`. This is equivalent to `name = MPCobj.Model.Plant.InputName{I}`. The `name` property is equal to the contents of the corresponding `Name` field of `MPCobj.DisturbanceVariables` or `MPCobj.ManipulatedVariables`.

`name = getname(MPCobj, 'output', I)` returns the name of the Ith output signal in variable `name`. This is equivalent to `name=MPCobj.Model.Plant.OutputName{I}`. The `name` property is equal to the contents of the corresponding `Name` field of `MPCobj.OutputVariables`.

See Also

`mpc` | `set` | `setname`

Introduced before R2006a

getoutdist

Retrieve unmeasured output disturbance model

Syntax

```
outdist = getoutdist(MPCobj)
[outdist,channels] = getoutdist(MPCobj)
```

Description

`outdist = getoutdist(MPCobj)` returns the output disturbance model, `outdist`, used by the model predictive controller, `MPCobj`.

`[outdist,channels] = getoutdist(MPCobj)` also returns the output channels to which integrated white noise has been added by default. For more information on the default model, see "MPC Modeling".

Examples

Retrieve Output Disturbance Model

Define a plant model with no direct feedthrough, and create an MPC controller for that plant.

```
plant = rss(3,2,2);
plant.D = 0;
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Extract the output disturbance model.

```
outdist = getoutdist(MPCobj);

-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->Assuming output disturbance added to measured output channel #2 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Retrieve Output Disturbance Model Channels with Default Integrated White Noise

Define a plant model with no direct feedthrough, and create an MPC controller for that plant.

```
plant = rss(3,3,3);
plant.d = 0;
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Extract the default output disturbance model.

```
[outdist,channels] = getoutdist(MPCobj);
```

```
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->Assuming output disturbance added to measured output channel #2 is integrated white noise.
-->Assuming output disturbance added to measured output channel #3 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Check which channels have default integrated white noise disturbances.

```
channels
```

```
channels = 1x3
```

```
    1    2    3
```

Integrators have been added to all three output channels.

Input Arguments

MPCobj — Model predictive controller

MPC controller object

Model predictive controller, specified as an MPC controller object. To create an MPC controller, use `mpc`.

Output Arguments

outdist — Output disturbance model

discrete-time, delay-free, state-space model

Output disturbance model used by the model predictive controller, `MPCobj`, returned as a discrete-time, delay-free, state-space model.

The output disturbance model has:

- n_y outputs, where n_y is the number of plant outputs defined in `MPCobj.Model.Plant`. Each disturbance model output is added to the corresponding plant output. By default, disturbance models corresponding to unmeasured output channels are zero.
- Unit-variance white noise input signals. By default, the number of inputs is equal to the number of default integrators added.

This model, in combination with the input disturbance model (if any), governs how well the controller compensates for unmeasured disturbances and modeling errors. For more information on the disturbance modeling in MPC and about the model used during state estimation, see “MPC Modeling” and “Controller State Estimation”.

channels — Output channels with integrated white noise

vector of output indices

Output channels with integrated white noise added by default, returned as a vector of output indices. If you set `outdist` to a custom output disturbance model using `setoutdist`, `channels` is empty.

Tips

- To specify a custom output disturbance model, use the `setoutdist` command.

See Also

`getEstimator` | `getindist` | `mpc` | `setEstimator` | `setoutdist`

Topics

“MPC Modeling”

“Controller State Estimation”

Introduced before R2006a

gpc2mpc

Generate MPC controller using generalized predictive controller (GPC) settings

Syntax

```
mpcObj = gpc2mpc(plant)
gpcOptions = gpc2mpc
mpcObj = gpc2mpc(plant,gpcOptions)
```

Description

`mpcObj = gpc2mpc(plant)` generates a single-input single-output MPC controller with default GPC settings and sample time of the specified plant, `plant`. The GPC is a nonminimal state-space representation described in [1]. `plant` is a discrete-time LTI model with sample time greater than 0.

`gpcOptions = gpc2mpc` creates a structure `gpcOptions` containing default values of GPC settings.

`mpcObj = gpc2mpc(plant,gpcOptions)` generates an MPC controller using the GPC settings in `gpcOptions`.

Input Arguments

`plant`

Discrete-time LTI model with sampling time greater than 0.

`gpcOptions`

GPC settings, specified as a structure with the following fields.

<code>N1</code>	Starting interval in prediction horizon, specified as a positive integer. Default: 1
<code>N2</code>	Last interval in prediction horizon, specified as a positive integer greater than <code>N1</code> . Default: 10
<code>NU</code>	Control horizon, specified as a positive integer less than the prediction horizon. Default: 1
<code>Lam</code>	Penalty weight on changes in manipulated variable, specified as a positive integer greater than or equal to 0. Default: 0

T	Numerator of the GPC disturbance model, specified as a row vector of polynomial coefficients whose roots lie within the unit circle. Default: [1].
MVindex	Index of the manipulated variable for multi-input plants, specified as a positive integer. Default: 1

Default:**Examples**

Design an MPC controller using GPC settings:

```
% Specify the plant described in Example 1.8 of
% [1].
G = tf(9.8*[1 -0.5 6.3],conv([1 0.6565],[1 -0.2366 0.1493]));

% Discretize the plant with sample time of 0.6 seconds.
Ts = 0.6;
Gd = c2d(G, Ts);

% Create a GPC settings structure.
GPCoptions = gpc2mpc;

% Specify the GPC settings described in example 4.11 of
% [1].
% Hu
GPCoptions.NU = 2;
% Hp
GPCoptions.N2 = 5;
% R
GPCoptions.Lam = 0;
GPCoptions.T = [1 -0.8];

% Convert GPC to an MPC controller.
mpc = gpc2mpc(Gd, GPCoptions);

% Simulate for 50 steps with unmeasured disturbance between
% steps 26 and 28, and reference signal of 0.
SimOptions = mpcsimopt(mpc);
SimOptions.UnmeasuredDisturbance = [zeros(25,1); ...
-0.1*ones(3,1); 0];
sim(mpc, 50, 0, SimOptions);
```

Tips

- For plants with multiple inputs, only one input is the manipulated variable, and the remaining inputs are measured disturbances in feedforward compensation. The plant output is the measured output of the MPC controller.
- Use the MPC controller with Model Predictive Control Toolbox software for simulation and analysis of the closed-loop performance.

References

- [1] Maciejowski, J. M. *Predictive Control with Constraints*, Pearson Education Ltd., 2002, pp. 133-142.

See Also

mpc

Topics

“Design Controller Using MPC Designer”

“Design MPC Controller at the Command Line”

Introduced in R2010a

mpcActiveSetOptions

Create default option set for mpcActiveSetSolver

Syntax

```
options = mpcActiveSetOptions  
options = mpcActiveSetOptions(type)
```

Description

`options = mpcActiveSetOptions` creates a structure of default options for `mpcActiveSetSolver`, which solves a quadratic programming (QP) problem using an active-set algorithm.

`options = mpcActiveSetOptions(type)` creates a default option set using the specified input data type. All real options are specified using this data type.

Examples

Create Default Option Set for Active-Set QP Solver

```
opt = mpcActiveSetOptions;
```

Create and Modify Default Active-Set QP Solver Option Set

Create default option set.

```
opt = mpcActiveSetOptions;
```

Specify the maximum number of iterations allowed during computation.

```
opt.MaxIterations = 100;
```

Specify a constraint tolerance for verifying that the optimal solution satisfies the inequality constraints.

```
opt.ConstraintTolerance = 1.0e-4;
```

Create Active-Set Option Set Specifying Input Argument Type

```
opt = mpcActiveSetOptions('single');
```

Input Arguments

type — Solver input argument data type

'double' (default) | 'single'

Solver input argument data type, specified as either 'double' or 'single'. This data type is used for both simulation and code generation. All real options in the option set are specified using this data type, and all real input arguments to `mpcActiveSetSolver` must match this type.

Output Arguments

options — Option set for `mpcActiveSetSolver`

structure

Option set for `mpcActiveSetSolver`, returned as a structure with the following fields.

Field	Description	Default
<code>DataType</code>	Input argument data type, specified as either 'double' or 'single'. This data type is used for both simulation and code generation, and all real input arguments to the solver function must match this type.	'double'
<code>MaxIterations</code>	Maximum number of iterations allowed when computing the QP solution, specified as a positive integer.	200
<code>ConstraintTolerance</code>	Tolerance used to verify that inequality constraints are satisfied by the optimal solution, specified as a positive scalar. A larger <code>ConstraintTolerance</code> value allows for larger constraint violations.	1e-6
<code>UseHessianAsInput</code>	Indicator of whether the first input argument to <code>mpcActiveSetSolver</code> is the Hessian matrix, specified as a logical value. If <code>UseHessianAsInput</code> is true, pass the Hessian to <code>mpcActiveSetSolver</code> . Otherwise, use the inverse of the lower-triangular Cholesky decomposition (<code>Lin_v</code>) of the Hessian matrix. If your application requires repetitive calls of <code>mpcInteriorPointSolver</code> using a constant Hessian matrix, you can improve computational efficiency by passing <code>Lin_v</code> to <code>mpcActiveSetSolver</code> instead the Hessian.	true
<code>IntegrityChecks</code>	Indicator of whether integrity checks are performed on the solver function input data, specified as a logical value. If <code>IntegrityChecks</code> is true, then integrity checks are performed and diagnostic messages are displayed. Use false for code generation only.	true

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- You can use `mpcActiveSetSolver` as a general-purpose QP solver that supports code generation. To specify solver options, use `mpcActiveSetOptions`. Create the function `myCode` that uses `mpcActiveSetSolver` and `mpcActiveSetOptions`.

```
function [out1,out2] = myCode(in1,in2)
%#codegen
...
options = mpcActiveSetOptions;
[x,status] = mpcActiveSetSolver(Linv,f,A,b,Aeq,Beq,iA0,options);
...
```

Generate C code with MATLAB Coder™.

```
func = 'myCode';
cfg = coder.config('mex'); % or 'lib', 'dll'
codegen('-config',cfg,func,'-o',func);
```

- For code generation, use the same precision for all real inputs, including options. Configure the precision as 'double' or 'single' using `mpcActiveSetOptions`.

See Also

`mpcActiveSetSolver`

Introduced in R2020a

mpcActiveSetSolver

Solve a quadratic programming problem using an active-set algorithm

Syntax

```
[x,exitflag] = mpcActiveSetSolver(H,f,A,b,Aeq,beq,iA0,options)
[x,exitflag,iA,lambda] = mpcActiveSetSolver(H,f,A,b,Aeq,beq,iA0,options)
```

Description

Using `mpcActiveSetSolver`, you can solve a quadratic programming (QP) problem using an active-set algorithm. This function provides access to the built-in Model Predictive Control Toolbox active-set QP solver.

Using an active-set solver can provide fast and robust performance for small-scale and medium-scale optimization problems in both double and single precision.

This solver is useful for:

- Advanced MPC applications that are beyond the scope of Model Predictive Control Toolbox software.
- Custom QP applications, including applications that require code generation.

Alternatively, you can also access the built-in interior-point QP solver using `mpcInteriorPointSolver`.

`[x,exitflag] = mpcActiveSetSolver(H,f,A,b,Aeq,beq,iA0,options)` finds an optimal solution, x , to a quadratic programming problem by minimizing the objective function:

$$J = \frac{1}{2}x^T H x + f^T x$$

subject to inequality constraints $Ax \leq b$, and equality constraints $A_{eq}x = b_{eq}$. `exitflag` indicates the validity of x .

`[x,exitflag,iA,lambda] = mpcActiveSetSolver(H,f,A,b,Aeq,beq,iA0,options)` also returns the active inequalities, `iA`, at the solution, and the Lagrange multipliers, `lambda`, for the solution.

Examples

Solve Quadratic Programming Problem Using Active-Set Solver

Find the values of x that minimize

$$f(x) = 0.5x_1^2 + x_2^2 - x_1x_2 - 2x_1 - 6x_2,$$

subject to the constraints

$$\begin{aligned}x_1 &\geq 0 \\x_2 &\geq 0 \\x_1 + x_2 &\leq 2 \\-x_1 + 2x_2 &\leq 2 \\2x_1 + x_2 &\leq 3.\end{aligned}$$

Specify the Hessian and linear multiplier vector for the objective function.

```
H = [1 -1; -1 2];  
f = [-2; -6];
```

Specify the inequality constraint parameters.

```
A = [-1 0; 0 -1; 1 1; -1 2; 2 1];  
b = [0; 0; 2; 2; 3];
```

Define Aeq and beq to indicate that there are no equality constraints.

```
n = length(f);  
Aeq = zeros(0,n);  
beq = zeros(0,1);
```

Create a default option set for `mpcActiveSetSolver`.

```
opt = mpcActiveSetOptions;
```

To cold start the solver, define all inequality constraints as inactive.

```
iA0 = false(size(b));
```

Solve the QP problem.

```
[x,exitflag] = mpcActiveSetSolver(H,f,A,b,Aeq,beq,iA0,opt);
```

Examine the solution, `x`.

```
x  
x = 2×1  
  
0.6667  
1.3333
```

When solving the QP problem, you can also determine which inequality constraints are active for the solution.

```
[x,exitflag,iA,lambda] = mpcActiveSetSolver(H,f,A,b,Aeq,beq,iA0,opt);
```

Check the active inequality constraints. An active inequality constraint is at equality for the optimal solution.

```
iA  
iA = 5×1 logical array  
  
0
```



```
0
1
1
0
```

There is a single active inequality constraint. View the Lagrange multiplier for this constraint.

```
lambda.ineqlin(1)
```

```
ans = 0
```

Input Arguments

H — Hessian matrix

n-by-*n* matrix

Hessian matrix, specified as a symmetric *n*-by-*n* matrix, where $n > 0$ is the number of optimization variables.

The active-set QP algorithm requires that the Hessian matrix be positive definite. To determine whether H is positive definite, use the `chol` function.

```
[~,p] = chol(H);
```

If $p = 0$, then H is positive definite. Otherwise, p is a positive integer.

The active-set QP algorithm computes the lower-triangular Cholesky decomposition (`Linv`) of the Hessian matrix. If your application requires repetitive calls of `mpcInteriorPointSolver` using a constant Hessian matrix, you can improve computational efficiency by computing `Linv` once and passing it to `mpcActiveSetSolver` instead of the Hessian. To do so, you must set the `UseHessianAsInput` field of options to `false`.

```
options = mpcActiveSetOptions;
options.UseHessianAsInput = false;
```

To compute `Linv`, use the following code.

```
[L,p] = chol(H,'lower');
Linv = linsolve(L,eye(size(L)),struct('LT',true));
```

f — Multiplier of objective function linear term

column vector of length *n*

Multiplier of objective function linear term, specified as a column vector of length *n*, where *n* is the number of optimization variables.

A — Linear inequality constraint coefficients

m-by-*n* matrix

Linear inequality constraint coefficients, specified as an *m*-by-*n* matrix, where *n* is the number of optimization variables and *m* is the number of inequality constraints.

If your problem has no inequality constraints, use `zeros(0,n)`.

b — Right-hand side of inequality constraintscolumn vector of length m

Right-hand side of inequality constraints, specified as a column vector of length m , where m is the number of inequality constraints.

If your problem has no inequality constraints, use `zeros(0,1)`.

Aeq — Linear equality constraint coefficients q -by- n matrix

Linear equality constraint coefficients, specified as a q -by- n matrix, where n is the number of optimization variables and $q \leq n$ is the number of equality constraints. Equality constraints must be linearly independent with `rank(Aeq) = q`.

If your problem has no equality constraints, use `zeros(0,n)`.

beq — Right-hand side of equality constraintscolumn vector of length q

Right-hand side of equality constraints, specified as a column vector of length q , where q is the number of equality constraints.

If your problem has no equality constraints, use `zeros(0,1)`.

iA0 — Initial active inequalitieslogical vector of length m

Initial active inequalities, where the equal portion of the inequality is true, specified as a logical vector of length m , where m is the number of inequality constraints. Specify `iA0` as follows:

- If your problem has no inequality constraints, use `false(0,1)`.
- For a *cold start*, use `false(m,1)`.
- For a *warm start*, set `iA0(i) == true` to start the algorithm with the i th inequality constraint active. Use the optional output argument `iA` from a previous solution to specify `iA0` in this way. If both `iA0(i)` and `iA0(j)` are `true`, then rows i and j of A should be linearly independent. Otherwise, the solution can fail with `exitflag = -2`.

options — Option set for mpcActiveSetSolver

structure

Option set for `mpcActiveSetSolver`, specified as a structure created using `mpcActiveSetOptions`.

Output Arguments**x — Optimal solution to the QP problem**column vector of length n

Optimal solution to the QP problem, returned as a column vector of length n , where n is the number of optimization variables. `mpcActiveSetSolver` always returns a value for `x`. To determine whether the solution is optimal or feasible, check `exitflag`.

exitflag — Solution validity indicator

positive integer | 0 | -1 | -2

Solution validity indicator, returned as an integer according to the following table.

Value	Description
> 0	x is optimal. In this case, <code>exitflag</code> represents the number of iterations performed during optimization.
0	The maximum number of iterations was reached. Solution x might be suboptimal or infeasible. To determine if x is infeasible, check whether the solution violates the constraint tolerance specified in <code>options</code> . <code>feasible = (A*x-b) <= options.ConstraintTolerance;</code> If any element of <code>feasible</code> is <code>false</code> , then x is infeasible.
-1	The problem appears to be infeasible, that is, the constraint $Ax \leq b$ cannot be satisfied.
-2	An unrecoverable numerical error occurred.

iA — Active inequalitieslogical vector of length m

Active inequalities, where the equal portion of the inequality is true, returned as a logical vector of length m . If `iA(i) == true`, then the i th inequality is active for solution x .

Use `iA` to *warm start* a subsequent `mpcActiveSetSolver` solution.

lambda — Lagrange multipliers

structure

Lagrange multipliers, returned as a structure with the following fields:

Field	Description
<code>ineqlin</code>	Multipliers of the inequality constraints, returned as a vector of length n . When the solution is optimal, the elements of <code>ineqlin</code> are nonnegative.
<code>eqlin</code>	Multipliers of the equality constraints, returned as a vector of length q . There are no sign restrictions in the optimal solution.

Tips

- The KWIK algorithm requires that the Hessian matrix, H , be positive definite. When calculating `Lin`, use:

```
[L,p] = chol(H, 'lower');
```

If `p = 0`, then H is positive definite. Otherwise, `p` is a positive integer.

- `mpcActiveSetSolver` provides access to the default active-set QP solver used by Model Predictive Control Toolbox software. Use this command to solve QP problems in your own custom MPC applications. For an example of a custom MPC application using `mpcActiveSetSolver`, see “Solve Custom MPC Quadratic Programming Problem and Generate Code”.

Algorithms

`mpcActiveSetSolver` solves the QP problem using an active-set method, the KWIK algorithm, based on [1]. For more information, see “QP Solvers”.

References

- [1] Schmid, C., and L.T. Biegler. ‘Quadratic Programming Methods for Reduced Hessian SQP’. *Computers & Chemical Engineering* 18, no. 9 (September 1994): 817–32. [https://doi.org/10.1016/0098-1354\(94\)E0001-4](https://doi.org/10.1016/0098-1354(94)E0001-4).

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- You can use `mpcActiveSetSolver` as a general-purpose QP solver that supports code generation. To specify solver options, use `mpcActiveSetOptions`. Create the function `myCode` that uses `mpcActiveSetSolver` and `mpcActiveSetOptions`.

```
function [out1,out2] = myCode(in1,in2)
    %#codegen
    ...
    options = mpcActiveSetOptions;
    [x,status] = mpcActiveSetSolver(Linv,f,A,b,Aeq,Beq,iA0,options);
    ...
```

Generate C code with MATLAB Coder.

```
func = 'myCode';
cfg = coder.config('mex'); % or 'lib', 'dll'
codegen('-config',cfg,func,'-o',func);
```

- For code generation, use the same precision for all real inputs, including options. Configure the precision as 'double' or 'single' using `mpcActiveSetOptions`.

See Also

`mpcActiveSetOptions` | `mpcInteriorPointSolver` | `quadprog`

Topics

“QP Solvers”

“Solve Custom MPC Quadratic Programming Problem and Generate Code”

Introduced in R2020a

mpcInteriorPointOptions

Create default option set for `mpcInteriorPointSolver`

Syntax

```
options = mpcInteriorPointOptions
options = mpcInteriorPointOptions(type)
```

Description

`options = mpcInteriorPointOptions` creates a structure of default options for `mpcInteriorPointSolver`, which solves a quadratic programming (QP) problem using an interior-point algorithm.

`options = mpcInteriorPointOptions(type)` creates a default option set using the specified input data type. All real options are specified using this data type.

Examples

Create Default Option Set for Interior-Point QP Solver

```
opt = mpcInteriorPointOptions;
```

Create and Modify Default Interior-Point QP Solver Option Set

Create default option set.

```
opt = mpcInteriorPointOptions;
```

Specify the maximum number of iterations allowed during computation.

```
opt.MaxIterations = 100;
```

Specify a constraint tolerance for verifying that the optimal solution satisfies the inequality constraints.

```
opt.ConstraintTolerance = 1.0e-4;
```

Create Interior-Point Option Set Specifying Input Argument Type

```
opt = mpcInteriorPointOptions('single');
```

Input Arguments

type — Solver input argument data type

'double' (default) | 'single'

Solver input argument data type, specified as either 'double' or 'single'. This data type is used for both simulation and code generation. All real options in the option set are specified using this data type, and all real input arguments to `mpcInteriorPointSolver` must match this type.

Output Arguments

options — Option set for `mpcInteriorPointSolver`

structure

Option set for `mpcInteriorPointSolver`, returned as a structure with the following fields.

Field	Description	Default
DataType	Input argument data type, specified as either 'double' or 'single'. This data type is used for both simulation and code generation, and all real input arguments to the solver function must match this type.	'double'
MaxIterations	Maximum number of iterations allowed when computing the QP solution, specified as a positive integer.	50
ConstraintTolerance	Tolerance used to verify that equality and inequality constraints are satisfied by the optimal solution, specified as a positive scalar. A larger <code>ConstraintTolerance</code> value allows for larger constraint violations.	1e-6
OptimalityTolerance	Termination tolerance for first-order optimality (KKT dual residual), specified as a positive scalar. Increasing this value relaxes the condition for the optimality check.	1e-6
ComplementarityTolerance	Termination tolerance for first-order optimality (KKT average complementarity residual), specified as a positive scalar. Increasing this value improves robustness, while decreasing this value increases accuracy.	1e-8
StepTolerance	Termination tolerance for decision variables, specified as a positive scalar.	1e-8
IntegrityChecks	Indicator of whether integrity checks are performed on the solver function input data, specified as a logical value. If <code>IntegrityChecks</code> is true, then integrity checks are performed and diagnostic messages are displayed. Use false for code generation only.	true

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- You can use `mpInteriorPointSolver` as a general-purpose QP solver that supports code generation. To specify solver options, use `mpcInteriorPointOptions`. Create the function `myCode` that uses `mpInteriorPointSolver` and `mpcInteriorPointOptions`.

```
function [out1,out2] = myCode(in1,in2)
    %#codegen
    ...
    options = mpcInteriorPointOptions;
    [x,exitflag] = mpcInteriorPointSolver(H,f,A,b,Aeq,Beq,x0,options);
    ...
```

Generate C code with MATLAB Coder.

```
func = 'myCode';
cfg = coder.config('mex'); % or 'lib', 'dll'
codegen('-config',cfg,func,'-o',func);
```

- For code generation, use the same precision for all real inputs, including options. Configure the precision as 'double' or 'single' using `mpcInteriorPointOptions`.

See Also

`mpcInteriorPointSolver`

Introduced in R2020a

mpcInteriorPointSolver

Solve a quadratic programming problem using an interior-point algorithm

Syntax

```
[x,exitflag] = mpcInteriorPointSolver(H,f,A,b,Aeq,beq,x0,options)
[x,exitflag,feasible,lambda] = mpcInteriorPointSolver(H,f,A,b,Aeq,beq,x0,
options)
```

Description

Using `mpcInteriorPointSolver`, you can solve a quadratic programming (QP) problem using a primal-dual interior-point algorithm with Mehrotra predictor-corrector. This function provides access to the built-in Model Predictive Control Toolbox interior-point QP solver.

Using an interior-point solver can provide superior performance for large-scale optimization problems, such as MPC applications that enforce constraints over large prediction and control horizons.

This solver is useful for:

- Advanced MPC applications that are beyond the scope of Model Predictive Control Toolbox software.
- Custom QP applications, including applications that require code generation.

Alternatively, you can also access the built-in active-set QP solver using `mpcActiveSetSolver`.

`[x,exitflag] = mpcInteriorPointSolver(H,f,A,b,Aeq,beq,x0,options)` finds an optimal solution, x , to a quadratic programming problem by minimizing the objective function:

$$J = \frac{1}{2}x^T H x + f^T x$$

subject to inequality constraints $Ax \leq b$, and equality constraints $A_{eq}x = b_{eq}$. `exitflag` indicates the validity of x .

`[x,exitflag,feasible,lambda] = mpcInteriorPointSolver(H,f,A,b,Aeq,beq,x0,options)` also returns a logical flag, `feasible`, which indicates the feasibility of the solution, and the Lagrange multipliers, `lambda`, for the solution.

Examples

Solve Quadratic Programming Problem Using Interior-Point Solver

Find the values of x that minimize

$$f(x) = 0.5x_1^2 + x_2^2 - x_1x_2 - 2x_1 - 6x_2,$$

subject to the constraints

$$\begin{aligned}x_1 &\geq 0 \\x_2 &\geq 0 \\x_1 + x_2 &\leq 2 \\-x_1 + 2x_2 &\leq 2 \\2x_1 + x_2 &\leq 3.\end{aligned}$$

Specify the Hessian and linear multiplier vector for the objective function.

$$\begin{aligned}H &= [1 \ -1; \ -1 \ 2]; \\f &= [-2; \ -6];\end{aligned}$$

Specify the inequality constraint parameters.

$$\begin{aligned}A &= [-1 \ 0; \ 0 \ -1; \ 1 \ 1; \ -1 \ 2; \ 2 \ 1]; \\b &= [0; \ 0; \ 2; \ 2; \ 3];\end{aligned}$$

Define Aeq and beq to indicate that there are no equality constraints.

$$\begin{aligned}n &= \text{length}(f); \\Aeq &= \text{zeros}(0,n); \\beq &= \text{zeros}(0,1);\end{aligned}$$

It is good practice to verify that H is positive definite using the chol function.

$$[\sim,p] = \text{chol}(H);$$

If $p = 0$, then H is positive definite.

$$\begin{aligned}p \\p &= 0\end{aligned}$$

Create a default option set for mpcInteriorPointSolver.

$$\text{opt} = \text{mpcInteriorPointOptions};$$

To cold start the solver, specify an initial guess of zeros for the elements of x.

$$x0 = \text{zeros}(n,1);$$

Solve the QP problem.

$$[x,\text{exitflag}] = \text{mpcInteriorPointSolver}(H,f,A,b,Aeq,beq,x0,\text{opt});$$

Examine the solution, x.

$$\begin{aligned}x \\x &= 2 \times 1 \\ &0.6667 \\ &1.3333\end{aligned}$$

Input Arguments

H — Hessian matrix

n-by-*n* matrix

Hessian matrix, specified as an *n*-by-*n* matrix, where $n > 0$ is the number of optimization variables.

The interior-point QP algorithm requires that the Hessian matrix be positive definite. To determine whether H is positive definite, use the `chol` function.

`[~,p] = chol(H);`

If $p = 0$, then H is positive definite. Otherwise, p is a positive integer.

f — Multiplier of objective function linear term

column vector of length *n*

Multiplier of objective function linear term, specified as a column vector of length *n*, where *n* is the number of optimization variables.

A — Linear inequality constraint coefficients

m-by-*n* matrix | []

Linear inequality constraint coefficients, specified as an *m*-by-*n* matrix, where *n* is the number of optimization variables and *m* is the number of inequality constraints.

If your problem has no inequality constraints, use `zeros(0,n)`.

b — Right-hand side of inequality constraints

column vector of length *m*

Right-hand side of inequality constraints, specified as a column vector of length *m*, where *m* is the number of inequality constraints.

If your problem has no inequality constraints, use `zeros(0,1)`.

Aeq — Linear equality constraint coefficients

q-by-*n* matrix | []

Linear equality constraint coefficients, specified as a *q*-by-*n* matrix, where *n* is the number of optimization variables and $q \leq n$ is the number of equality constraints. Equality constraints must be linearly independent with $\text{rank}(\text{Aeq}) = q$.

If your problem has no equality constraints, use `zeros(0,n)`.

beq — Right-hand side of equality constraints

column vector of length *q*

Right-hand side of equality constraints, specified as a column vector of length *q*, where *q* is the number of equality constraints.

If your problem has no equality constraints, use `zeros(0,1)`.

x0 — Initial guess

column vector of length *n*

Initial guess for the solution, where the equal portion of the inequality is true, specified as a column vector of length n , where n is the number of optimization variables. For a *cold start*, specify the initial guess as `zeros(n,1)`.

options — Option set for mpcInteriorPointSolver

structure

Option set for `mpcInteriorPointSolver`, specified as a structure created using `mpcInteriorPointOptions`.

Output Arguments

x — Optimal solution to the QP problem

column vector of length n

Optimal solution to the QP problem, returned as a column vector of length n , where n is the number of optimization variables. `mpcInteriorPointSolver` always returns a value for `x`. To determine whether the solution is optimal or feasible, check `exitflag` and `feasible`.

exitflag — Solution validity indicator

positive integer | 0 | -1 | -2

Solution validity indicator, returned as an integer according to the following:

Value	Description
> 0	<code>x</code> is optimal. <code>exitflag</code> represents the number of iterations performed during optimization.
0	The maximum number of iterations was reached before the solver could find an optimal solution. Solution <code>x</code> is feasible only if <code>feasible</code> is true.
-1	The problem appears to be infeasible; that is, the constraint $Ax \leq b$ cannot be satisfied.

feasible — Solution feasibility

logical scalar

Solution feasibility, returned as a logical scalar. When `exitflag` is 0, the solver reached the maximum number of iterations without finding an optimal solution. This suboptimal solution, returned in `x`, is feasible only if `feasible` is true.

lambda — Lagrange multipliers

structure

Lagrange multipliers, returned as a structure with the following fields:

Field	Description
<code>ineqlin</code>	Multipliers of the inequality constraints, returned as a vector of length n . When the solution is optimal, the elements of <code>ineqlin</code> are nonnegative.
<code>eqlin</code>	Multipliers of the equality constraints, returned as a vector of length q . There are no sign restrictions in the optimal solution.

Tips

- To determine whether H is positive definite, use the `chol` function.

```
[~,p] = chol(H);
```

If $p = 0$, then H is positive definite. Otherwise, p is a positive integer.

- `mpcInteriorPointSolver` provides access to the interior-point QP solver used by Model Predictive Control Toolbox software. Use this command to solve QP problems in your own custom MPC applications. For an example of a custom MPC application, see “Solve Custom MPC Quadratic Programming Problem and Generate Code”. This example uses a `mpcActiveSetSolver`, however the workflow applies to `mpcInteriorPointSolver` as well.

Algorithms

`mpcInteriorPointSolver` solves the QP problem using an interior-point method. For more information, see “QP Solvers”.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- You can use `mpInteriorPointSolver` as a general-purpose QP solver that supports code generation. To specify solver options, use `mpcInteriorPointOptions`. Create the function `myCode` that uses `mpInteriorPointSolver` and `mpcInteriorPointOptions`.

```
function [out1,out2] = myCode(in1,in2)
    %#codegen
    ...
    options = mpcInteriorPointOptions;
    [x,exitflag] = mpcInteriorPointSolver(H,f,A,b,Aeq,Beq,x0,options);
    ...
```

Generate C code with MATLAB Coder.

```
func = 'myCode';
cfg = coder.config('mex'); % or 'lib', 'dll'
codegen('-config',cfg,func,'-o',func);
```

- For code generation, use the same precision for all real inputs, including options. Configure the precision as 'double' or 'single' using `mpcInteriorPointOptions`.

See Also

`mpcActiveSetSolver` | `mpcInteriorPointOptions` | `quadprog`

Topics

“QP Solvers”

“Solve Custom MPC Quadratic Programming Problem and Generate Code”

Introduced in R2020a

mpcmove

Compute optimal control action

Syntax

```
mv = mpcmove(MPCobj,x,ym,r,v)
[mv,info] = mpcmove(MPCobj,x,ym,r,v)
[ ___ ] = mpcmove( ___,options)
```

Description

`mv = mpcmove(MPCobj,x,ym,r,v)` computes the optimal manipulated variable moves, $u(k)$, at the current time. $u(k)$ is calculated given the current estimated extended state, $x(k)$, the measured plant outputs, $y_m(k)$, the output references, $r(k)$, and the measured disturbances, $v(k)$, at the current time k . Call `mpcmove` repeatedly to simulate closed-loop model predictive control.

`[mv,info] = mpcmove(MPCobj,x,ym,r,v)` returns additional information regarding the model predictive controller in the second output argument `info`.

`[___] = mpcmove(___,options)` overrides default constraints and weights settings in `MPCobj` with the values specified by `Options`, an `mpcmoveopt` object. Use `Options` to provide run-time adjustment of constraints and weights during the closed-loop simulation.

Input Arguments

MPCobj — Model predictive controller

MPC controller object

Model predictive controller, specified as an MPC controller object. To create an MPC controller, use `mpc`.

x — Current controller state

`mpcstate` object

Current controller state, specified as an `mpcstate` object.

Before you begin a simulation with `mpcmove`, initialize the controller state using `x = mpcstate(MPCobj)`. Then, modify the default properties of `x` as appropriate. `mpcmove` modifies the value of `x` to reflect the current state of the controller.

If you are using default state estimation, `mpcmove` expects `x` to represent $x[n|n-1]$. The `mpcmove` command updates the state values in the previous control interval with that information. Therefore, you should not programmatically update `x` at all. The default state estimator employs a steady-state Kalman filter.

If you are using custom state estimation, `mpcmove` expects `x` to represent $x[n|n]$. Therefore, prior to each `mpcmove` command, you must set `x.Plant`, `x.Disturbance`, and `x.Noise` to the best estimates of these states (using the latest measurements) at the current control interval.

ym — Current measured output valuescolumn vector of length N_{ym}

Current measured output values at time k , specified as a column vector of length N_{ym} , where N_{ym} is the number of measured outputs.

If you are using custom state estimation, set $ym = []$.

r — Plant output reference values p -by- N_y array

Plant output reference values, specified as a p -by- N_y array, where p is the prediction horizon of MPCobj and N_y is the number of outputs. Row $r(i, :)$ defines the reference values at step i of the prediction horizon.

r must contain at least one row. If r contains fewer than p rows, `mpcmove` duplicates the last row to fill the p -by- N_y array. If you supply exactly one row, therefore, a constant reference applies for the entire prediction horizon.

To implement reference previewing, which can improve tracking when a reference varies in a predictable manner, r must contain the anticipated variations, ideally for p steps.

v — Current and anticipated measured disturbances $(p+1)$ -by- N_{md} array

Current and anticipated measured disturbances, specified as a $(p+1)$ -by- N_{md} array, where p is the prediction horizon of MPCobj and N_{md} is the number of measured disturbances. The first row of v specifies the current measured disturbance values. Row $v(i+1, :)$ defines the anticipated disturbance values at step i of the prediction horizon.

Modeling of measured disturbances provides feedforward control action. If your plant model does not include measured disturbances, use $v = []$.

If your model includes measured disturbances, v must contain at least one row. If v contains fewer than $p+1$ rows, `mpcmove` duplicates the last row to fill the $(p+1)$ -by- N_{md} array. If you supply exactly one row, a constant measured disturbance applies for the entire prediction horizon.

To implement disturbance previewing, which can improve tracking when a disturbance varies in a predictable manner, v must contain the anticipated variations, ideally for p steps.

options — Run-time options

mpcmoveopt object

Run-time options, specified as an `mpcmoveopt` object. Use `options` to override selected properties of MPCobj during simulation. These options apply to the current `mpcmove` time instant only. Using `options` yields the same result as redefining or modifying MPCobj before each call to `mpcmove`, but involves considerably less overhead. Using `options` is equivalent to using an MPC Controller Simulink block in combination with optional input signals that modify controller settings, such as MV and OV constraints.

Output Arguments**mv — Optimal manipulated variable moves**

column vector

Optimal manipulated variable moves, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the controller detects an infeasible optimization problem or encounters numerical difficulties in solving an ill-conditioned optimization problem, `mv` remains at its most recent successful solution, `x.LastMove`.

Otherwise, if the optimization problem is feasible and the solver reaches the specified maximum number of iterations without finding an optimal solution, `mv`:

- Remains at its most recent successful solution if the `Optimizer.UseSuboptimalSolution` property of the controller is `false`.
- Is the suboptimal solution reached after the final iteration if the `Optimizer.UseSuboptimalSolution` property of the controller is `true`. For more information, see “Suboptimal QP Solution”.

info — Solution details

structure

Solution details, returned as a structure with the following fields.

Uopt — Optimal manipulated variable sequence

$(p+1)$ -by- N_{mv} array

Predicted optimal manipulated variable adjustments (moves), returned as a $(p+1)$ -by- N_{mv} array, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

`Uopt(i, :)` contains the calculated optimal values at time $k+i-1$, for $i = 1, \dots, p$, where k is the current time. The first row of `Info.Uopt` contains the same manipulated variable values as output argument `mv`. Since the controller does not calculate optimal control moves at time $k+p$, `Uopt(p+1, :)` is equal to `Uopt(p, :)`.

Yopt — Optimal output variable sequence

$(p+1)$ -by- N_y array

Optimal output variable sequence, returned as a $(p+1)$ -by- N_y array, where p is the prediction horizon and N_y is the number of outputs.

The first row of `Info.Yopt` contains the calculated outputs at time k based on the estimated states and measured disturbances; it is not the measured output at time k . `Yopt(i, :)` contains the predicted output values at time $k+i-1$, for $i = 1, \dots, p+1$.

`Yopt(i, :)` contains the calculated output values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Yopt(1, :)` is computed based on the estimated states and measured disturbances.

Xopt — Optimal prediction model state sequence

$(p+1)$ -by- N_x array

Optimal prediction model state sequence, returned as a $(p+1)$ -by- N_x array, where p is the prediction horizon and N_x is the number of states in the plant and unmeasured disturbance models (states from noise models are not included).

`Xopt(i, :)` contains the calculated state values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Xopt(1, :)` is the same as the current states state values.

Topt — Time intervalscolumn vector of length $p+1$

Time intervals, returned as a column vector of length $p+1$. $\text{Topt}(1) = 0$, representing the current time. Subsequent time steps $\text{Topt}(i)$ are given by $T_s \cdot (i-1)$, where $T_s = \text{MPCobj.Ts}$. T_s is the controller sample time.

Use Topt when plotting Uopt , Xopt , or Yopt sequences.

Slack — Slack variable

nonnegative scalar

Slack variable, ε , used in constraint softening, returned as \emptyset or a positive scalar value.

- $\varepsilon = 0$ — All constraints were satisfied for the entire prediction horizon.
- $\varepsilon > 0$ — At least one soft constraint is violated. When more than one constraint is violated, ε represents the worst-case soft constraint violation (scaled by your ECR values for each constraint).

See “Optimization Problem” for more information.

Iterations — Number of solver iterations

positive integer | 0 | -1 | -2

Number of solver iterations, returned as one of the following:

- Positive integer — Number of iterations needed to solve the optimization problem that determines the optimal sequences.
- 0 — Optimization problem could not be solved in the specified maximum number of iterations.
- -1 — Optimization problem was infeasible. An optimization problem is infeasible if no solution can satisfy all the hard constraints.
- -2 — Numerical error occurred when solving the optimization problem.

QPCode — Optimization solution status

'feasible' | 'infeasible' | 'unreliable'

Optimization solution status, returned as one of the following:

- 'feasible' — Optimal solution was obtained ($\text{Iterations} > 0$)
- 'infeasible' — Solver detected a problem with no feasible solution ($\text{Iterations} = -1$) or a numerical error occurred ($\text{Iterations} = -2$)
- 'unreliable' — Solver failed to converge ($\text{Iterations} = 0$). In this case, if $\text{MPCobj.Optimizer.UseSuboptimalSolution}$ is false, u freezes at the most recent successful solution. Otherwise, it uses the suboptimal solution found during the last solver iteration.

Cost — Objective function cost

nonnegative scalar

Objective function cost, returned as a nonnegative scalar value. The cost quantifies the degree to which the controller has achieved its objectives. For more information, see “Optimization Problem”.

The cost value is only meaningful when `QPCode = 'feasible'`, or when `QPCode = 'feasible'` and `MPCobj.Optimizer.UseSuboptimalSolution` is true.

Examples

Analyze Closed-Loop Response

Perform closed-loop simulation of a plant with one MV and one measured OV.

Define a plant model and create a model predictive controller with MV constraints.

```
ts = 2;
Plant = ss(0.8,0.5,0.25,0,ts);
MPCobj = mpc(Plant);

-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.

MPCobj.MV(1).Min = -2;
MPCobj.MV(1).Max = 2;
```

Initialize an `mpcstate` object for simulation. Use the default state properties.

```
x = mpcstate(MPCobj);

-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Set the reference signal. There is no measured disturbance.

```
r = 1;
```

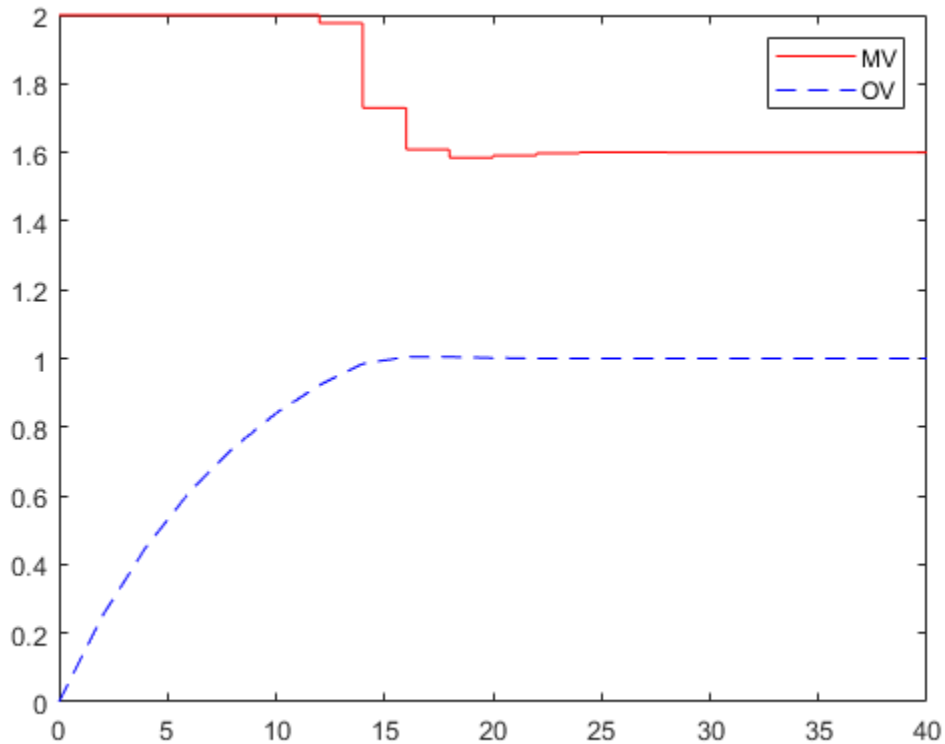
Simulate the closed-loop response by calling `mpcmove` iteratively.

```
t = [0:ts:40];
N = length(t);
y = zeros(N,1);
u = zeros(N,1);
for i = 1:N
    % simulated plant and predictive model are identical
    y(i) = 0.25*x.Plant;
    u(i) = mpcmove(MPCobj,x,y(i),r);
end
```

`y` and `u` store the OV and MV values.

Analyze the result.

```
[ts,us] = stairs(t,u);
plot(ts,us,'r-',t,y,'b--')
legend('MV','OV')
```



Modify the MV upper bound as the simulation proceeds using an `mpcmoveopt` object.

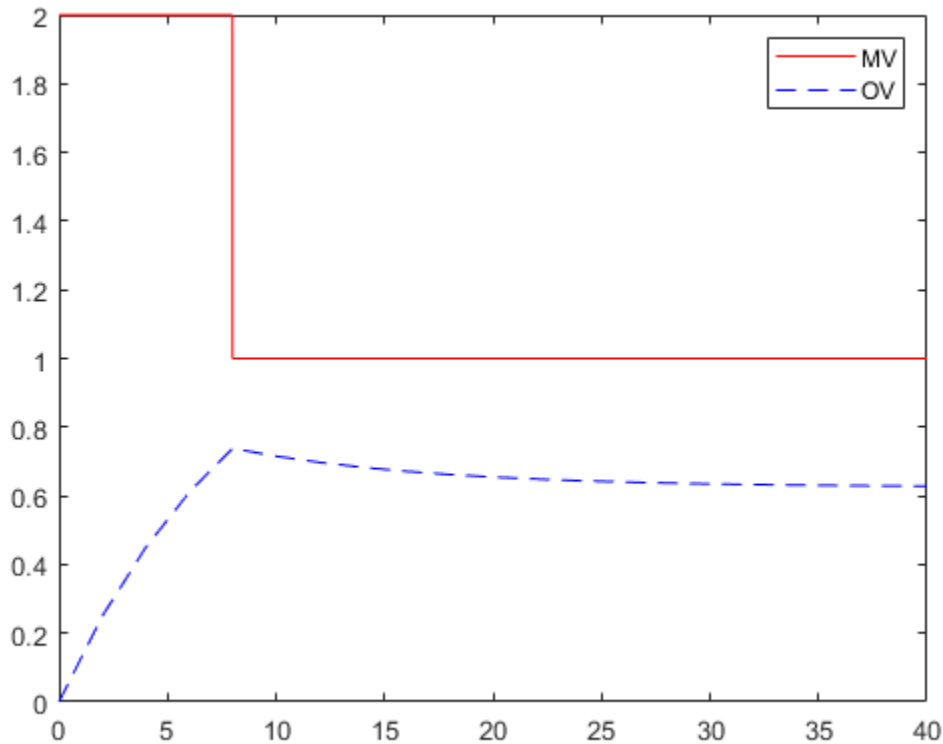
```
MPCopt = mpcmoveopt;
MPCopt.MVMin = -2;
MPCopt.MVMax = 2;
```

Simulate the closed-loop response and introduce the real-time upper limit change at eight seconds (the fifth iteration step).

```
x = mpcstate(MPCobj);
y = zeros(N,1);
u = zeros(N,1);
for i = 1:N
    % simulated plant and predictive model are identical
    y(i) = 0.25*x.Plant;
    if i == 5
        MPCopt.MVMax = 1;
    end
    u(i) = mpcmove(MPCobj,x,y(i),r,[],MPCopt);
end
```

Analyze the result.

```
[ts,us] = stairs(t,u);
plot(ts,us,'r-',t,y,'b--')
legend('MV','OV')
```



Evaluate Scenario at Specific Time Instant

Define a plant model.

```
ts = 2;
Plant = ss(0.8,0.5,0.25,0,ts);
```

Create a model predictive controller with constraints on both the manipulated variable and the rate of change of the manipulated variable. The prediction horizon is 10 intervals, and the control horizon is blocked.

```
MPCobj = mpc(Plant,ts,10,[2 3 5]);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

```
MPCobj.MV(1).Min = -2;
MPCobj.MV(1).Max = 2;
MPCobj.MV(1).RateMin = -1;
MPCobj.MV(1).RateMax = 1;
```

Initialize an `mpcstate` object for simulation from a particular state.

```
x = mpcstate(MPCobj);
```

```
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

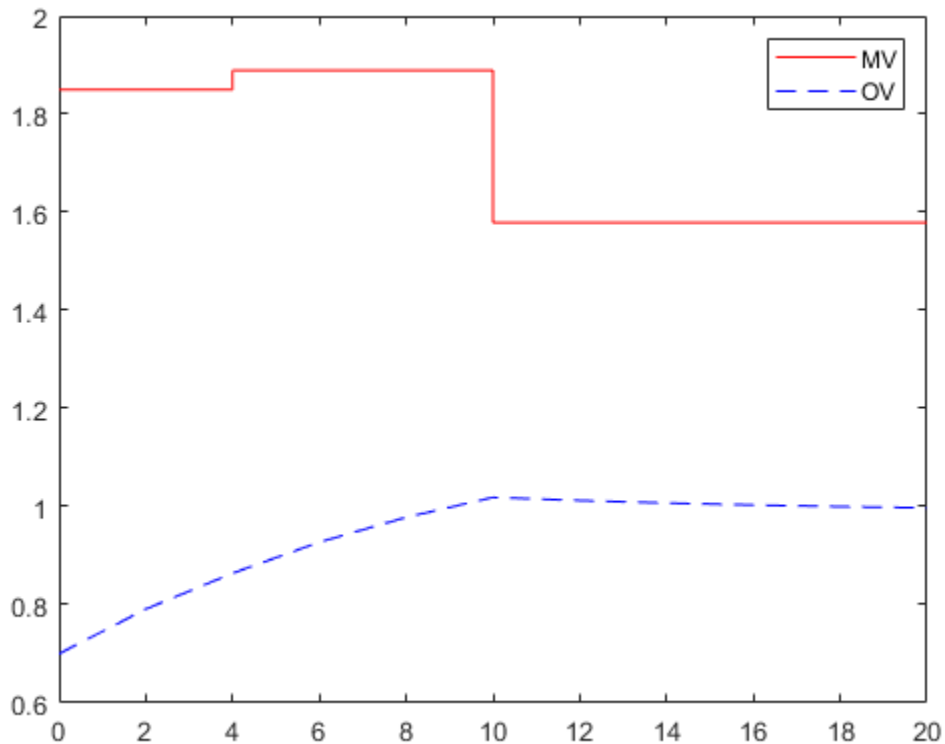
```
x.Plant = 2.8;
x.LastMove = 0.85;
```

Compute the optimal control at current time.

```
y = 0.25*x.Plant;
r = 1;
[u,Info] = mpcmove(MPCobj,x,y,r);
```

Analyze the predicted optimal sequences.

```
[ts,us] = stairs(Info.Topt,Info.Uopt);
plot(ts,us,'r-'),Info.Topt,Info.Yopt,'b--')
legend('MV','OV')
```



plot ignores Info.Uopt(end) as it is NaN.

Examine the optimal cost.

```
Info.Cost
```

```
ans = 0.0793
```

Tips

- `mpcmove` updates `x`.
- If `ym`, `r` or `v` is specified as `[]`, `mpcmove` uses the appropriate `MPCobj.Model.Nominal` value instead.
- To view the predicted optimal behavior for the entire prediction horizon, plot the appropriate sequences provided in `Info`.
- To determine the optimization status, check `Info.Iterations` and `Info.QPCode`.

Alternatives

- Use `sim` for plant mismatch and noise simulation when not using run-time constraints or weight changes.
- Use the **MPC Designer** app to interactively design and simulate model predictive controllers.
- Use the MPC Controller block in Simulink and for code generation.
- Use `mpcmoveCodeGeneration` for code generation.

See Also

`getEstimator` | `mpc` | `mpcmoveopt` | `mpcstate` | `review` | `setEstimator` | `sim`

Topics

“Improving Control Performance with Look-Ahead (Previewing)”

“Switching Controllers Based on Optimal Costs”

“Understanding Control Behavior by Examining Optimal Control Sequence”

Introduced before R2006a

mpcmoveAdaptive

Compute optimal control with prediction model updating

Syntax

```
mv = mpcmoveAdaptive(MPCobj,x,Plant,Nominal,ym,r,v)
[mv,info] = mpcmoveAdaptive(MPCobj,x,Plant,Nominal,ym,r,v)
[___] = mpcmoveAdaptive( ___,options)
```

Description

`mv = mpcmoveAdaptive(MPCobj,x,Plant,Nominal,ym,r,v)` computes the optimal manipulated variable moves at the current time. This result depends on the properties contained in the MPC controller, the controller states, an updated prediction model, and the nominal values. The result also depends on the measured output variables, the output references (setpoints), and the measured disturbance inputs. `mpcmoveAdaptive` updates the controller state, `x`, when using default state estimation. Call `mpcmoveAdaptive` repeatedly to simulate closed-loop model predictive control.

`[mv,info] = mpcmoveAdaptive(MPCobj,x,Plant,Nominal,ym,r,v)` returns additional details about the solution in a structure. To view the predicted optimal trajectory for the entire prediction horizon, plot the sequences provided in `info`. To determine whether the optimal control calculation completed normally, check `info.Iterations` and `info.QPCode`.

`[___] = mpcmoveAdaptive(___,options)` alters selected controller settings using options you specify with `mpcmoveopt`. These changes apply for the current time instant only, enabling a command-line simulation using `mpcmoveAdaptive` to mimic the Adaptive MPC Controller block in Simulink in a computationally efficient manner.

Input Arguments

MPCobj — MPC controller

MPC controller object

MPC controller, specified as an implicit MPC controller object. To create the MPC controller, use the `mpc` command.

x — Current MPC controller state

`mpcstate` object

Current MPC controller state, specified as an `mpcstate` object.

Before you begin a simulation with `mpcmoveAdaptive`, initialize the controller state using `x = mpcstate(MPCobj)`. Then, modify the default properties of `x` as appropriate.

If you are using default state estimation, `mpcmoveAdaptive` expects `x` to represent `x[n|n-1]`. The `mpcmoveAdaptive` command updates the state values in the previous control interval with that information. Therefore, you should not programmatically update `x` at all. The default state estimator employs a linear time-varying Kalman filter.

If you are using custom state estimation, `mpcmoveAdaptive` expects `x` to represent `x[n|n]`. Therefore, prior to each `mpcmoveAdaptive` command, you must set `x.Plant`, `x.Disturbance`, and

`x.Noise` to the best estimates of these states (using the latest measurements) at the current control interval.

For more information on state estimation for adaptive MPC and time-varying MPC, see “State Estimation”.

Plant — Updated prediction model

discrete-time state-space model | model array

Updated prediction model, specified as one of the following:

- A delay-free, discrete-time state-space (ss) model. This plant is the update to `MPCobj.Model.Plant` and it must:
 - Have the same sample time as the controller; that is, `Plant.Ts` must match `MPCobj.Ts`
 - Have the same input and output signal configurations, such as type, order, and dimensions
 - Define the same states as the controller prediction model, `MPCobj.Model.Plant`
- An array of up to $p+1$ delay-free, discrete-time state-space models, where p is the prediction horizon of `MPCobj`. Use this option to vary the controller prediction model over the prediction horizon.

If `Plant` contains fewer than $p+1$ models, the last model repeats for the rest of the prediction horizon.

Tip If you use a plant other than a delay-free, discrete-time state-space model to define the prediction model in `MPCobj`, you can convert it to such a model to determine the prediction model structure.

If the original plant is	Then
Not a state-space model	Convert it to a state-space model using <code>ss</code> .
A continuous-time model	Convert it to a discrete-time model with the same sample time as the controller, <code>MPCobj.Ts</code> , using <code>c2d</code> with default forward Euler discretization.
A model with delays	Convert the delays to states using <code>absorbDelay</code> .

Nominal — Updated nominal conditions

structure | structure array | []

Updated nominal conditions, specified as one of the following:

- A structure of with the following fields:

Field	Description	Default
X	Plant state at operating point	[]
U	Plant input at operating point, including manipulated variables and measured and unmeasured disturbances	[]
Y	Plant output at operating point	[]
DX	For continuous-time models, DX is the state derivative at operating point: $DX=f(X,U)$. For discrete-time models, $DX=x(k+1)-x(k)=f(X,U)-X$.	[]

- An array of up to $p+1$ nominal condition structures, where p is the prediction horizon of `MPCobj`. Use this option to vary controller nominal conditions over the prediction horizon.

If `Nominal` contains fewer than $p+1$ structures, the last structure repeats for the rest of the prediction horizon.

If `Nominal` is empty, [], or if a field is missing or empty, `mpcmoveAdaptive` uses the corresponding `MPCobj.Model.Nominal` value.

ym – Current measured outputs

row vector of length N_{ym}

Current measured outputs, specified as a row vector of length N_{ym} vector, where N_{ym} is the number of measured outputs.

If you are using custom state estimation, `ym` is ignored. If you set `ym = []`, then `mpcmoveAdaptive` uses the appropriate nominal value.

r – Plant output reference values

p -by- N_y array | []

Plant output reference values, specified as a p -by- N_y array, where p is the prediction horizon of `MPCobj` and N_y is the number of outputs. Row `r(i, :)` defines the reference values at step i of the prediction horizon.

`r` must contain at least one row. If `r` contains fewer than p rows, `mpcmoveAdaptive` duplicates the last row to fill the p -by- N_y array. If you supply exactly one row, therefore, a constant reference applies for the entire prediction horizon.

If you set `r = []`, then `mpcmoveAdaptive` uses the appropriate nominal value.

To implement reference previewing, which can improve tracking when a reference varies in a predictable manner, `r` must contain the anticipated variations, ideally for p steps.

v – Current and anticipated measured disturbances

p -by- N_{md} array | []

Current and anticipated measured disturbances, specified as a p -by- N_{md} array, where p is the prediction horizon of `MPCobj` and N_{md} is the number of measured disturbances. Row `v(i, :)` defines the expected measured disturbance values at step i of the prediction horizon.

Modeling of measured disturbances provides feedforward control action. If your plant model does not include measured disturbances, use `v = []`.

v must contain at least one row. If v contains fewer than p rows, `mpcmoveAdaptive` duplicates the last row to fill the p -by- N_{md} array. If you supply exactly one row, therefore, a constant measured disturbance applies for the entire prediction horizon.

If you set $v = []$, then `mpcmoveAdaptive` uses the appropriate nominal value.

To implement disturbance previewing, which can improve tracking when a disturbance varies in a predictable manner, v must contain the anticipated variations, ideally for p steps.

options — Override values for selected controller properties

`mpcmoveopt` object

Override values for selected properties of `MPCobj`, specified as an options object you create with `mpcmoveopt`. These options apply to the current `mpcmoveAdaptive` time instant only. Using `options` yields the same result as redefining or modifying `MPCobj` before each call to `mpcmoveAdaptive`, but involves considerably less overhead. Using `options` is equivalent to using an Adaptive MPC Controller Simulink block in combination with optional input signals that modify controller settings, such as MV and OV constraints.

Output Arguments

mv — Optimal manipulated variable moves

column vector

Optimal manipulated variable moves, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the controller detects an infeasible optimization problem or encounters numerical difficulties in solving an ill-conditioned optimization problem, `mv` remains at its most recent successful solution, `x.LastMove`.

Otherwise, if the optimization problem is feasible and the solver reaches the specified maximum number of iterations without finding an optimal solution, `mv`:

- Remains at its most recent successful solution if the `Optimizer.UseSuboptimalSolution` property of the controller is `false`.
- Is the suboptimal solution reached after the final iteration if the `Optimizer.UseSuboptimalSolution` property of the controller is `true`. For more information, see “Suboptimal QP Solution”.

info — Solution details

structure

Solution details, returned as a structure with the following fields.

Uopt — Optimal manipulated variable sequence

$(p+1)$ -by- N_{mv} array

Predicted optimal manipulated variable adjustments (moves), returned as a $(p+1)$ -by- N_{mv} array, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

`Uopt(i, :)` contains the calculated optimal values at time $k+i-1$, for $i = 1, \dots, p$, where k is the current time. The first row of `Info.Uopt` contains the same manipulated variable values as output

argument `mv`. Since the controller does not calculate optimal control moves at time $k+p$, `Uopt(p+1, :)` is equal to `Uopt(p, :)`.

Yopt — Optimal output variable sequence

$(p+1)$ -by- N_y array

Optimal output variable sequence, returned as a $(p+1)$ -by- N_y array, where p is the prediction horizon and N_y is the number of outputs.

The first row of `Info.Yopt` contains the calculated outputs at time k based on the estimated states and measured disturbances; it is not the measured output at time k . `Yopt(i, :)` contains the predicted output values at time $k+i-1$, for $i = 1, \dots, p+1$.

`Yopt(i, :)` contains the calculated output values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Yopt(1, :)` is computed based on the estimated states and measured disturbances.

Xopt — Optimal prediction model state sequence

$(p+1)$ -by- N_x array

Optimal prediction model state sequence, returned as a $(p+1)$ -by- N_x array, where p is the prediction horizon and N_x is the number of states in the plant and unmeasured disturbance models (states from noise models are not included).

`Xopt(i, :)` contains the calculated state values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Xopt(1, :)` is the same as the current states state values.

Topt — Time intervals

column vector of length $p+1$

Time intervals, returned as a column vector of length $p+1$. `Topt(1) = 0`, representing the current time. Subsequent time steps `Topt(i)` are given by $Ts*(i-1)$, where $Ts = MPCobj.Ts$ is the controller sample time.

Use `Topt` when plotting `Uopt`, `Xopt`, or `Yopt` sequences.

Slack — Slack variable

nonnegative scalar

Slack variable, ε , used in constraint softening, returned as `0` or a positive scalar value.

- $\varepsilon = 0$ — All constraints were satisfied for the entire prediction horizon.
- $\varepsilon > 0$ — At least one soft constraint is violated. When more than one constraint is violated, ε represents the worst-case soft constraint violation (scaled by your ECR values for each constraint).

See “Optimization Problem” for more information.

Iterations — Number of solver iterations

positive integer | `0` | `-1` | `-2`

Number of solver iterations, returned as one of the following:

- Positive integer — Number of iterations needed to solve the optimization problem that determines the optimal sequences.

- 0 — Optimization problem could not be solved in the specified maximum number of iterations.
- -1 — Optimization problem was infeasible. An optimization problem is infeasible if no solution can satisfy all the hard constraints.
- -2 — Numerical error occurred when solving the optimization problem.

QPCode — Optimization solution status

'feasible' | 'infeasible' | 'unreliable'

Optimization solution status, returned as one of the following:

- 'feasible' — Optimal solution was obtained (`Iterations > 0`)
- 'infeasible' — Solver detected a problem with no feasible solution (`Iterations = -1`) or a numerical error occurred (`Iterations = -2`)
- 'unreliable' — Solver failed to converge (`Iterations = 0`). In this case, if `MPCobj.Optimizer.UseSuboptimalSolution` is `false`, `u` freezes at the most recent successful solution. Otherwise, it uses the suboptimal solution found during the last solver iteration.

Cost — Objective function cost

nonnegative scalar

Objective function cost, returned as a nonnegative scalar value. The cost quantifies the degree to which the controller has achieved its objectives. For more information, see “Optimization Problem”.

The cost value is only meaningful when `QPCode = 'feasible'`, or when `QPCode = 'feasible'` and `MPCobj.Optimizer.UseSuboptimalSolution` is `true`.

Tips

- If the prediction model is time-invariant, use `mpcmove`.
- Use the Adaptive MPC Controller Simulink block for simulations and code generation.

See Also

`getEstimator` | `mpc` | `mpcmove` | `mpcmoveopt` | `mpcstate` | `review` | `setEstimator` | `sim`

Topics

“Adaptive MPC”

“Time-Varying MPC”

“Optimization Problem”

Introduced in R2014b

mpcmoveCodeGeneration

Compute optimal control moves with code generation support

Syntax

```
[mv,newStateData] = mpcmoveCodeGeneration(configData,stateData,onlineData)
[ ____,info] = mpcmoveCodeGeneration( ____ )
```

Description

`[mv,newStateData] = mpcmoveCodeGeneration(configData,stateData,onlineData)` computes optimal MPC control moves and supports code generation for deployment to real-time targets. The input data structures, generated using `getCodeGenerationData`, define the MPC controller to simulate.

`mpcmoveCodeGeneration` does not check input arguments for correct dimensions and data types.

`[____,info] = mpcmoveCodeGeneration(____)` returns additional information about the optimization result, including the number of iterations and the objective function cost.

Examples

Compute Optimal Control Moves Using Code Generation Data Structures

Create a proper plant model.

```
plant = rss(3,1,1);
plant.D = 0;
```

Specify the controller sample time.

```
Ts = 0.1;
```

Create an MPC controller.

```
mpcObj = mpc(plant,Ts);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Create code generation data structures.

```
[configData,stateData,onlineData] = getCodeGenerationData(mpcObj);
```

```
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured output.
-->Converting model to discrete time.
```

-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
 -->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured

Initialize the plant states to zero to match the default states used by the MPC controller.

Run a closed-loop simulation. At each control interval, update the online data structure and call `mpcmoveCodeGeneration` to compute the optimal control moves.

```
x = zeros(size(plant.B,1),1); % Initialize plant states to zero (|mpcObj| default).
Tsim = 20;
for i = 1:round(Tsim/Ts)+1
    % Update plant output.
    y = plant.C*x;
    % Update measured output in online data.
    onlineData.signals.ym = y;
    % Update reference signal in online data.
    onlineData.signals.ref = 1;
    % Compute control actions.
    [u, statedata] = mpcmoveCodeGeneration(configData, stateData, onlineData);
    % Update plant state.
    x = plant.A*x + plant.B*u;
end
```

Generate MEX function with MATLAB® Coder™, specifying `configData` as a constant.

```
func = 'mpcmoveCodeGeneration';
funcOutput = 'mpcmoveMEX';
Cfg = coder.config('mex');
Cfg.DynamicMemoryAllocation = 'off';
codegen('-config', Cfg, func, '-o', funcOutput, '-args', ...
    {coder.Constant(configData), stateData, onlineData});
```

Input Arguments

configData — MPC configuration parameters

structure

MPC configuration parameters that are constant at run time, specified as a structure generated using `getCodeGenerationData`.

Note When using `codegen`, `configData` must be defined as `coder.Constant`.

stateData — Controller state

structure

Controller state at run time, specified as a structure. Generate the initial state structure using `getCodeGenerationData`. For subsequent control intervals, use the updated controller state from the previous interval. In general, use the `newStateData` structure directly.

If custom state estimation is enabled, you must manually update the `stateData` structure during each control interval. For more information, see “Custom State Estimation”.

`stateData` has the following fields:

Plant — Plant model state estimatesMPCobj nominal plant states (default) | column vector of length n_{xp}

Plant model state estimates, specified as a column vector of length N_{xp} , where N_{xp} is the number of plant model states.

Note If custom state estimation is enabled, update **Plant** at each control interval. Otherwise, do not change this field. Instead use the values returned by either `getCodeGenerationData` or `mpcmoveCodeGeneration`.

Disturbance — Unmeasured disturbance model state estimates

[] (default) | column vector

Unmeasured disturbance model state estimates, specified as a column vector of length N_{xd} , where N_{xd} is the number of unmeasured disturbance model states. **Disturbance** contains the input disturbance model states followed by the output disturbance model states.

To view the input and output disturbance models, use `getindist` and `getoutdist` respectively.

Note If custom state estimation is enabled, update **Disturbance** at each control interval. Otherwise, do not change this field. Instead use the values returned by either `getCodeGenerationData` or `mpcmoveCodeGeneration`.

Noise — Output measurement noise model state estimates

[] (default) | column vector

Output measurement noise model state estimates, specified as a column vector of length N_{xn} , where N_{xn} is the number of noise model states.

Note If custom state estimation is enabled, update **Noise** at each control interval. Otherwise, do not change this field. Instead use the values returned by either `getCodeGenerationData` or `mpcmoveCodeGeneration`.

LastMove — Manipulated variable control moves from previous control interval

MPCobj nominal MV values (default) | column vector

Manipulated variable control moves from previous control interval, specified as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

Note Do not change the value of **LastMove**. Always use the values returned by either `getCodeGenerationData` or `mpcmoveCodeGeneration`.

Covariance — Covariance matrix for controller state estimates

symmetrical array

Covariance matrix for controller state estimates, specified as a symmetrical N -by- N array, where N is number of extended controller states; that is, the sum of N_{xp} , N_{xd} , and N_{xn} .

If the controller uses custom state estimation, `Covariance` is empty.

Note Do not change the value of `Covariance`. Always use the values returned by either `getCodeGenerationData` or `mpcmoveCodeGeneration`.

iA — Active inequality constraints

false (default) | logical vector

Active inequality constraints, where the equal portion of the inequality is `true`, specified as a logical vector of length M . If `iA(i)` is `true`, then the i th inequality is active for the latest QP solver solution.

Note Do not change the value of `iA`. Always use the values returned by either `getCodeGenerationData` or `mpcmoveCodeGeneration`.

onlineData — Online controller data

structure

Online controller data that you must update at run time, specified as a structure with the following fields. Generate the initial structure using `getCodeGenerationData`.

signals — Updated input and output signals

structure

Updated input and output signals, specified as a structure with the following fields:

ym — Measured outputs

vector

Measured outputs, specified as a vector of length N_{ym} , where N_{ym} is the number of measured outputs.

By default, `getCodeGenerationData` sets `ym` to the nominal measured output values from the controller.

ref — Output references

row vector | array

Output references, specified as one of the following:

- Row vector of length N_y , where N_y is the number of outputs.
- If you are using reference signal previewing with implicit or adaptive MPC, specify a p -by- N_y array, where p is the prediction horizon.

By default, `getCodeGenerationData` sets `ref` to the nominal output values from the controller.

md — Measured disturbances

row vector | array

Measured disturbances, specified as:

- A row vector of length N_{md} , where N_{md} is the number of measured disturbances.
- If you are using signal previewing with implicit or adaptive MPC, specify a p -by- N_{md} array.

By default, if your controller has measured disturbances, `getCodeGenerationData` sets `md` to the nominal measured disturbance values from the controller. Otherwise, this field is empty and ignored by `mpcmoveCodeGeneration`.

mvTarget — Targets for manipulated variables

`[]` (default) | vector

Targets for manipulated variables, which replace the targets defined in `configData.uTarget`, specified as one of the following:

- Vector of length N_{mv} , where N_{mv} is the number of manipulated variables
- `[]` to use the default targets defined in `configData.uTarget`

This field is ignored when using an explicit MPC controller.

externalMV — Manipulated variables externally applied to the plant

`[]` (default) | vector

Manipulated variables externally applied to the plant, specified as:

- A vector of length N_{mv} .
- `[]` to apply the optimal control moves to the plant.

weights — Updated QP optimization weights

structure

Updated QP optimization weights, specified as a structure. If you do not expect tuning weights to change at run time, ignore `weights`. This field is ignored when using an explicit MPC controller.

This structure contains the following fields:

y — Output variable tuning weights

`[]` (default) | row vector | array

Output variable tuning weights that replace the original controller output weights at run time at run time, specified as a row vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_y , where N_y is the number of output variables.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the output variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

If `y` is empty, `[]`, the default weights defined in the original MPC controller are used.

u — Manipulated variable tuning weights

`[]` (default) | row vector | array

Manipulated variable tuning weights that replace the original controller manipulated variable weights at run time, specified as a row vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

If u is empty, `[]`, the default weights defined in the original MPC controller are used.

du — Manipulated variable rate tuning weights

`[]` (default) | row vector | array

Manipulated variable rate tuning weights that replace the original controller manipulated variable rate weights at run time, specified as a row vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable rate tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

If du is empty, `[]`, the default weights defined in the original MPC controller are used.

ecr — Weight on slack variable used for constraint softening

`[]` (default) | nonnegative scalar

Weight on slack variable used for constraint softening, specified as a nonnegative scalar.

If ecr is empty, `[]`, the default weight defined in the original MPC controller are used.

limits — Updated input and output constraints

structure

Updated input and output constraints, specified as a structure. If you do not expect constraints to change at run time, ignore `limits`. This field is ignored when using an explicit MPC controller.

This structure contains the following fields:

ymin — Output variable lower bounds

`[]` (default) | column vector

Output variable lower bounds, specified as a column vector of length N_y . `ymin(i)` replaces the `OutputVariables(i).Min` constraint from the original controller. If the `OutputVariables(i).Min` property of the controller is specified as a vector, `ymin(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

If `ymin` is empty, `[]`, the default bounds defined in the original MPC controller are used.

ymax — Output variable upper bounds

`[]` (default) | column vector

Output variable upper bounds, specified as a column vector of length N_y . `ymax(i)` replaces the `OutputVariables(i).Max` constraint from the original controller. If the

`OutputVariables(i).Max` property of the controller is specified as a vector, `ymax(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

If `ymax` is empty, `[]`, the default bounds defined in the original MPC controller are used.

umin — Manipulated variable lower bounds

`[]` (default) | column vector

Manipulated variable lower bounds, specified as a column vector of length N_{mv} . `umin(i)` replaces the `ManipulatedVariables(i).Min` constraint from the original controller. If the `ManipulatedVariables(i).Min` property of the controller is specified as a vector, `umin(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

If `umin` is empty, `[]`, the default bounds defined in the original MPC controller are used.

umax — Manipulated variable upper bounds

`[]` (default) | column vector

Manipulated variable upper bounds, specified as a column vector of length N_{mv} . `umax(i)` replaces the `ManipulatedVariables(i).Max` constraint from the original controller. If the `ManipulatedVariables(i).Max` property of the controller is specified as a vector, `umax(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

If `umax` is empty, `[]`, the default bounds defined in the original MPC controller are used.

customconstraints — Updated custom mixed input/output constraints

structure

Updated custom mixed input/output constraints, specified as a structure. This field is ignored when using an explicit MPC controller.

This structure has the following fields:

E — Manipulated variable constraint constant

`[]` (default) | N_c -by- N_{mv} array

Manipulated variable constraint constant, specified as an N_c -by- N_{mv} array, where N_c is the number of constraints, and N_{mv} is the number of manipulated variables.

If `E` is empty, `[]`, the corresponding constraint defined in the original MPC controller are used.

F — Controlled output constraint constant

`[]` (default) | N_c -by- N_y array

Controlled output constraint constant, specified as an N_c -by- N_y array, where N_y is the number of controlled outputs (measured and unmeasured).

G — Mixed input/output constraint constant

`[]` (default) | column vector of length N_c

Mixed input/output constraint constant, specified as a column vector of length N_c .

S — Measured disturbance constraint constant

`[]` (default) | N_c -by- N_v array

Measured disturbance constraint constant, specified as an N_c -by- N_{md} array, where N_{md} is the number of measured disturbances.

horizons — Updated controller horizons

structure

Updated controller horizons, specified as a structure. To vary horizons at run time, first create your data structures using `getCodeGenerationData` setting the `UseVariableHorizon` name-value pair to `true`. When you vary the horizons, you must specify both the prediction horizon and the control horizon. For more information, see “Adjust Horizons at Run Time”.

This field is ignored when using an explicit MPC controller.

This structure has the following fields:

p — Prediction horizon

[] (default) | positive integer

Prediction horizon, which replaces the value of `configData.p` at run time, specified as a positive integer.

Specifying `p` changes the:

- Number of rows in the optimal sequences returned in `info`
- The maximum dimensions of the fields in `model` when `configData.IsLTV` is `true`

m — Control horizon

[] (default) | positive integer | vector of positive integers

Control horizon, which replaces the value of `configData.m` at run time, specified as one of the following:

- Positive integer, m , between 1 and p , inclusive, where p is the prediction horizon (`horizons.p`). In this case, the controller computes m free control moves occurring at times k through $k+m-1$, and holds the controller output constant for the remaining prediction horizon steps from $k+m$ through $k+p-1$. Here, k is the current control interval. For optimal trajectory planning set m equal to p .
- Vector of positive integers, $[m_1, m_2, \dots]$, where the sum of the integers equals the prediction horizon, p . In this case, the controller computes M blocks of free moves, where M is the length of the control horizon vector. The first free move applies to times k through $k+m_1-1$, the second free move applies from time $k+m_1$ through $k+m_1+m_2-1$, and so on. Using block moves can improve the robustness of your controller compared to the default case.

model — Updated plant and nominal values

structure

Updated plant and nominal values for adaptive MPC and time-varying MPC, specified as a structure. `model` is only available if you specify `isAdaptive` or `isLTV` as `true` when creating code generation data structures.

This structure contains the following fields:

A — State matrix of discrete-time state-space plant model

N_x -by- N_x array | N_x -by- N_x -by- $(p+1)$ array

State matrix of discrete-time state-space plant model, specified as an:

- N_x -by- N_x array when using adaptive MPC,
- N_x -by- N_x -by- $(p+1)$ array when using time-varying MPC,

where N_x is the number of plant states.

B — Input-to-state matrix of discrete-time state-space plant model

N_x -by- N_u array | N_x -by- N_u -by- $(p+1)$ array

Input-to-state matrix of discrete-time state-space plant model, specified as an:

- N_x -by- N_u array when using adaptive MPC,
- N_x -by- N_u -by- $(p+1)$ array when using time-varying MPC,

where N_u is the number of plant inputs.

C — State-to-output matrix of discrete-time state-space plant model

N_y -by- N_x array | N_y -by- N_x -by- $(p+1)$ array

State-to-output matrix of discrete-time state-space plant model, specified as an:

- N_y -by- N_x array when using adaptive MPC.
- N_y -by- N_x -by- $(p+1)$ array when using time-varying MPC.

D — Feedthrough matrix of discrete-time state-space plant model

N_y -by- N_u array | N_y -by- N_u -by- $(p+1)$ array

Feedthrough matrix of discrete-time state-space plant model, specified as an:

- N_y -by- N_u array when using adaptive MPC.
- N_y -by- N_u -by- $(p+1)$ array when using time-varying MPC.

Since MPC controllers do not support plants with direct feedthrough, specify D as an array of zeros.

X — Nominal plant states

column vector of length N_x | N_x -by-1-by- $(p+1)$ array

Nominal plant states, specified as:

- A column vector of length N_x when using adaptive MPC.
- An N_x -by-1-by- $(p+1)$ array when using time-varying MPC.

U — Nominal plant inputs

column vector of length N_u | N_u -by-1-by- $(p+1)$ array

Nominal plant inputs, specified as:

- A column vector of length N_u when using adaptive MPC.
- An N_u -by-1-by- $(p+1)$ array when using time-varying MPC.

Y — Nominal plant outputs

column vector of length N_y | N_y -by-1-by- $(p+1)$ array

Nominal plant outputs, specified as:

- A column vector of length N_y when using adaptive MPC.
- An N_y -by-1-by- $(p+1)$ array when using time-varying MPC.

DX — Nominal plant state derivatives

column vector of length N_x | N_x -by-1-by- $(p+1)$ array

Nominal plant state derivatives, specified as:

- A column vector of length N_x when using adaptive MPC.
- An N_x -by-1-by- $(p+1)$ array when using time-varying MPC.

Output Arguments

mv — Optimal manipulated variable moves

column vector

Optimal manipulated variable moves, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the controller detects an infeasible optimization problem or encounters numerical difficulties in solving an ill-conditioned optimization problem, `mv` remains at its most recent successful solution, `x.LastMove`.

Otherwise, if the optimization problem is feasible and the solver reaches the specified maximum number of iterations without finding an optimal solution, `mv`:

- Remains at its most recent successful solution if the `Optimizer.UseSuboptimalSolution` property of the controller is `false`.
- Is the suboptimal solution reached after the final iteration if the `Optimizer.UseSuboptimalSolution` property of the controller is `true`. For more information, see “Suboptimal QP Solution”.

newStateData — Updated controller state

structure

Updated controller state, returned as a structure. For subsequent control intervals, pass `newStateData` to `mpcmoveCodeGeneration` as `stateData`.

If custom state estimation is enabled, use `newStateData` to manually update the state structure before the next control interval. For more information, see “Custom State Estimation”.

info — Controller optimization information

structure

Controller optimization information, returned as a structure.

If you are using implicit or adaptive MPC, `info` contains the following fields:

Field	Description
Iterations	Number of QP solver iterations
QPCode	QP solver status code

Field	Description
Cost	Objective function cost
Uopt	Optimal manipulated variable adjustments
Yopt	Optimal predicted output variable sequence
Xopt	Optimal predicted state variable sequence
Topt	Time horizon intervals
Slack	Slack variable used in constraint softening

If `configData.OnlyComputeCost` is true, the optimal sequence information, `Uopt`, `Yopt`, `Xopt`, `Topt`, and `Slack`, is not available:

For more information, see `mpcmove` and `mpcmoveAdaptive`.

If you are using explicit MPC, `info` contains the following fields:

Field	Description
Region	Region in which the optimal solution was found
ExitCode	Solution status code

For more information, see `mpcmoveExplicit`.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- You can generate code for both implicit and explicit MPC controllers.
- To generate code for computing optimal MPC control moves:
 - 1 Generate data structures from an MPC controller or explicit MPC controller using `getCodeGenerationData`.
 - 2 To verify that your controller produces the expected closed-loop results, simulate it using `mpcmoveCodeGeneration` in place of `mpcmove`.
 - 3 Generate code for `mpcmoveCodeGeneration` using `codegen`. This step requires MATLAB Coder software.

See Also

`codegen` | `getCodeGenerationData` | `mpcmove` | `mpcmoveAdaptive` | `mpcmoveExplicit`

Topics

“Generate Code To Compute Optimal MPC Moves in MATLAB”

“Generate Code and Deploy Controller to Real-Time Targets”

Introduced in R2016a

mpcmoveExplicit

Compute optimal control using explicit MPC

Syntax

```
mv = mpcmoveExplicit(EMPCobj,x,ym,r,v)
[mv,info] = mpcmoveExplicit(EMPCobj,x,ym,r,v)
[mv,info] = mpcmoveExplicit(EMPCobj,x,ym,r,v,MVused)
```

Description

`mv = mpcmoveExplicit(EMPCobj,x,ym,r,v)` computes the optimal manipulated variable moves at the current time using an explicit model predictive control law. This result depends on the properties contained in the explicit MPC controller and the controller states. The result also depends on the measured output variables, the output references (setpoints), and the measured disturbance inputs. `mpcmoveExplicit` updates the controller state, `x`, when using default state estimation. Call `mpcmoveExplicit` repeatedly to simulate closed-loop model predictive control.

`[mv,info] = mpcmoveExplicit(EMPCobj,x,ym,r,v)` returns additional details about the computation in a structure. To determine whether the optimal control calculation completed normally, check the data in `info`.

`[mv,info] = mpcmoveExplicit(EMPCobj,x,ym,r,v,MVused)` specifies the manipulated variable values used in the previous `mpcmoveExplicit` command, allowing a command-line simulation to mimic the Explicit MPC Controller Simulink block with the optional external MV input signal.

Input Arguments

EMPCobj — Explicit MPC controller

explicit MPC controller object

Explicit MPC controller to simulate, specified as an Explicit MPC controller object. Use `generateExplicitMPC` to create an explicit MPC controller.

x — Current MPC controller state

mpcstate object

Current MPC controller state, specified as an `mpcstate` object.

Before you begin a simulation with `mpcmoveExplicit`, initialize the controller state using `x = mpcstate(EMPCobj)`. Then, modify the default properties of `x` as appropriate.

If you are using default state estimation, `mpcmoveExplicit` expects `x` to represent `x[n|n-1]`. The `mpcmoveExplicit` command updates the state values in the previous control interval with that information. Therefore, you should not programmatically update `x` at all. The default state estimator employs a linear time-varying Kalman filter.

If you are using custom state estimation, `mpcmoveExplicit` expects `x` to represent `x[n|n]`. Therefore, prior to each `mpcmoveExplicit` command, you must set `x.Plant`, `x.Disturbance`, and

`x.Noise` to the best estimates of these states (using the latest measurements) at the current control interval.

ym — Current measured outputs

vector

Current measured outputs, specified as a row vector of length N_{ym} , where N_{ym} is the number of measured outputs. If you are using custom state estimation, `ym` is ignored. If you set `ym = []`, then `mpcmoveExplicit` uses the appropriate nominal value.

r — Plant output reference values

vector

Plant output reference values, specified as a vector of length N_y . `mpcmoveExplicit` uses a constant reference for the entire prediction horizon. In contrast to `mpcmove` and `mpcmoveAdaptive`, `mpcmoveExplicit` does not support reference previewing.

If you set `r = []`, then `mpcmoveExplicit` uses the appropriate nominal value.

v — Current and anticipated measured disturbances

vector

Current and anticipated measured disturbances, specified as a vector of length N_{md} , where N_{md} is the number of measured disturbances. In contrast to `mpcmove` and `mpcmoveAdaptive`, `mpcmoveExplicit` does not support disturbance previewing. If your plant model does not include measured disturbances, use `v = []`.

MVused — Manipulated variable values from previous interval

vector

Manipulated variable values applied to the plant during the previous control interval, specified as a vector of length N_{mv} , where N_{mv} is the number of manipulated variables. If this is the first `mpcmoveExplicit` command in a simulation sequence, omit this argument. Otherwise, if the MVs calculated by `mpcmoveExplicit` in the previous interval were overridden, set `MVused` to the correct values in order to improve the controller state estimation accuracy. If you omit `MVused`, `mpcmoveExplicit` assumes `MVused = x.LastMove`.

Output Arguments

mv — Optimal manipulated variable moves

column vector

Optimal manipulated variable moves, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the controller detects an infeasible optimization problem or encounters numerical difficulties in solving an ill-conditioned optimization problem, `mv` remains at its most recent successful solution, `x.LastMove`.

Otherwise, if the optimization problem is feasible and the solver reaches the specified maximum number of iterations without finding an optimal solution, `mv`:

- Remains at its most recent successful solution if the `Optimizer.UseSuboptimalSolution` property of the controller is `false`.

- Is the suboptimal solution reached after the final iteration if the `Optimizer.UseSuboptimalSolution` property of the controller is `true`. For more information, see “Suboptimal QP Solution”.

info — Explicit MPC solution status

structure

Explicit MPC solution status, returned as a structure having the following fields.

ExitCode — Solution status code

1 | 0 | -1

Solution status code, returned as one of the following values:

- 1 — Successful solution.
- 0 — Failure. One or more controller input parameters is out of range.
- -1 — Undefined. Parameters are in range but an extrapolation must be used.

Region — Region to which current controller input parameters belong

positive integer | 0

Region to which current controller input parameters belong, returned as either a positive integer or 0. The integer value is the index of the polyhedron (region) to which the current controller input parameters belong. If the solution failed, `Region = 0`.

Tips

- Use the Explicit MPC Controller Simulink block for simulation and code generation.

See Also

`generateExplicitMPC`

Topics

“Explicit MPC Control of a Single-Input-Single-Output Plant”

“Explicit MPC”

“Design Workflow for Explicit MPC”

Introduced in R2014b

mpcmoveMultiple

Compute gain-scheduling MPC control action at a single time instant

Syntax

```
mv = mpcmoveMultiple(MPCArray,states,index,ym,r,v)
[mv,info] = mpcmoveMultiple(MPCArray,states,index,ym,r,v)
[ ___ ] = mpcmoveMultiple( ___ ,options)
```

Description

`mv = mpcmoveMultiple(MPCArray,states,index,ym,r,v)` computes the optimal manipulated variable moves at the current time using a model predictive controller selected by `index` from an array of MPC controllers. This result depends upon the properties contained in the MPC controller and the controller states. The result also depends on the measured plant outputs, the output references (setpoints), and the measured disturbance inputs. `mpcmoveMultiple` updates the controller state when default state estimation is used. Call `mpcmoveMultiple` repeatedly to simulate closed-loop model predictive control.

`[mv,info] = mpcmoveMultiple(MPCArray,states,index,ym,r,v)` returns additional details about the computation in a structure. To determine whether the optimal control calculation completed normally, check the data in `info`.

`[___] = mpcmoveMultiple(___ ,options)` alters selected controller settings using options you specify with `mpcmoveopt`. These changes apply for the current time instant only, allowing a command-line simulation using `mpcmoveMultiple` to mimic the Multiple MPC Controllers block in Simulink in a computationally efficient manner.

Input Arguments

MPCArray — MPC controllers

cell array of MPC controller objects

MPC controllers to simulate, specified as a cell array of traditional (implicit) MPC controller objects. Use the `mpc` command to create the MPC controllers.

All the controllers in `MPCArray` must use either default state estimation or custom state estimation. Mismatch is not permitted.

states — Current MPC controller states

cell array of `mpcstate` objects

Current controller states for each MPC controller in `MPCArray`, specified as a cell array of `mpcstate` objects.

Before you begin a simulation with `mpcmoveMultiple`, initialize each controller state using `x = mpcstate(MPCobj)`. Then, modify the default properties of each state as appropriate.

If you are using default state estimation, `mpcmoveMultiple` expects `x` to represent `x[n|n-1]` (where `x` is one entry in `states`, the current state of one MPC controller in `MPCArray`). The

`mpcmoveMultiple` command updates the state values in the previous control interval with that information. Therefore, you should not programmatically update `x` at all. The default state estimator employs a steady-state Kalman filter.

If you are using custom state estimation, `mpcmoveMultiple` expects `x` to represent `x[n|n]`. Therefore, prior to each `mpcmoveMultiple` command, you must set `x.Plant`, `x.Disturbance`, and `x.Noise` to the best estimates of these states (using the latest measurements) at the current control interval.

index — Index of selected controller

positive integer

Index of selected controller in the cell array `MPCArray`, specified as a positive integer.

ym — Current measured outputs

row vector

Current measured outputs, specified as a row vector of length N_{ym} , where N_{ym} is the number of measured outputs. If you are using custom state estimation, `ym` is ignored. If you set `ym = []`, then `mpcmoveMultiple` uses the appropriate nominal value.

r — Plant output reference values

array

Plant output reference values, specified as a p -by- N_y array, where p is the prediction horizon of the selected controller and N_y is the number of outputs. Row `r(i, :)` defines the reference values at step i of the prediction horizon.

`r` must contain at least one row. If `r` contains fewer than p rows, `mpcmoveMultiple` duplicates the last row to fill the p -by- N_y array. If you supply exactly one row, therefore, a constant reference applies for the entire prediction horizon.

If you set `r = []`, then `mpcmoveMultiple` uses the appropriate nominal value.

To implement reference previewing, which can improve tracking when a reference varies in a predictable manner, `r` must contain the anticipated variations, ideally for p steps.

v — Current and anticipated measured disturbances

array

Current and anticipated measured disturbances, specified as a p -by- N_{md} array, where p is the prediction horizon of the selected controller and N_{md} is the number of measured disturbances. Row `v(i, :)` defines the expected measured disturbance values at step i of the prediction horizon.

Modeling of measured disturbances provides feedforward control action. If your plant model does not include measured disturbances, use `v = []`.

`v` must contain at least one row. If `v` contains fewer than p rows, `mpcmoveMultiple` duplicates the last row to fill the p -by- N_{md} array. If you supply exactly one row, therefore, a constant measured disturbance applies for the entire prediction horizon.

If you set `v = []`, then `mpcmoveMultiple` uses the appropriate nominal value.

To implement disturbance previewing, which can improve tracking when a disturbance varies in a predictable manner, `v` must contain the anticipated variations, ideally for p steps.

options — Override values for selected controller properties

mpcmoveopt object

Override values for selected properties of the selected MPC controller, specified as an options object you create with `mpcmoveopt`. These options apply to the current `mpcmoveMultiple` time instant only. Using `options` yields the same result as redefining or modifying the selected controller before each call to `mpcmoveMultiple`, but involves considerably less overhead. Using `options` is equivalent to using a Multiple MPC Controllers Simulink block in combination with optional input signals that modify controller settings, such as MV and OV constraints.

Output Arguments**mv — Optimal manipulated variable moves**

column vector

Optimal manipulated variable moves, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the controller detects an infeasible optimization problem or encounters numerical difficulties in solving an ill-conditioned optimization problem, `mv` remains at its most recent successful solution, `x.LastMove`.

Otherwise, if the optimization problem is feasible and the solver reaches the specified maximum number of iterations without finding an optimal solution, `mv`:

- Remains at its most recent successful solution if the `Optimizer.UseSuboptimalSolution` property of the controller is `false`.
- Is the suboptimal solution reached after the final iteration if the `Optimizer.UseSuboptimalSolution` property of the controller is `true`. For more information, see “Suboptimal QP Solution”.

info — Solution details

structure

Solution details, returned as a structure with the following fields.

Uopt — Optimal manipulated variable sequence $(p+1)$ -by- N_{mv} array

Predicted optimal manipulated variable adjustments (moves), returned as a $(p+1)$ -by- N_{mv} array, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

`Uopt(i, :)` contains the calculated optimal values at time $k+i-1$, for $i = 1, \dots, p$, where k is the current time. The first row of `Info.Uopt` contains the same manipulated variable values as output argument `mv`. Since the controller does not calculate optimal control moves at time $k+p$, `Uopt(p+1, :)` is equal to `Uopt(p, :)`.

Yopt — Optimal output variable sequence $(p+1)$ -by- N_y array

Optimal output variable sequence, returned as a $(p+1)$ -by- N_y array, where p is the prediction horizon and N_y is the number of outputs.

The first row of `Info.Yopt` contains the calculated outputs at time k based on the estimated states and measured disturbances; it is not the measured output at time k . `Yopt(i, :)` contains the predicted output values at time $k+i-1$, for $i = 1, \dots, p+1$.

`Yopt(i, :)` contains the calculated output values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Yopt(1, :)` is computed based on the estimated states and measured disturbances.

Xopt — Optimal prediction model state sequence

$(p+1)$ -by- N_x array

Optimal prediction model state sequence, returned as a $(p+1)$ -by- N_x array, where p is the prediction horizon and N_x is the number of states in the plant and unmeasured disturbance models (states from noise models are not included).

`Xopt(i, :)` contains the calculated state values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Xopt(1, :)` is the same as the current states state values.

Topt — Time intervals

column vector of length $p+1$

Time intervals, returned as a column vector of length $p+1$. `Topt(1) = 0`, representing the current time. Subsequent time steps `Topt(i)` are given by $T_s * (i-1)$, where $T_s = \text{MPCobj.Ts}$ is the controller sample time.

Use `Topt` when plotting `Uopt`, `Xopt`, or `Yopt` sequences.

Slack — Slack variable

nonnegative scalar

Slack variable, ε , used in constraint softening, returned as $\mathbf{0}$ or a positive scalar value.

- $\varepsilon = 0$ — All constraints were satisfied for the entire prediction horizon.
- $\varepsilon > 0$ — At least one soft constraint is violated. When more than one constraint is violated, ε represents the worst-case soft constraint violation (scaled by your ECR values for each constraint).

See “Optimization Problem” for more information.

Iterations — Number of solver iterations

positive integer | $\mathbf{0}$ | -1 | -2

Number of solver iterations, returned as one of the following:

- Positive integer — Number of iterations needed to solve the optimization problem that determines the optimal sequences.
- $\mathbf{0}$ — Optimization problem could not be solved in the specified maximum number of iterations.
- -1 — Optimization problem was infeasible. An optimization problem is infeasible if no solution can satisfy all the hard constraints.
- -2 — Numerical error occurred when solving the optimization problem.

QPCode — Optimization solution status

'feasible' | 'infeasible' | 'unreliable'

Optimization solution status, returned as one of the following:

- 'feasible' — Optimal solution was obtained (`Iterations > 0`)
- 'infeasible' — Solver detected a problem with no feasible solution (`Iterations = -1`) or a numerical error occurred (`Iterations = -2`)
- 'unreliable' — Solver failed to converge (`Iterations = 0`). In this case, if `MPCobj.Optimizer.UseSuboptimalSolution` is `false`, `u` freezes at the most recent successful solution. Otherwise, it uses the suboptimal solution found during the last solver iteration.

Cost — Objective function cost

nonnegative scalar

Objective function cost, returned as a nonnegative scalar value. The cost quantifies the degree to which the controller has achieved its objectives. For more information, see “Optimization Problem”.

The cost value is only meaningful when `QPCode = 'feasible'`, or when `QPCode = 'feasible'` and `MPCobj.Optimizer.UseSuboptimalSolution` is `true`.

Tips

- Use the Multiple MPC Controllers Simulink block for simulations and code generation.

See Also

`generateExplicitMPC` | `getEstimator` | `mpcmove` | `mpcstate` | `review` | `setEstimator` | `sim`

Introduced in R2014b

mpcprops

Provide help on MPC controller properties

Syntax

mpcprops

Description

mpcprops displays details on the generic properties of MPC controllers. It provides a complete list of all the fields of MPC objects with a brief description of each field and the corresponding default values.

See Also

get | set

Introduced before R2006a

mpcqp solver

(To be removed) Solve a quadratic programming problem using the KWIK algorithm

Note mpcqp solver will be removed in a future release. Use `mpcActiveSetSolver` instead. For more information, see “Compatibility Considerations”.

Syntax

```
[x,status] = mpcqp solver(Linv,f,A,b,Aeq,beq,iA0,options)
[x,status,iA,lambda] = mpcqp solver(Linv,f,A,b,Aeq,beq,iA0,options)
```

Description

`[x,status] = mpcqp solver(Linv,f,A,b,Aeq,beq,iA0,options)` finds an optimal solution, x , to a quadratic programming problem by minimizing the objective function:

$$J = \frac{1}{2}x^T Hx + f^T x$$

subject to inequality constraints $Ax \geq b$, and equality constraints $A_{eq}x = b_{eq}$. `status` indicates the validity of x .

`[x,status,iA,lambda] = mpcqp solver(Linv,f,A,b,Aeq,beq,iA0,options)` also returns the active inequalities, `iA`, at the solution, and the Lagrange multipliers, `lambda`, for the solution.

Examples

Solve Quadratic Programming Problem Using Active-Set Solver

Find the values of x that minimize

$$f(x) = 0.5x_1^2 + x_2^2 - x_1x_2 - 2x_1 - 6x_2,$$

subject to the constraints

$$\begin{aligned} x_1 &\geq 0 \\ x_2 &\geq 0 \\ x_1 + x_2 &\leq 2 \\ -x_1 + 2x_2 &\leq 2 \\ 2x_1 + x_2 &\leq 3. \end{aligned}$$

Specify the Hessian and linear multiplier vector for the objective function.

$$\begin{aligned} H &= [1 \ -1; \ -1 \ 2]; \\ f &= [-2; \ -6]; \end{aligned}$$

Specify the inequality constraint parameters.

```
A = [1 0; 0 1; -1 -1; 1 -2; -2 -1];
b = [0; 0; -2; -2; -3];
```

Define Aeq and beq to indicate that there are no equality constraints.

```
Aeq = [];
beq = zeros(0,1);
```

Find the lower-triangular Cholesky decomposition of H.

```
[L,p] = chol(H, 'lower');
Linv = inv(L);
```

It is good practice to verify that H is positive definite by checking if $p = 0$.

```
p
p = 0
```

Create a default option set for mpcActiveSetSolver.

```
opt = mpcqpsolverOptions;
```

To cold start the solver, define all inequality constraints as inactive.

```
iA0 = false(size(b));
```

Solve the QP problem.

```
[x,status] = mpcqpsolver(Linv,f,A,b,Aeq,beq,iA0,opt);
```

Examine the solution, x.

```
x
x = 2×1
    0.6667
    1.3333
```

Check Active Inequality Constraints for QP Solution

Find the values of x that minimize

$$f(x) = 3x_1^2 + 0.5x_2^2 - 2x_1x_2 - 3x_1 + 4x_2,$$

subject to the constraints

$$\begin{aligned} x_1 &\geq 0 \\ x_1 + x_2 &\leq 5 \\ x_1 + 2x_2 &\leq 7. \end{aligned}$$

Specify the Hessian and linear multiplier vector for the objective function.

```
H = [6 -2; -2 1];  
f = [-3; 4];
```

Specify the inequality constraint parameters.

```
A = [1 0; -1 -1; -1 -2];  
b = [0; -5; -7];
```

Define Aeq and beq to indicate that there are no equality constraints.

```
Aeq = [];  
beq = zeros(0,1);
```

Find the lower-triangular Cholesky decomposition of H.

```
[L,p] = chol(H, 'lower');  
Linv = inv(L);
```

Verify that H is positive definite by checking if $p = \emptyset$.

```
p
```

```
p =  $\emptyset$ 
```

Create a default option set for `mpcqpsolver`.

```
opt = mpcqpsolverOptions;
```

To cold start the solver, define all inequality constraints as inactive.

```
iA0 = false(size(b));
```

Solve the QP problem.

```
[x,status,iA,lambda] = mpcqpsolver(Linv,f,A,b,Aeq,beq,iA0,opt);
```

Check the active inequality constraints. An active inequality constraint is at equality for the optimal solution.

```
iA
```

```
iA = 3x1 logical array
```

```
 1  
 0  
 0
```

There is a single active inequality constraint.

View the Lagrange multiplier for this constraint.

```
lambda.ineqlin(1)
```

ans = 5.0000

Input Arguments

Lin — Inverse of lower-triangular Cholesky decomposition of Hessian matrix

n-by-*n* matrix

Inverse of lower-triangular Cholesky decomposition of Hessian matrix, specified as an *n*-by-*n* matrix, where $n > 0$ is the number of optimization variables. For a given Hessian matrix, *H*, **Lin** can be computed as follows:

```
[L,p] = chol(H, 'lower');
Lin = inv(L);
```

H is an *n*-by-*n* matrix, which must be symmetric and positive definite. If $p = 0$, then *H* is positive definite.

Note The KWIK algorithm requires the computation of **Lin** instead of using *H* directly, as in the `quadprog` command.

f — Multiplier of objective function linear term

column vector

Multiplier of objective function linear term, specified as a column vector of length *n*.

A — Linear inequality constraint coefficients

m-by-*n* matrix | []

Linear inequality constraint coefficients, specified as an *m*-by-*n* matrix, where *m* is the number of inequality constraints.

If your problem has no inequality constraints, use [].

b — Right-hand side of inequality constraints

column vector of length *m*

Right-hand side of inequality constraints, specified as a column vector of length *m*.

If your problem has no inequality constraints, use `zeros(0,1)`.

Aeq — Linear equality constraint coefficients

q-by-*n* matrix | []

Linear equality constraint coefficients, specified as a *q*-by-*n* matrix, where *q* is the number of equality constraints, and $q \leq n$. Equality constraints must be linearly independent with $\text{rank}(\text{Aeq}) = q$.

If your problem has no equality constraints, use [].

beq — Right-hand side of equality constraints

column vector of length *q*

Right-hand side of equality constraints, specified as a column vector of length *q*.

If your problem has no equality constraints, use `zeros(0,1)`.

iA0 — Initial active inequalitieslogical vector of length m

Initial active inequalities, where the equal portion of the inequality is true, specified as a logical vector of length m according to the following:

- If your problem has no inequality constraints, use `false(0,1)`.
- For a *cold start*, `false(m,1)`.
- For a *warm start*, set `iA0(i) == true` to start the algorithm with the i th inequality constraint active. Use the optional output argument `iA` from a previous solution to specify `iA0` in this way. If both `iA0(i)` and `iA0(j)` are `true`, then rows i and j of A should be linearly independent. Otherwise, the solution can fail with `status = -2`.

options — Option set for mpcqpsolver

structure

Option set for `mpcqpsolver`, specified as a structure created using `mpcqpsolverOptions`.

Output Arguments**x — Optimal solution to the QP problem**

column vector

Optimal solution to the QP problem, returned as a column vector of length n . `mpcqpsolver` always returns a value for x . To determine whether the solution is optimal or feasible, check the solution `status`.

status — Solution validity indicator

positive integer | 0 | -1 | -2

Solution validity indicator, returned as an integer according to the following:

Value	Description
> 0	x is optimal. <code>status</code> represents the number of iterations performed during optimization.
0	The maximum number of iterations was reached. The solution, x , may be suboptimal or infeasible.
-1	The problem appears to be infeasible, that is, the constraint $Ax \geq b$ cannot be satisfied.
-2	An unrecoverable numerical error occurred.

iA — Active inequalitieslogical vector of length m

Active inequalities, where the equal portion of the inequality is true, returned as a logical vector of length m . If `iA(i) == true`, then the i th inequality is active for the solution x .

Use `iA` to *warm start* a subsequent `mpcqpsolver` solution.

lambda — Lagrange multipliers

structure

Lagrange multipliers, returned as a structure with the following fields:

Field	Description
<code>ineqlin</code>	Multipliers of the inequality constraints, returned as a vector of length n . When the solution is optimal, the elements of <code>ineqlin</code> are nonnegative.
<code>eqlin</code>	Multipliers of the equality constraints, returned as a vector of length q . There are no sign restrictions in the optimal solution.

Tips

- The KWIK algorithm requires that the Hessian matrix, H , be positive definite. When calculating `Lin`, use:

```
[L, p] = chol(H, 'lower');
```

If $p = 0$, then H is positive definite. Otherwise, p is a positive integer.

- `mpcqp solver` provides access to the QP solver used by Model Predictive Control Toolbox software. Use this command to solve QP problems in your own custom MPC applications.

Algorithms

`mpcqp solver` solves the QP problem using an active-set method, the KWIK algorithm, based on [1]. For more information, see “QP Solvers”.

Compatibility Considerations

mpcqp solver will be removed

Warns starting in R2020a

`mpcqp solver` will be removed in a future release. Use `mpcActiveSetSolver` instead. There are differences between these functions that require updates to your code.

Update Code

The following differences require updates to your code:

- For `mpcActiveSetSolver`, you define inequality constraints in the form $Ax \leq b$. Previously, for `mpcqp solver`, you defined inequality constraints in the form $Ax \geq b$.
- For `mpcActiveSetSolver`, you specify solver options with a structure created using the `mpcActiveSetOptions` function. Previously, for `mpcqp solver`, you created an option structure using the `mpcqp solverOptions` function. These option structures contain the same options, though some option names have changed.
- By default, you pass the Hessian matrix to `mpcActiveSetSolver`. Previously, you passed the inverse of lower-triangular Cholesky decomposition (`Lin`) of the Hessian matrix to `mpcqp solver`. To continue to use `Lin`, set the `UseHessianAsInput` field of the structure returned by `mpcActiveSetSolver` to `false`.
- When your QP problem has either no inequality constraints or no equality constraints, the corresponding `A` or `Aeq` input argument to `mpcActiveSetSolver` must be `zeros(0, n)`, where n is the number of decision variables. Previously, for `mpcqp solver`, you specified these input arguments as `[]`.

This table shows some typical usages of `mpcqp solver` and how to update your code to use `mpcActiveSetSolver` instead.

Not Recommended	Recommended
<pre>opt = mpcqpsolverOptions; [x,status] = mpcqpsolver(Linv,f,A,b,... Aeq,beq,iA0,opt);</pre>	<pre>opt = mpcActiveSetOptions; opt.UseHessianAsInput = false; [x,status] = mpcActiveSetSolver(Linv,f,... -A,-b,Aeq,beq,iA0,opt);</pre> <p>Alternatively, you can use the Hessian matrix, H.</p> <pre>opt = mpcActiveSetOptions; [x,status] = mpcActiveSetSolver(H,f,... -A,-b,Aeq,beq,iA0,opt);</pre>
<pre>opt = mpcqpsolverOptions('single'); [x,status] = mpcqpsolver(Linv,f,A,b,... Aeq,beq,iA0,opt);</pre>	<pre>opt = mpcActiveSetOptions('single'); opt.UseHessianAsInput = false; [x,status] = mpcActiveSetSolver(Linv,f,... -A,-b,Aeq,beq,iA0,opt);</pre>
<pre>opt = mpcqpsolverOptions; opt.MaxIter = 300; opt.FeasibilityTol = 1e-5; [x,status] = mpcqpsolver(Linv,f,A,b,... Aeq,beq,iA0,opt);</pre>	<pre>opt = mpcActiveSetOptions; opt.UseHessianAsInput = false; opt.MaxIterations = 300; opt.ConstraintTolerance = 1e-5; [x,status] = mpcActiveSetSolver(Linv,f,... -A,-b,Aeq,beq,iA0,opt);</pre>
<pre>[x,status] = mpcqpsolver(Linv,f,[],... zeros(0,1),Aeq,beq,iA0,opt);</pre>	<pre>n = length(f); opt.UseHessianAsInput = false; [x,status] = mpcActiveSetSolver(Linv,f,... zeros(0,n),zeros(0,1),Aeq,beq,iA0,opt);</pre>
<pre>[x,status] = mpcqpsolver(Linv,f,A,b,... [],zeros(0,1),iA0,opt);</pre>	<pre>n = length(f); opt.UseHessianAsInput = false; [x,status] = mpcActiveSetSolver(Linv,f,... -A,-b,zeros(0,n),zeros(0,1),iA0,opt);</pre>

References

- [1] Schmid, C., and L.T. Biegler. 'Quadratic Programming Methods for Reduced Hessian SQP'. *Computers & Chemical Engineering* 18, no. 9 (September 1994): 817-32. [https://doi.org/10.1016/0098-1354\(94\)E0001-4](https://doi.org/10.1016/0098-1354(94)E0001-4).

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- You can use `mpcqpsolver` as a general-purpose QP solver that supports code generation. Create the function `myCode` that uses `mpcqpsolver`.

```
function [out1,out2] = myCode(in1,in2)
    %#codegen
    ...
    [x,status] = mpcqpsolver(Linv,f,A,b,Aeq,Beq,iA0,options);
    ...
```

Generate C code with MATLAB Coder.

```
func = 'myCode';  
cfg = coder.config('mex'); % or 'lib', 'dll'  
codegen('-config',cfg,func,'-o',func);
```

- For code generation, use the same precision for all real inputs, including options. Configure the precision as 'double' or 'single' using `mpcqsolverOptions`.

See Also

`mpcActiveSetOptions` | `mpcActiveSetSolver` | `mpcqsolverOptions`

Topics

“QP Solvers”

Introduced in R2015b

mpcqpSolverOptions

(To be removed) Create default option set for `mpcqpSolver`

Note `mpcqpSolverOptions` will be removed in a future release. Use `mpcActiveSetOptions` instead. For more information, see “Compatibility Considerations”.

Syntax

```
options = mpcqpSolverOptions
options = mpcqpSolverOptions(type)
```

Description

`options = mpcqpSolverOptions` creates a structure of default options for `mpcqpSolver`, which solves a quadratic programming (QP) problem using the KWIK algorithm.

`options = mpcqpSolverOptions(type)` creates a default option set using the specified input data type. All real options are specified using this data type.

Examples

Create Default Option Set for MPC QP Solver

```
opt = mpcqpSolverOptions;
```

Create and Modify Default MPC QP Solver Option Set

Create default option set.

```
opt = mpcqpSolverOptions;
```

Specify the maximum number of iterations allowed during computation.

```
opt.MaxIter = 100;
```

Specify a feasibility tolerance for verifying that the optimal solution satisfies the inequality constraints.

```
opt.FeasibilityTol = 1.0e-3;
```


Create Option Set Specifying Input Argument Type

```
opt = mpcqpsolverOptions('single');
```

Input Arguments

type — MPC QP solver input argument data type

'double' (default) | 'single'

MPC QP solver input argument data type, specified as either 'double' or 'single'. This data type is used for both simulation and code generation. All real options in the option set are specified using this data type, and all real input arguments to `mpcqpsolver` must match this type.

Output Arguments

options — Option set for mpcqpsolver

structure

Option set for `mpcqpsolver`, returned as a structure with the following fields:

Field	Description	Default
DataType	Input argument data type, specified as either 'double' or 'single'. This data type is used for both simulation and code generation, and all real input arguments to <code>mpcqpsolver</code> must match this type.	'double'
MaxIter	Maximum number of iterations allowed when computing the QP solution, specified as a positive integer.	200
FeasibilityTol	Tolerance used to verify that inequality constraints are satisfied by the optimal solution, specified as a positive scalar. A larger <code>FeasibilityTol</code> value allows for larger constraint violations.	1.0e-6
IntegrityChecks	Indicator of whether integrity checks are performed on the <code>mpcqpsolver</code> input data, specified as a logical value. If <code>IntegrityChecks</code> is true, then integrity checks are performed and diagnostic messages are displayed. Use false for code generation only.	true

Compatibility Considerations

mpcqpsolverOptions will be removed

Warns starting in R2020a

`mpcqpsolverOptions` will be removed in a future release. Use `mpcActiveSetOptions` instead. There are differences between these functions that require updates to your code.

Update Code

To update your code:

- Change the function name from `mpcqpsolverOptions` to `mpcActiveSetOptions`. The syntaxes are equivalent.
- Some field names of the returned structure have changed. The default field values are the same. This table shows the new property names.

Previous Property Name	New Property Name
MaxIter	MaxIterations
FeasibilityTol	ConstraintTolerance

- The returned structure of `mpcActiveSetOptions` contains the new field `UseHessianAsInput`. To continue to use the inverse of the lower-triangular decomposition of the Hessian matrix with `mpcActiveSetSolver`, you must set `UseHessianAsInput` to `false`.

For syntax examples showing how to update your code, see `mpcqpsolver`.

See Also

`mpcActiveSetOptions` | `mpcActiveSetSolver` | `mpcqpsolver`

Introduced in R2015b

mpcverbosity

Change toolbox verbosity level

Syntax

```
mpcverbosity on  
mpcverbosity off  
old_status = mpcverbosity(new_status)  
mpcverbosity
```

Description

`mpcverbosity on` enables messages displaying default operations taken by Model Predictive Control Toolbox software during the creation and manipulation of model predictive control objects.

`mpcverbosity off` turns messages off.

`old_status = mpcverbosity(new_status)` sets the verbosity level to the specified value, `new_status`. The function returns the original value of the verbosity level as `old_status`. Specify `new_status` as either 'on' or 'off' .

`mpcverbosity` shows the verbosity status.

By default, messages are turned on.

See Also

`mpc`

Introduced before R2006a

nlpmove

Compute optimal control action for nonlinear MPC controller

Syntax

```
mv = nlpmove(nlmpcobj,x,lastmv)
mv = nlpmove(nlmpcobj,x,lastmv,ref)
mv = nlpmove(nlmpcobj,x,lastmv,ref,md)
mv = nlpmove(nlmpcobj,x,lastmv,ref,md,options)
[mv,opt] = nlpmove(____)
[mv,opt,info] = nlpmove(____)
```

Description

`mv = nlpmove(nlmpcobj,x,lastmv)` computes the optimal manipulated variable control action for the current time. To simulate closed-loop nonlinear MPC control, call `nlpmove` repeatedly.

`mv = nlpmove(nlmpcobj,x,lastmv,ref)` specifies reference values for the plant outputs. If you do not specify reference values, `nlpmove` uses zeros by default.

`mv = nlpmove(nlmpcobj,x,lastmv,ref,md)` specifies run-time measured disturbance values. If your controller has measured disturbances, you must specify `md`.

`mv = nlpmove(nlmpcobj,x,lastmv,ref,md,options)` specifies additional run-time options for computing optimal control moves. Using `options`, you can specify initial guesses for state and manipulated variable trajectories, update tuning weights at constraints, or modify prediction model parameters.

`[mv,opt] = nlpmove(____)` returns an `nlpmoveopt` object that contains initial guesses for the state and manipulated trajectories to be used in the next control interval.

`[mv,opt,info] = nlpmove(____)` returns additional solution details, including the final optimization cost function value and the optimal manipulated variable, state, and output trajectories.

Examples

Plan Optimal Trajectory Using Nonlinear MPC

Create nonlinear MPC controller with six states, six outputs, and four inputs.

```
nx = 6;
ny = 6;
nu = 4;
nlobj = nlpmove(nlmpcobj,x,lastmv,ref,md,options);
```

In standard cost function, zero weights are applied by default to one or more OVs because there a

Specify the controller sample time and horizons.

```
Ts = 0.4;
p = 30;
```

```

c = 4;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = p;
nlobj.ControlHorizon = c;

```

Specify the prediction model state function and the Jacobian of the state function. For this example, use a model of a flying robot.

```

nlobj.Model.StateFcn = "FlyingRobotStateFcn";
nlobj.Jacobian.StateFcn = "FlyingRobotStateJacobianFcn";

```

Specify a custom cost function for the controller that replaces the standard cost function.

```

nlobj.Optimization.CustomCostFcn = @(X,U,e,data) Ts*sum(sum(U(1:p,:)));
nlobj.Optimization.ReplaceStandardCost = true;

```

Specify a custom constraint function for the controller.

```

nlobj.Optimization.CustomEqConFcn = @(X,U,data) X(end,:)';

```

Specify linear constraints on the manipulated variables.

```

for ct = 1:nu
    nlobj.MV(ct).Min = 0;
    nlobj.MV(ct).Max = 1;
end

```

Validate the prediction model and custom functions at the initial states (x_0) and initial inputs (u_0) of the robot.

```

x0 = [-10;-10;pi/2;0;0;0];
u0 = zeros(nu,1);
validateFcns(nlobj,x0,u0);

```

```

Model.StateFcn is OK.
Jacobian.StateFcn is OK.
No output function specified. Assuming "y = x" in the prediction model.
Optimization.CustomCostFcn is OK.
Optimization.CustomEqConFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.

```

Compute the optimal state and manipulated variable trajectories, which are returned in the `info`.

```

[~,~,info] = nlmpcmove(nlobj,x0,u0);

```

Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard.

Plot the optimal trajectories.

```

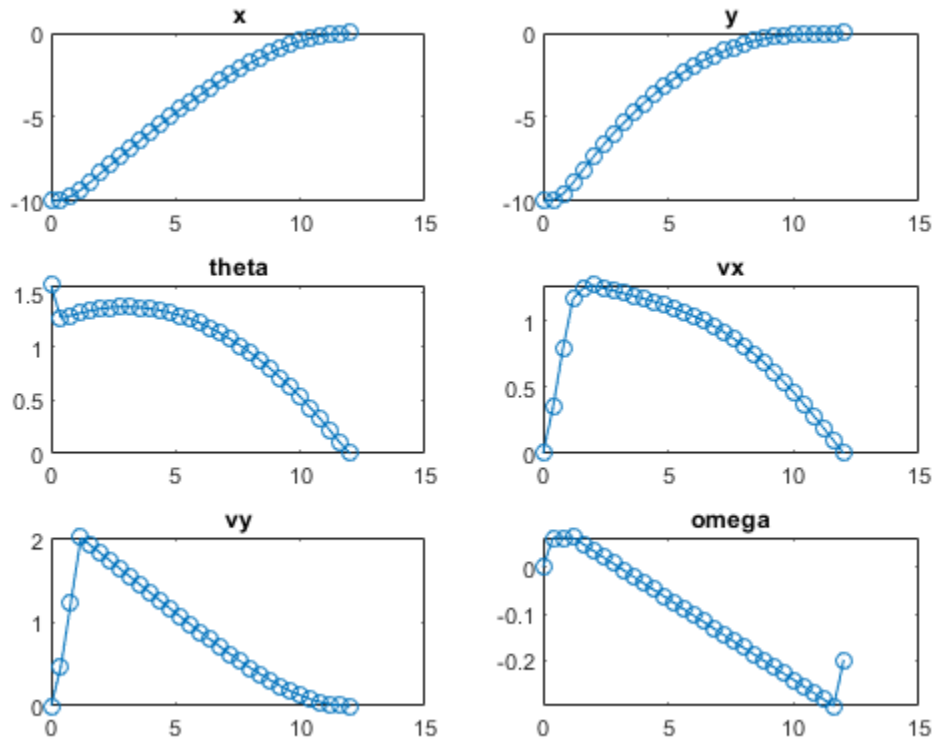
FlyingRobotPlotPlanning(info)

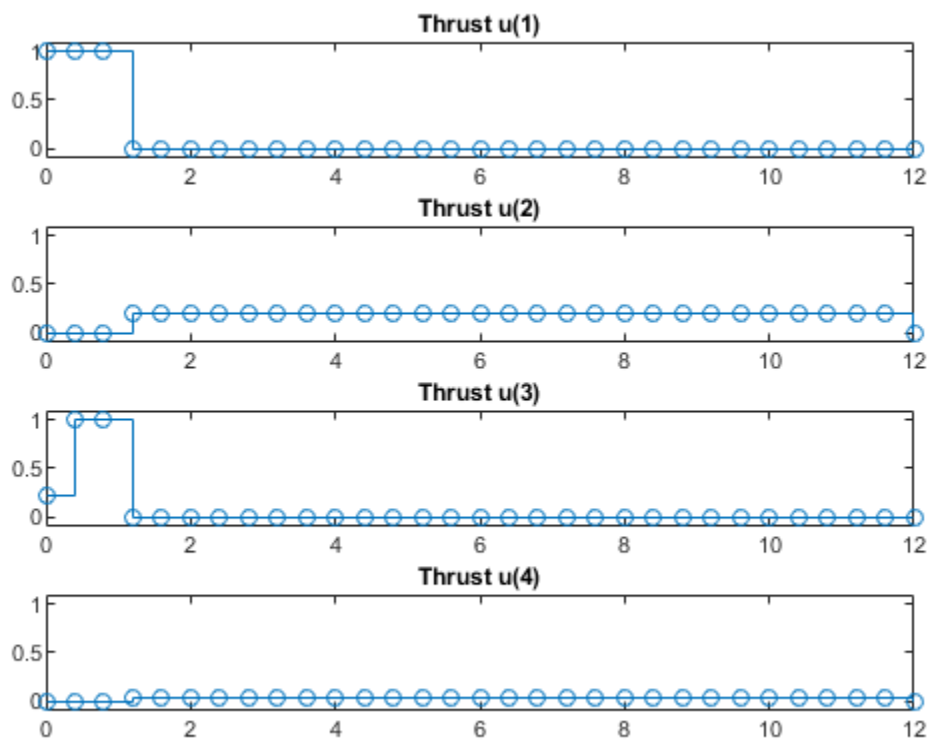
```

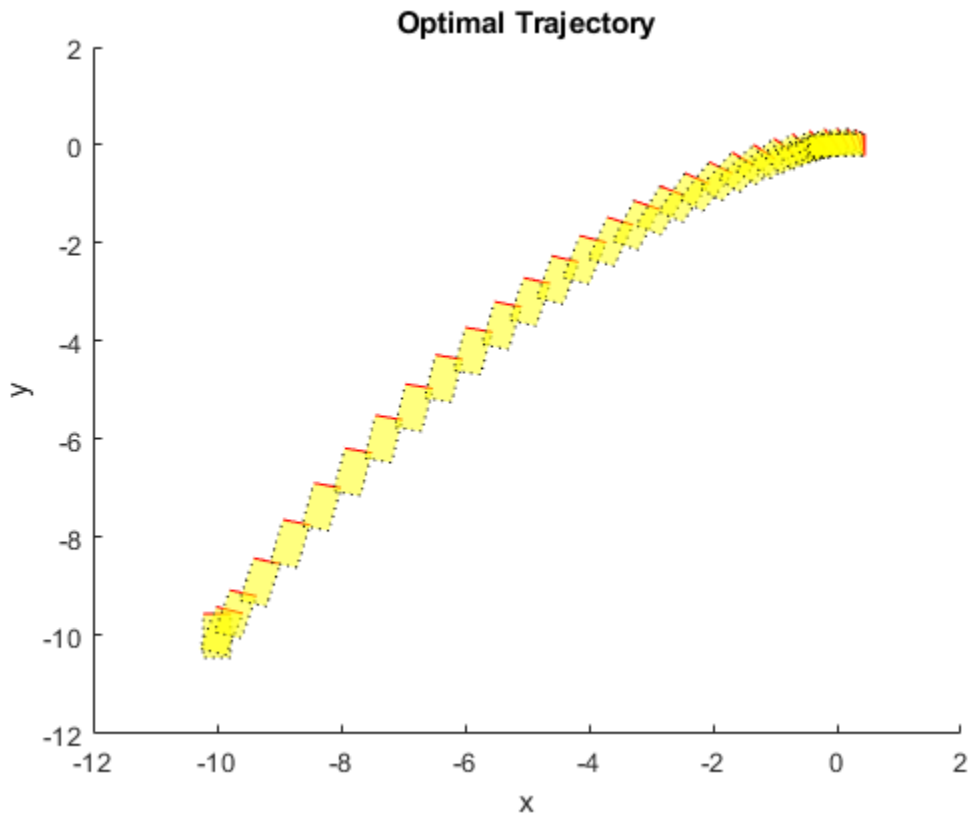
```

Optimal fuel consumption = 4.712383

```







Simulate Closed-Loop Control using Nonlinear MPC Controller

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nlobj = nlmpc(4,2,1);
```

In standard cost function, zero weights are applied by default to one or more OVs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The prediction model uses an optional parameter, `Ts`, to represent the sample time. Specify the number of parameters.


```
nlobj.Model.NumberOfParameters = 1;
```

Specify the output function of the model, passing the sample time parameter as an input argument.

```
nlobj.Model.OutputFcn = @(x,u,Ts) [x(1); x(3)];
```

Define standard constraints for the controller.

```
nlobj.Weights.OutputVariables = [3 3];
nlobj.Weights.ManipulatedVariablesRate = 0.1;
nlobj.OV(1).Min = -10;
nlobj.OV(1).Max = 10;
nlobj.MV.Min = -100;
nlobj.MV.Max = 100;
```

Validate the prediction model functions.

```
x0 = [0.1;0.2;-pi/2;0.3];
u0 = 0.4;
validateFcns(nlobj, x0, u0, [], {Ts});
```

```
Model.StateFcn is OK.
```

```
Model.OutputFcn is OK.
```

```
Analysis of user-provided model, cost, and constraint functions complete.
```

Only two of the plant states are measurable. Therefore, create an extended Kalman filter for estimating the four plant states. Its state transition function is defined in `pendulumStateFcn.m` and its measurement function is defined in `pendulumMeasurementFcn.m`.

```
EKF = extendedKalmanFilter(@pendulumStateFcn,@pendulumMeasurementFcn);
```

Define initial conditions for the simulation, initialize the extended Kalman filter state, and specify a zero initial manipulated variable value.

```
x = [0;0;-pi;0];
y = [x(1);x(3)];
EKF.State = x;
mv = 0;
```

Specify the output reference value.

```
yref = [0 0];
```

Create an `nlmpcmoveopt` object, and specify the sample time parameter.

```
nloptions = nlmpcmoveopt;
nloptions.Parameters = {Ts};
```

Run the simulation for 10 seconds. During each control interval:

- 1 Correct the previous prediction using the current measurement.
- 2 Compute optimal control moves using `nlmpcmove`. This function returns the computed optimal sequences in `nloptions`. Passing the updated options object to `nlmpcmove` in the next control interval provides initial guesses for the optimal sequences.
- 3 Predict the model states.
- 4 Apply the first computed optimal control move to the plant, updating the plant states.

- 5 Generate sensor data with white noise.
- 6 Save the plant states.

```

Duration = 10;
xHistory = x;
for ct = 1:(Duration/Ts)
    % Correct previous prediction
    xk = correct(EKF,y);
    % Compute optimal control moves
    [mv,nloptions] = nlmpcmove(nlobj,xk,mv,yref,[],nloptions);
    % Predict prediction model states for the next iteration
    predict(EKF,[mv; Ts]);
    % Implement first optimal control move
    x = pendulumDT0(x,mv,Ts);
    % Generate sensor data
    y = x([1 3]) + randn(2,1)*0.01;
    % Save plant states
    xHistory = [xHistory x];
end

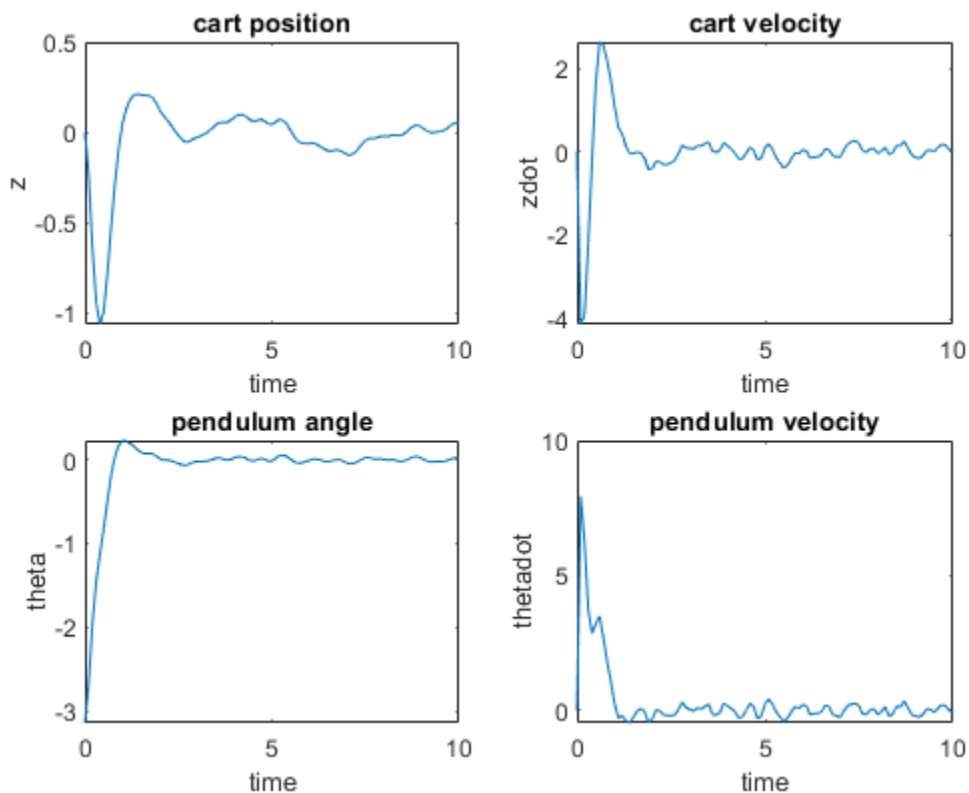
```

Plot the resulting state trajectories.

```

figure
subplot(2,2,1)
plot(0:Ts:Duration,xHistory(1,:))
xlabel('time')
ylabel('z')
title('cart position')
subplot(2,2,2)
plot(0:Ts:Duration,xHistory(2,:))
xlabel('time')
ylabel('zdot')
title('cart velocity')
subplot(2,2,3)
plot(0:Ts:Duration,xHistory(3,:))
xlabel('time')
ylabel('theta')
title('pendulum angle')
subplot(2,2,4)
plot(0:Ts:Duration,xHistory(4,:))
xlabel('time')
ylabel('thetadot')
title('pendulum velocity')

```



Input Arguments

nlmpcobj — Nonlinear MPC controller

nlmpc object

Nonlinear MPC controller, specified as an nlmpc object.

x — Current prediction model states

vector

Current prediction model states, specified as a vector of length N_x , where N_x is the number of prediction model states. Since the nonlinear MPC controller does not perform state estimation, you must either measure or estimate the current prediction model states at each control interval. For more information on nonlinear MPC prediction models, see “Specify Prediction Model for Nonlinear MPC”.

lastmv — Control signals used in plant at previous control interval

vector

Control signals used in plant at previous control interval, specified as a vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

Note Specify `lastmv` as the manipulated variable signals applied to the plant in the previous control interval. Typically, these signals are the values generated by the controller, though this is not always

the case. For example, if your controller is offline and running in tracking mode; that is, the controller output is not driving the plant, then feeding the actual control signal to `last_mv` can help achieve bumpless transfer when the controller is switched back online.

ref — Plant output reference values

`[]` (default) | row vector | array

Plant output reference values, specified as a row vector of length N_y or an array with N_y columns, where N_y is the number of output variables. If you do not specify `ref`, the default reference values are zero.

To use the same reference values across the prediction horizon, specify a row vector.

To vary the reference values over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the reference values for one prediction horizon step. If you specify fewer than p rows, the values in the final row are used for the remaining steps of the prediction horizon.

md — Measured disturbance values

`[]` (default) | row vector | array

Measured disturbance values, specified as a row vector of length N_{md} or an array with N_{md} columns, where N_{md} is the number of measured disturbances. If your controller has measured disturbances, you must specify `md`. If your controller has no measured disturbances, specify `md` as `[]`.

To use the same disturbance values across the prediction horizon, specify a row vector.

To vary the disturbance values over the prediction horizon from time k to time $k+p$, specify an array with up to $p+1$ rows. Here, k is the current time and p is the prediction horizon. Each row contains the disturbance values for one prediction horizon step. If you specify fewer than p rows, the values in the final row are used for the remaining steps of the prediction horizon.

options — Run-time options

`nlpmoveopt` object

Run-time options, specified as an `nlpmoveopt` object. Using these options, you can:

- Tune controller weights
- Update linear constraints
- Set manipulated variable targets
- Specify prediction model parameters
- Provide initial guesses for state and manipulated variable trajectories

These options apply to only the current `nlpmove` time instant.

To improve solver efficiency, it is best practice to specify initial guesses for the state and manipulated variable trajectories.

Output Arguments

mv — Optimal manipulated variable control action

column vector

Optimal manipulated variable control action, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the solver converges to a local optimum solution (`info.ExitFlag` is positive), then `mv` contains the optimal solution.

If the solver reaches the maximum number of iterations without finding an optimal solution (`info.ExitFlag = 0`) and:

- `nlmpcobj.Optimization.UseSuboptimalSolution` is true, then `mv` contains the suboptimal solution
- `nlmpcobj.Optimization.UseSuboptimalSolution` is false, then `mv` contains `lastmv`

If the solver fails (`info.ExitFlag` is negative), then `mv` contains `lastmv`.

opt — Run-time options with initial guesses

nlmpcmoveopt object

Run-time options with initial guesses for the state and manipulated variable trajectories to be used in the next control interval, returned as an `nlmpcmoveopt` object. Any run-time options that you specified using `options`, such as weights, constraints, or parameters, are copied to `opt`.

The initial guesses for the states (`opt.X0`) and manipulated variables (`opt.MV0`) are the optimal trajectories computed by `nlmpcmove` and correspond to the last $p-1$ rows of `info.Xopt` and `info.MVopt`, respectively.

To use these initial guesses in the next control interval, specify `opt` as the `options` input argument to `nlmpcmove`.

info — Solution details

structure

Solution details, returned as a structure with the following fields.

MVopt — Optimal manipulated variable sequence

array

Optimal manipulated variable sequence, returned as a $(p+1)$ -by- N_{mv} array, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

`MVopt(i, :)` contains the calculated optimal manipulated variable values at time $k+i-1$, for $i = 1, \dots, p$, where k is the current time. `MVopt(1, :)` contains the same manipulated variable values as output argument `mv`. Since the controller does not calculate optimal control moves at time $k+p$, `MVopt(p+1, :)` is equal to `MVopt(p, :)`.

Xopt — Optimal prediction model state sequence

array

Optimal prediction model state sequence, returned as a $(p+1)$ -by- N_x array, where p is the prediction horizon and N_x is the number of states in the prediction model.

`Xopt(i, :)` contains the calculated state values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Xopt(1, :)` is the same as the current states in `x`.

Yopt — Optimal output variable sequence

array

Optimal output variable sequence, returned as a $(p+1)$ -by- N_y array, where p is the prediction horizon and N_y is the number of outputs.

`Yopt(i, :)` contains the calculated output values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. `Yopt(1, :)` is computed based on the current states in `x` and the current measured disturbances in `md`, if any.

Topt — Prediction horizon time sequence

column vector

Prediction horizon time sequence, returned as a column vector of length $p+1$, where p is the prediction horizon. `Topt` contains the time sequence from time k to time $k+p$, where k is the current time.

`Topt(1) = 0` represents the current time. Subsequent time steps `Topt(i)` are $T_s \cdot (i-1)$, where T_s is the controller sample time.

Use `Topt` when plotting the `MVopt`, `Xopt`, or `Yopt` sequences.

Slack — Slack variable

nonnegative scalar

Slack variable, ε , used in constraint softening, returned as a nonnegative scalar value.

- $\varepsilon = 0$ — All soft constraints are satisfied over the entire prediction horizon.
- $\varepsilon > 0$ — At least one soft constraint is violated. When more than one constraint is violated, ε represents the worst-case soft constraint violation (scaled by your ECR values for each constraint).

ExitFlag — Optimization exit code

integer

Optimization exit code, returned as one of the following:

- Positive Integer — Optimal solution found
- 0 — Feasible suboptimal solution found after the maximum number of iterations
- Negative integer — No feasible solution found

Cost — Objective function cost

nonnegative scalar

Objective function cost, returned as a nonnegative scalar value. The cost quantifies the degree to which the controller has achieved its objectives.

The cost value is only meaningful when `ExitFlag` is nonnegative.

Tips

During closed-loop simulations, it is best practice to *warm start* the nonlinear solver by using the predicted state and manipulated variable trajectories from the previous control interval as the initial guesses for the current control interval. To use these trajectories as initial guesses:

- 1 Return the `opt` output argument when calling `nlmpcmove`. This `nlmpcmoveopt` object contains any run-time options you specified in the previous call to `nlmpcmove`, along with the initial guesses for the state (`opt.X0`) and manipulated variable (`opt.MV0`) trajectories.
- 2 Pass this object in as the `options` input argument to `nlmpcmove` for the next control interval.

These steps are a best practice, even if you do not specify any other run-time options.

See Also

`nlmpc` | `nlmpcmoveopt`

Topics

“Nonlinear MPC”

“Trajectory Optimization and Control of Flying Robot Using Nonlinear MPC”

Introduced in R2018b

nlpmoveCodeGeneration

Compute nonlinear MPC control moves with code generation support

Syntax

```
[mv,newOnlineData] = nlpmoveCodeGeneration(coreData,x,lastMV,onlineData)
[ ____,info] = nlpmoveCodeGeneration( ____ )
```

Description

`[mv,newOnlineData] = nlpmoveCodeGeneration(coreData,x,lastMV,onlineData)` computes optimal nonlinear MPC control moves and supports code generation for deployment to real-time targets. Control moves are calculated using the current prediction model states (x), the control moves from the previous control interval (`lastMV`), and input data structures (`coreData` and `nlonlineData`) generated using `getCodeGenerationData`.

`nlpmoveCodeGeneration` does not check input arguments for correct dimensions and data types.

`[____,info] = nlpmoveCodeGeneration(____)` returns additional information about the optimization result, including the number of iterations and the objective function cost.

Examples

Compute Nonlinear MPC Control Moves Using Code Generation Data Structures

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nlobj = nlpmove(4,2,1);
```

In standard cost function, zero weights are applied by default to one or more OVs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The prediction model uses an optional parameter, `Ts`, to represent the sample time. Specify the number of parameters and create a parameter vector.

```
nlobj.Model.NumberOfParameters = 1;
params = {Ts};
```


Specify the output function of the model, passing the sample time parameter as an input argument.

```
nlobj.Model.OutputFcn = "pendulumOutputFcn";
```

Define standard constraints for the controller.

```
nlobj.Weights.OutputVariables = [3 3];
nlobj.Weights.ManipulatedVariablesRate = 0.1;
nlobj.OV(1).Min = -10;
nlobj.OV(1).Max = 10;
nlobj.MV.Min = -100;
nlobj.MV.Max = 100;
```

Validate the prediction model functions.

```
x0 = [0.1;0.2;-pi/2;0.3];
u0 = 0.4;
validateFcns(nlobj,x0,u0,[],params);
```

```
Model.StateFcn is OK.
```

```
Model.OutputFcn is OK.
```

```
Analysis of user-provided model, cost, and constraint functions complete.
```

Only two of the plant states are measurable. Therefore, create an extended Kalman filter for estimating the four plant states. Its state transition function is defined in `pendulumStateFcn.m` and its measurement function is defined in `pendulumMeasurementFcn.m`.

```
EKF = extendedKalmanFilter(@pendulumStateFcn,@pendulumMeasurementFcn);
```

Define initial conditions for the simulation, initialize the extended Kalman filter state, and specify a zero initial manipulated variable value.

```
x0 = [0;0;-pi;0];
y0 = [x0(1);x0(3)];
EKF.State = x0;
mv0 = 0;
```

Create code generation data structures for the controller, specifying the initial conditions and parameters.

```
[coreData,onlineData] = getCodeGenerationData(nlobj,x0,mv0,params);
```

Specify the output reference value in the online data structure.

```
onlineData.ref = [0 0];
```

To verify the controller operation, run a simulation for 10 seconds. During each control interval:

- 1 Correct the previous prediction using the current measurement.
- 2 Compute optimal control moves using `nImpcmoveCodeGeneration`. This function returns the computed optimal sequences in `onlineData`. Passing the updated data structure to `nImpcmoveCodeGeneration` in the next control interval provides initial guesses for the optimal sequences.
- 3 Predict the model states.
- 4 Apply the first computed optimal control move to the plant, updating the plant states.
- 5 Generate sensor data with white noise.

6 Save the plant states.

```

mv = mv0;
y = y0;
x = x0;
Duration = 10;
xHistory = x0;
for ct = 1:(Duration/Ts)
    % Correct previous prediction
    xk = correct(EKF,y);
    % Compute optimal control move
    [mv,onlineData] = nlmpcmoveCodeGeneration(coreData,xk,mv,onlineData);
    % Predict prediction model states for the next iteration
    predict(EKF,[mv; Ts]);
    % Implement first optimal control move
    x = pendulumDT0(x,mv,Ts);
    % Generate sensor data
    y = x([1 3]) + randn(2,1)*0.01;
    % Save plant states
    xHistory = [xHistory x];
end

```

Generate a MEX function with MATLAB® Coder™, specifying `coreData` as a constant.

```

func = 'nlmpcmoveCodeGeneration';
funcOutput = 'nlmpcmoveMEX';
Cfg = coder.config('mex');
Cfg.DynamicMemoryAllocation = 'off';
codegen('-config',Cfg,func,'-o',funcOutput,'-args',...
    {coder.Constant(coreData),xk,mv,onlineData});

```

Input Arguments

coreData — Nonlinear MPC configuration parameters

structure

Nonlinear MPC configuration parameters that are constant at run time, specified as a structure generated using `getCodeGenerationData`.

Note When using `codegen`, `coreData` must be defined as `coder.Constant`.

x — Current prediction model states

column vector

Current prediction model states, specified as a vector of length N_x , where N_x is the number of prediction model states. The prediction model state function is defined in `nlobj.Model.StateFcn`.

Since the nonlinear MPC controller does not perform state estimation, you must either measure or estimate the current prediction model states at each control interval. For more information on nonlinear MPC prediction models, see “Specify Prediction Model for Nonlinear MPC”.

lastMV — Control signals used in plant at previous control interval

column vector

Control signals used in plant at previous control interval, specified as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

Note Specify `lastMV` as the manipulated variable signals applied to the plant in the previous control interval. Typically, these signals are the values generated by the controller (`mv`). However, this is not always the case. For example, if your controller is offline and running in tracking mode; that is, the controller output is not driving the plant, then feeding the actual control signal to `last_mv` can help achieve bumpless transfer when the controller is switched back online.

onlineData — Online controller data

structure

Online controller data that you must update at run time, specified as a structure with the following fields. Generate the initial structure using `getCodeGenerationData`. Some structure fields are not required, depending on the configuration of the controller and what weights or constraints vary at run time.

ref — Output reference values

row vector | array

Plant output reference values, specified as a row vector of length N_y or an array with N_y columns, where N_y is the number of output variables.

To use the same reference values across the prediction horizon, specify a row vector.

To vary the reference values over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the reference values for one prediction horizon step. If you specify fewer than p rows, the values in the final row are used for the remaining steps of the prediction horizon.

If your controller cost function does not use `ref`, leave `ref` at its default value.

mvTarget — Manipulated variable targets

row vector | array

Manipulated variable targets, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables.

To use the same manipulated variable targets across the prediction horizon, specify a row vector.

To vary the targets over the prediction horizon (previewing) from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the targets for one prediction horizon step. If you specify fewer than p rows, the final targets are used for the remaining steps of the prediction horizon.

If your controller cost function does not use `mvTarget`, leave `mvTarget` at its default value.

X0 — Initial guesses for the optimal state solutions

vector | array

Initial guesses for the optimal state solutions, specified as a row vector of length N_x or an array with N_x columns, where N_x is the number of states.

To use the same initial guesses across the prediction horizon, specify a row vector.

To vary the initial guesses over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the initial guesses for one prediction horizon step. If you specify fewer than p rows, the final guesses are used for the remaining steps of the prediction horizon.

In general, during closed-loop simulation, you do not specify $X\theta$ yourself. Instead, when calling `nlpmoveCodeGeneration`, return the `newOnlineData` output argument, which contains updated $X\theta$ estimates. You can then pass `newOnlineData` in as the `onlineData` input argument to `nlpmoveCodeGeneration` for the next control interval.

MV0 — Initial guesses for the optimal manipulated variable solutions

vector | array

Initial guesses for the optimal manipulated variable solutions, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables.

To use the same initial guesses across the prediction horizon, specify a row vector.

To vary the initial guesses over the prediction horizon from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the initial guesses for one prediction horizon step. If you specify fewer than p rows, the final guesses are used for the remaining steps of the prediction horizon.

In general, during closed-loop simulation, you do not specify $MV\theta$ yourself. Instead, when calling `nlpmoveCodeGeneration`, return the `newOnlineData` output argument, which contains updated $MV\theta$ estimates. You can then pass `newOnlineData` in as the `onlineData` input argument to `nlpmoveCodeGeneration` for the next control interval.

Slack0 — Initial guess for the slack variable at the solution

nonnegative scalar

Initial guess for the slack variable at the solution, specified as a nonnegative scalar.

In general, during closed-loop simulation, you do not specify `Slack0` yourself. Instead, when calling `nlpmoveCodeGeneration`, return the `newOnlineData` output argument, which contains updated `Slack0` estimates. You can then pass `newOnlineData` in as the `onlineData` input argument to `nlpmoveCodeGeneration` for the next control interval.

md — Measured disturbance values

row vector | array

Measured disturbance values, specified as a row vector of length N_{md} or an array with N_{md} columns, where N_{md} is the number of measured disturbances. If your controller has measured disturbances, you must specify `md`. If your controller has no measured disturbances, then `getCodeGenerationData` omits this field.

To use the same disturbance values across the prediction horizon, specify a row vector.

To vary the disturbance values over the prediction horizon from time k to time $k+p$, specify an array with up to $p+1$ rows. Here, k is the current time and p is the prediction horizon. Each row contains the disturbance values for one prediction horizon step. If you specify fewer than p rows, the values in the final row are used for the remaining steps of the prediction horizon.

Parameters — Parameter values

cell vector

Parameter values used by the prediction model, custom cost function, and custom constraints, specified as a cell vector with length equal to the `Model.NumberOfParameters` property of the controller. If the controller has no parameters, then `getCodeGenerationData` omits this field.

The order of the parameters must match the order defined for the prediction model, custom cost function, and custom constraints.

OutputWeights — Output variable tuning weights

row vector | array

Output variable tuning weights that replace the default tuning weights at run time, specified as a row vector of length N_y or an array with N_y columns, where N_y is the number of output variables. If you expect your output variable weights to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same weights across the prediction horizon, specify a row vector.

To vary the weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the weights for one prediction horizon step. If you specify fewer than p rows, the final weights are used for the remaining steps of the prediction horizon.

MVWeights — Manipulated variable tuning weights

row vector | array

Manipulated variable tuning weights that replace the default tuning weights at run time, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. If you expect your manipulated variable weights to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same weights across the prediction horizon, specify a row vector.

To vary the weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the weights for one prediction horizon step. If you specify fewer than p rows, the final weights are used for the remaining steps of the prediction horizon.

MVRateWeights — Manipulated variable rate tuning weights

row vector | array

Manipulated variable rate tuning weights that replace the default tuning weights at run time, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. If you expect your manipulated variable rate weights to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same weights across the prediction horizon, specify a row vector.

To vary the weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the weights for one prediction horizon step. If you specify fewer than p rows, the final weights are used for the remaining steps of the prediction horizon.

ECRWeight — Slack variable tuning weight

positive scalar

Slack variable rate tuning weight that replaces the default tuning weight at run time, specified as a positive scalar. If you expect your slack variable weight to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

OutputMin – Output variable lower bounds

row vector | array

Output variable lower bounds that replace the default lower bounds at run time, specified as a row vector of length N_y or an array with N_y columns, where N_y is the number of output variables. If you expect your output variable lower bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

OutputMax – Output variable upper bounds

row vector | array

Output variable upper bounds that replace the default upper bounds at run time, specified as a row vector of length N_y or an array with N_y columns, where N_y is the number of output variables. If you expect your output variable upper bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

StateMin – State lower bounds

row vector | array

State lower bounds that replace the default lower bounds at run time, specified as a row vector of length N_x or an array with N_x columns, where N_x is the number of states. If you expect your state lower bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

StateMax – State upper bounds

row vector | array

State upper bounds that replace the default upper bounds at run time, specified as a row vector of length N_x or an array with N_x columns, where N_x is the number of states. If you expect your state

upper bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVMin — Manipulated variable lower bounds

row vector | array

Manipulated variable lower bounds that replace the default lower bounds at run time, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. If you expect your manipulated variable lower bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVMax — Manipulated variable upper bounds

row vector | array

Manipulated variable upper bounds that replace the default upper bounds at run time, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. If you expect your manipulated variable upper bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVRateMin — Manipulated variable rate lower bounds

row vector | array

Manipulated variable rate lower bounds that replace the default lower bounds at run time, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. If you expect your manipulated variable rate lower bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVRateMax — Manipulated variable rate upper bounds

row vector | array

Manipulated variable rate upper bounds that replace the default upper bounds at run time, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. If you expect your manipulated variable rate upper bounds to vary at run time, you must add this field to the online data structure when you call `getCodeGenerationData`.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

Output Arguments**mv — Optimal manipulated variable control action**

column vector

Optimal manipulated variable control action, returned as a column vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the solver converges to a local optimum solution (`info.ExitFlag` is positive), then `mv` contains the optimal solution.

If the solver reaches the maximum number of iterations, finds a feasible suboptimal solution (`info.ExitFlag = 0`) and:

- `coredata.usesuboptimalsolution` is true, then `mv` contains the suboptimal solution
- `coredata.usesuboptimalsolution` is false, then `mv` contains `lastMV`

If the solver fails to find a feasible solution (`info.ExitFlag` is negative), then `mv` contains `lastMV`.

newOnlineData — Updated online controller data

structure

Updated online controller data, returned as a structure. This structure is the same as `onlineData`, except that the decision variable initial guesses (`X0`, `MV0`, and `Slack0`) are updated.

For subsequent control intervals, *warm start* the solver by modifying the online data in `newOnlineData` and passing the updated structure to `nLmpcmoveCodeGeneration` as `onlineData`. Doing so allows the solver to use the decision variable initial guesses as a starting point for its solution.

info — Solution details

structure

Solution details, returned as a structure with the following fields.

MVopt — Optimal manipulated variable sequence

array

Optimal manipulated variable sequence, returned as a $(p+1)$ -by- N_{mv} array, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

$MVopt(i, :)$ contains the calculated optimal manipulated variable values at time $k+i-1$, for $i = 1, \dots, p$, where k is the current time. $MVopt(1, :)$ contains the same manipulated variable values as output argument mv . Since the controller does not calculate optimal control moves at time $k+p$, $MVopt(p+1, :)$ is equal to $MVopt(p, :)$.

Xopt — Optimal prediction model state sequence

array

Optimal prediction model state sequence, returned as a $(p+1)$ -by- N_x array, where p is the prediction horizon and N_x is the number of states in the prediction model.

$Xopt(i, :)$ contains the calculated state values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. $Xopt(1, :)$ is the same as the current states in x .

Yopt — Optimal output variable sequence

array

Optimal output variable sequence, returned as a $(p+1)$ -by- N_y array, where p is the prediction horizon and N_y is the number of outputs.

$Yopt(i, :)$ contains the calculated output values at time $k+i-1$, for $i = 2, \dots, p+1$, where k is the current time. $Yopt(1, :)$ is computed based on the current states in x and the current measured disturbances in md , if any.

Topt — Prediction horizon time sequence

column vector

Prediction horizon time sequence, returned as a column vector of length $p+1$, where p is the prediction horizon. $Topt$ contains the time sequence from time k to time $k+p$, where k is the current time.

$Topt(1) = 0$ represents the current time. Subsequent time steps $Topt(i)$ are $Ts*(i-1)$, where Ts is the controller sample time.

Use $Topt$ when plotting the $MVopt$, $Xopt$, or $Yopt$ sequences.

Slack — Slack variable at optimum

nonnegative scalar

Slack variable at optimum, ϵ , used in constraint softening, returned as a nonnegative scalar value.

- $\epsilon = 0$ — All soft constraints are satisfied over the entire prediction horizon.
- $\epsilon > 0$ — At least one soft constraint is violated. When more than one constraint is violated, ϵ represents the worst-case soft constraint violation (scaled by your ECR values for each constraint).

ExitFlag — Optimization exit code

integer

Optimization exit code, returned as one of the following:

- Positive Integer — Optimal solution found
- 0 — Feasible suboptimal solution found after the maximum number of iterations
- Negative integer — No feasible solution found

Iterations — Number of iterations

positive integer

Number of iterations used by the solver, returned as a positive integer.

Cost — Objective function cost

nonnegative scalar

Objective function cost, returned as a nonnegative scalar value. The cost quantifies the degree to which the controller has achieved its objectives.

The cost value is only meaningful when `ExitFlag` is nonnegative.

Extended Capabilities**C/C++ Code Generation**

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- `nlpmoveCodeGeneration` supports generating code only for nonlinear MPC controllers that use the default `fmincon` solver with the SQP algorithm. However, you can simulate controllers using other `fmincon` algorithms.
- When used for code generation, nonlinear MPC controllers do not support anonymous functions for the prediction model, custom cost function, or custom constraint functions. However, `nlpmoveCodeGeneration` can still simulate controllers that use anonymous functions.
- Your custom functions must be on the MATLAB path and compatible with MATLAB Coder. For more information on checking compatibility, see “Check Code by Using the Code Generation Readiness Tool” (MATLAB Coder).
- Code generation for nonlinear MPC controllers supports only double-precision data.
- To generate code for computing optimal control moves for a nonlinear MPC controller:
 - 1 Generate data structures from a nonlinear MPC controller using `getCodeGenerationData`.
 - 2 To verify that your controller produces the expected closed-loop results, simulate it using `nlpmoveCodeGeneration` in place of `nlpmove`.
 - 3 Generate code for `nlpmoveCodeGeneration` using `codegen`. This step requires MATLAB Coder software.

See Also

`getCodeGenerationData` | `nlpmove`

Topics

“Generate Code and Deploy Controller to Real-Time Targets”

Introduced in R2020a

plot

Plot responses generated by MPC simulations

Syntax

```
plot(MPCobj,t,y,r,u,v,d)
```

Description

`plot(MPCobj,t,y,r,u,v,d)` plots the results of a simulation based on the MPC object `MPCobj`. `t` is a vector of length `Nt` of time values, `y` is a matrix of output responses of size $[Nt,Ny]$ where `Ny` is the number of outputs, `r` is a matrix of setpoints and has the same size as `y`, `u` is a matrix of manipulated variable inputs of size $[Nt,Nu]$ where `Nu` is the number of manipulated variables, `v` is a matrix of measured disturbance inputs of size $[Nt,Nv]$ where `Nv` is the number of measured disturbance inputs, and `d` is a matrix of unmeasured disturbance inputs of size $[Nt,Nd]$ where `Nd` is the number of unmeasured disturbances input.

See Also

`mpc` | `sim`

Introduced before R2006a

plotSection

Visualize explicit MPC control law as 2-D sectional plot

Syntax

```
plotsection(EMPCobj,plotParams)
```

Description

`plotsection(EMPCobj,plotParams)` displays a 2-D sectional plot of the piecewise affine regions used by an explicit MPC controller. All but two of the control law's free parameters are fixed, as specified by `plotParams`. The two remaining variables form the plot axes. By default, the `EMPCobj.Range` property sets the bounds for these axes.

Examples

Specify Fixed Parameters for 2-D Plot of Explicit Control Law

Define a double integrator plant model and create a traditional implicit MPC controller for this plant. Constrain the manipulated variable to have an absolute value less than 1.

```
plant = tf(1,[1 0 0]);
MPCobj = mpc(plant,0.1,10,3);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

```
MPCobj.MV = struct('Min',-1,'Max',1);
```

Define the parameter bounds for generating an explicit MPC controller.

```
range = generateExplicitRange(MPCobj);
```

```
-->Converting the "Model.Plant" property of "mpc" object to state-space.
```

```
-->Converting model to discrete time.
```

```
Assuming no disturbance added to measured output channel #1.
```

```
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
range.State.Min(:) = [-10;-10];
range.State.Max(:) = [10;10];
range.Reference.Min(:) = -2;
range.Reference.Max(:) = 2;
range.ManipulatedVariable.Min(:) = -1.1;
range.ManipulatedVariable.Max(:) = 1.1;
```

Create an explicit MPC controller.

```
EMPCobj = generateExplicitMPC(MPCobj,range);
```

```
Regions found / unexplored:      19/      0
```

Create a default plot parameter structure, which specifies that all of the controller parameters are fixed at their nominal values for plotting.

```
plotParams = generatePlotParameters(EMPCobj);
```

Allow the controller states to vary when creating a plot.

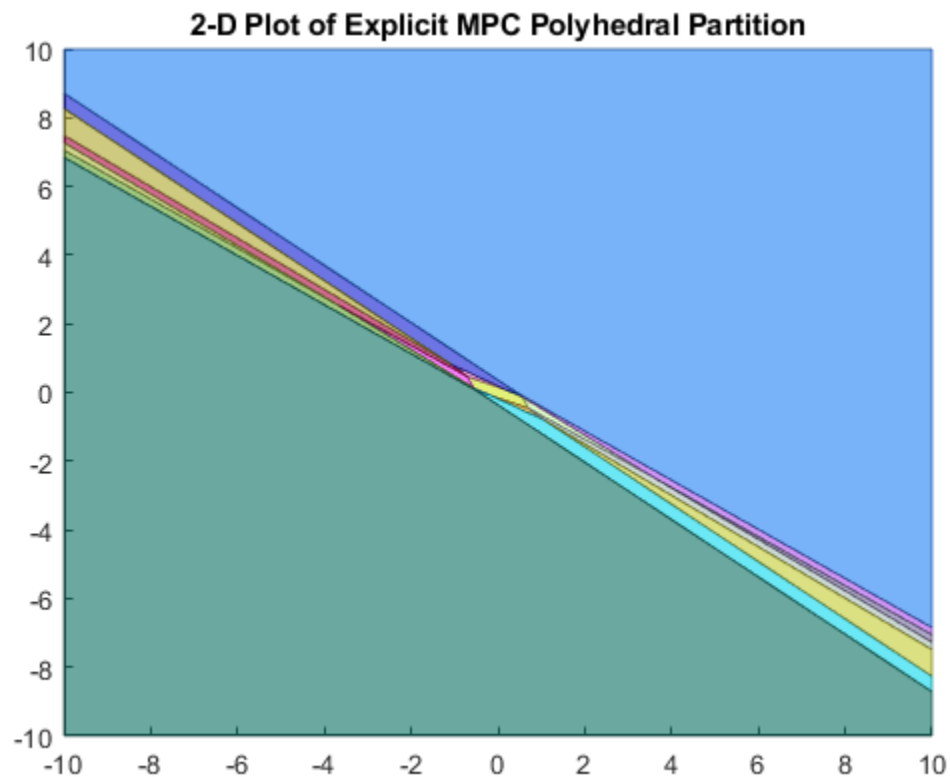
```
plotParams.State.Index = [];
plotParams.State.Value = [];
```

Fix the manipulated variable and reference signal to θ for plotting.

```
plotParams.ManipulatedVariable.Index(1) = 1;
plotParams.ManipulatedVariable.Value(1) = 0;
plotParams.Reference.Index(1) = 1;
plotParams.Reference.Value(1) = 0;
```

Generate the 2-D section plot for the explicit MPC controller.

```
plotSection(EMPCobj,plotParams)
```



ans =

Figure (1: PiecewiseAffineSectionPlot) with properties:

```
Number: 1
Name: 'PiecewiseAffineSectionPlot'
Color: [0.9400 0.9400 0.9400]
Position: [360 502 560 420]
```

Units: 'pixels'

Show all properties

Input Arguments

EMPCobj — Explicit MPC controller

explicit MPC controller object

Explicit MPC controller for which you want to create a 2-D sectional plot, specified as an Explicit MPC controller object. Use `generateExplicitMPC` to create an explicit MPC controller.

plotParams — Parameters for sectional plot

structure

Parameters for sectional plot of explicit MPC control law, specified as a structure. Use `generatePlotParameters` to create an initial structure in which all the parameters of the controller are fixed at their nominal values. Then, modify this structure as necessary before invoking `plotSection`. See `generatePlotParameters` for more information.

See Also

`generateExplicitMPC` | `generatePlotParameters`

Introduced in R2014b

review

Examine MPC controller for design errors and stability problems at run time

Syntax

```
review(mpcobj)

results = review(mpcobj)
```

Description

`review(mpcobj)` checks for potential design issues in the model predictive controller, `mpcobj`, and generates a testing report. The testing report provides information about each test, highlights test warnings and failures, and suggests possible solutions. For more information on the tests performed by the review function, see "Algorithms" on page 2-161.

`results = review(mpcobj)` returns the test results and suppresses the testing report.

Examples

Examine MPC Controller for Design Errors or Stability Problems

Define a plant model, and create an MPC controller.

```
plant = tf(1, [10 1]);
Ts = 2;
MPCobj = mpc(plant,Ts);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Set hard upper and lower bounds on the manipulated variable and its rate of change.

```
MV = MPCobj.MV;
MV.Min = -2;
MV.Max = 2;
MV.RateMin = -4;
MV.RateMax = 4;
MPCobj.MV = MV;
```

Review the controller design. The review function generates and opens a report in the Web Browser window.

```
review(MPCobj)

-->Converting the "Model.Plant" property of "mpc" object to state-space.
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Design Review for Model Predictive Controller "MPCobj"

Summary of Performed Tests

Test	Status
MPC Object Creation	Pass
QP Hessian Matrix Validity	Pass
Closed-Loop Internal Stability	Pass
Closed-Loop Nominal Stability	Pass
Closed-Loop Steady-State Gains	Pass
Hard MV Constraints	Warning
Other Hard Constraints	Pass
Soft Constraints	Pass
Memory Size for MPC Data	Pass

review flags a potential constraint conflict that could result if this controller was used to control a real process. To view details about the warning, click **Hard MV Constraints**.

Hard MV Constraints

The controller should always satisfy hard bounds on a manipulated variable *OR* its rate-of-change. If you specify both constraint types simultaneously, however, they might conflict during real-time use.

For example, if an event pushes an MV outside a specified hard bound and the hard MV rate bounds are too small, the resulting QP will be *infeasible*.

Avoid such conflicts by specifying hard MV bounds *OR* hard MV rate bounds, but not both. Or if you want to specify both, soften the lower-priority constraint by setting its ECR to a value greater than zero.

Warning: your constraint definitions may conflict. The following table lists potential conflicts for each MV. The tabular entries show the location of each conflict in the prediction horizon and the type of conflict.

MV name	Horizon k	Conflict Type
MV1	1	Min & RateMax
MV1	1	Max & RateMin

Obtain Test Results and Suppress Testing Report

Define a plant model, and create an MPC controller.

```
plant = rss(3,1,1);
plant.D = 0;
Ts = 0.1;
MPCobj = mpc(plant,Ts);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Specify constraints for the controller.

```
MV = MPCobj.MV;
MV.Min = -2;
MV.Max = 2;
MV.RateMin = -4;
MV.RateMax = 4;
MPCobj.MV = MV;
```

Review the controller design, and suppress the testing report.

```
results = review(MPCobj)
```

```
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
results = struct with fields:
    ObjectCreation: 1
    HessianMatrix: 1
    InternalStability: 1
    NominalStability: 1
    SteadyState: 1
    HardMVConstraints: 0
    HardOtherConstraints: 1
    SoftConstraints: 1
```

All of the tests passed, except for the hard MV constraints test, which generated a warning.

Obtain Test Results for Multiple Controllers

Create and review designs for gain-scheduled model predictive controllers for two plant operating conditions.

Define the model parameters.

```
M1 = 1;
M2 = 5;
k1 = 1;
k2 = 0.1;
```

```

b1 = 0.3;
b2 = 0.8;
yeq1 = 10;
yeq2 = -10;

```

Create plant models for each of the two operating conditions.

```

A1 = [0 1; -k1/M1 -b1/M1];
B1 = [0 0; -1/M1 k1*yeq1/M1];
C1 = [1 0];
D1 = [0 0];
sys1 = ss(A1,B1,C1,D1);
sys1 = setmpcsignals(sys1, 'MV',1, 'MD',2);

A2 = [0 1; -(k1+k2)/(M1+M2) -(b1+b2)/(M1+M2)];
B2 = [0 0; -1/(M1+M2) (k1*yeq1+k2*yeq2)/(M1+M2)];
C2 = [1 0];
D2 = [0 0];
sys2 = ss(A2,B2,C2,D2);
sys2 = setmpcsignals(sys2, 'MV',1, 'MD',2);

```

Design an MPC controller for each operating condition.

```

Ts = 0.2;
p = 6;
m = 2;
MPC1 = mpc(sys1,Ts,p,m);

```

```

-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.

```

```

MPC2 = mpc(sys2,Ts,p,m);

```

```

-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.

```

```

controllers = {MPC1,MPC2};

```

Review the controller designs, and store the test result structures.

```

for i = 1:2
    results(i) = review(controllers{i});
end

```

```

-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured.
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured.

```

Input Arguments

mpcobj — MPC controller
mpc object

MPC controller object, specified as an `mpc` object.

Output Arguments

results — Test results

structure

Test results, returned as a structure with the following fields:

- `ObjectCreation` — MPC object creation test
- `HessianMatrix` — QP Hessian matrix validity test
- `InternalStability` — Internal stability test
- `NominalStability` — Nominal stability test
- `SteadyState` — Closed-loop steady-state gains test
- `HardMVConstraints` — Hard MV constraints test
- `HardOtherConstraints` — Other hard constraints test
- `SoftConstraints` — Soft constraints test

For more information on the tests performed by the `review` function, see “Algorithms” on page 2-161.

The `results` structure does not contain a field for the **Memory Size for MPC Data** test.

For each test, the result is returned as one of the following:

- 1 — Pass
- 0 — Warning
- -1 — Fail

If a given test generates a warning or fails, generate a testing report by calling `review` without an output argument. The testing report provides details about the warnings and failures, and suggests possible solutions.

Tips

- You can also review your controller design in the **MPC Designer** app. On the **Tuning** tab, in the **Analysis** section, click **Review Design**.
- Test your controller design using techniques such as simulations, since `review` cannot detect all possible performance factors.

Algorithms

The `review` command performs the following tests.

Test	Description
MPC Object Creation	Test whether the controller specifications generate a valid MPC controller. If the controller is invalid, additional tests are not performed.

Test	Description
QP Hessian Matrix Validity	Test whether the MPC quadratic programming (QP) problem for the controller has a unique solution. You must choose cost function parameters (penalty weights) and horizons such that the QP Hessian matrix is positive-definite.
Closed-Loop Internal Stability	Extract the A matrix from the state-space realization of the unconstrained controller, and then calculate its eigenvalues. If the absolute value of each eigenvalue is less than or equal to 1 and the plant is stable, then your feedback system is internally stable.
Closed-Loop Nominal Stability	Extract the A matrix from the discrete-time state-space realization of the closed-loop system; that is, the plant and controller connected in a feedback configuration. Then calculate the eigenvalues of A. If the absolute value of each eigenvalue is less than or equal to 1, then the nominal (unconstrained) system is stable.
Closed-Loop Steady-State Gains	Test whether the controller forces all controlled output variables to their targets at steady state in the absence of constraints.
Hard MV Constraints	Test whether the controller has hard constraints on both a manipulated variable and its rate of change, and if so, whether these constraints may conflict at run time.
Other Hard Constraints	Test whether the controller has hard output constraints or hard mixed input/output constraints, and if so, whether these constraints may become impossible to satisfy at run time.
Soft Constraints	Test whether the controller has the proper balance of hard and soft constraints by evaluating the constraint ECR parameters.
Memory Size for MPC Data	Estimate the memory size required by the controller at run time.

Alternatives

review automates certain tests that you can perform at the command line.

- To test for steady-state tracking errors, use `cloffset`.
- To test the internal stability of a controller, check the eigenvalues of the `mpc` object. Convert the `mpc` object to a state-space model using `ss`, and call `isstable`.

See Also

`cloffset` | `mpc` | `ss`

Topics

“Simulation and Code Generation Using Simulink Coder”

“Review Model Predictive Controller for Stability and Robustness Issues”

Introduced in R2011b

sensitivity

Compute effect of controller tuning weights on performance

Syntax

```
[J,sens] = sensitivity(MPCobj,PerfFunc,PerfWeights,Tstop,r,v,simopt,utarget)
[J,sens] = sensitivity(MPCobj,'perf_fun',param1,param2,...)
```

Description

The `sensitivity` function is a controller tuning aid. `J` specifies a scalar performance metric. `sensitivity` computes `J` and its partial derivatives with respect to the controller tuning weights. These *sensitivities* suggest tuning weight adjustments that should improve performance; that is, reduce `J`.

`[J,sens] = sensitivity(MPCobj,PerfFunc,PerfWeights,Tstop,r,v,simopt,utarget)` calculates the scalar performance metric, `J`, and sensitivities, `sens`, for the controller defined by the MPC controller object `MPCobj`.

`PerfFunc` must be one of the following:

'ISE' (integral squared error) for which the performance metric is

$$J = \sum_{i=1}^{Tstop} \left(\sum_{j=1}^{n_y} (w_j^y e_{yij})^2 + \sum_{j=1}^{n_u} [(w_j^u e_{uij})^2 + (w_j^{Au} \Delta u_{ij})^2] \right)$$

'IAE' (integral absolute error) for which the performance metric is

$$J = \sum_{i=1}^{Tstop} \left(\sum_{j=1}^{n_y} |w_j^y e_{yij}| + \sum_{j=1}^{n_u} (|w_j^u e_{uij}| + |w_j^{Au} \Delta u_{ij}|) \right)$$

'ITSE' (integral of time-weighted squared error) for which the performance metric is

$$J = \sum_{i=1}^{Tstop} i \Delta t \left(\sum_{j=1}^{n_y} (w_j^y e_{yij})^2 + \sum_{j=1}^{n_u} [(w_j^u e_{uij})^2 + (w_j^{Au} \Delta u_{ij})^2] \right)$$

'ITAE' (integral of time-weighted absolute error) for which the performance metric is

$$J = \sum_{i=1}^{Tstop} i \Delta t \left(\sum_{j=1}^{n_y} |w_j^y e_{yij}| + \sum_{j=1}^{n_u} (|w_j^u e_{uij}| + |w_j^{Au} \Delta u_{ij}|) \right)$$

In the above expressions n_y is the number of controlled outputs and n_u is the number of manipulated variables. e_{yij} is the difference between output j and its setpoint (or reference) value at time interval i . e_{uij} is the difference between manipulated variable j and its target at time interval i .

The w parameters are nonnegative performance weights defined by the structure `PerfWeights`, which contains the following fields:

- `OutputVariables` — n_y element row vector that contains the w_j^y values
- `ManipulatedVariables` — n_u element row vector that contains the w_j^u values
- `ManipulatedVariablesRate` — n_u element row vector that contains the $w_j^{\Delta u}$ values

If `PerfWeights` is unspecified, it defaults to the corresponding weights in `MPCObj`. In general, however, the performance weights and those used in the controller have different purposes and should be defined accordingly.

Inputs `Tstop`, `r`, `v`, and `simopt` define the simulation scenario used to evaluate performance. See `sim` for details.

`Tstop` is the integer number of controller sampling intervals to be simulated. The final time for the simulations will be $Tstop \times \Delta t$, where Δt is the controller sampling interval specified in `MPCObj`.

The optional input `utarget` is a vector of n_u manipulated variable targets. Their defaults are the nominal values of the manipulated variables. Δu_{ij} is the change in manipulated variable j and its target at time interval i .

The structure variable `sens` contains the computed sensitivities (partial derivatives of J with respect to the `MPCObj` tuning weights.) Its fields are:

- `OutputVariables` — n_y element row vector of sensitivities with respect to `MPCObj.Weights.OutputVariables`
- `ManipulatedVariables` — n_u element row vector of sensitivities with respect to `MPCObj.Weights.ManipulatedVariables`
- `ManipulatedVariablesRate` — n_u element row vector of sensitivities with respect to `MPCObj.Weights.ManipulatedVariablesRate`

For more information on the tuning weights controller property, see `mpc`.

`[J,sens] = sensitivity(MPCObj, 'perf_fun', param1, param2, ...)` employs a performance function 'perf_fun' to define J . Its function definition must be in the form

```
function J = perf_fun(MPCObj, param1, param2, ...)
```

That is, it must compute J for the given controller and optional parameters `param1`, `param2`, ... and it must be on the MATLAB path.

Note While performing the sensitivity analysis, the software ignores time-varying, nondiagonal, and ECR slack variable weights.

Examples

Compute Controller Performance and Sensitivity

Define a third-order plant model with three manipulated variables and two controlled outputs.

```
plant = rss(3,2,3);
plant.D = 0;
```

Create an MPC controller for the plant.

```
MPCobj = mpc(plant,1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Specify an integral absolute error performance function and set the performance weights.

```
PerfFunc = 'IAE';
PerfWts.OutputVariables = [1 0.5];
PerfWts.ManipulatedVariables = zeros(1,3);
PerfWts.ManipulatedVariablesRate = zeros(1,3);
```

Define a 20 second simulation scenario with a unit step in the output 1 setpoint and a setpoint of zero for output 2.

```
Tstop = 20;
r = [1 0];
```

Define the nominal values of the manipulated variables to be zeros.

```
utarget = zeros(1,3);
```

Calculate the performance metric, J, and sensitivities, sens, for the specified controller and simulation scenario.

```
[J,sens] = sensitivity(MPCobj,PerfFunc,PerfWts,Tstop,r,[],[],utarget);
```

```
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->Assuming output disturbance added to measured output channel #2 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

See Also

[mpc](#) | [sim](#)

Introduced in R2009a

set

Set or modify MPC object properties

Syntax

```
set(MPCobj,Property,Value)
set(MPCobj,Property1,Value1,Property2,Value2,...)
set(MPCobj,Property)
set(sys)
```

Description

The `set` function is used to set or modify the properties of an MPC controller (see `mpc` for background on MPC properties). `set` uses property Name,Value pairs to update property values.

`set(MPCobj,Property,Value)` assigns the value `Value` to the property of the MPC controller `MPCobj` specified by the character vector or string `Property`. `Property` can be the full property name (for example, `'UserData'`) or any unambiguous case-insensitive abbreviation (for example, `'user'`).

`set(MPCobj,Property1,Value1,Property2,Value2,...)` sets multiple property values with a single statement. Each property Name,Value pair updates one particular property.

`set(MPCobj,Property)` displays admissible values for the property specified by the character vector `Property`. See `mpc` for an overview of legitimate MPC property values.

`set(sys)` displays all assignable properties of `sys` and their admissible values.

Examples

Change Signal Types of Existing Controller

To modify the signal types for an existing MPC controller, you must simultaneously modify any controller properties that depend on the signal type configuration.

Create a plant model with two outputs, one manipulated variable, one measured disturbance, and two unmeasured disturbances.

```
plant = rss(3,2,5);
plant.D = 0;
plant = setmpcsignals(plant,'MV',[1 2],'MD',3,'UD',[4 5]);
```

Create an MPC controller using this plant.

```
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000
```


-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.

Configure the controller properties. For example, set the scaling factors for the disturbance signals.

```
MPCObj.DisturbanceVariables(1).ScaleFactor = 10;  
MPCObj.DisturbanceVariables(2).ScaleFactor = 5;  
MPCObj.DisturbanceVariables(3).ScaleFactor = 20;
```

Suppose you want to change the second unmeasured disturbance to be a measured disturbance. To do so, you must simultaneously update the `DisturbanceVariables` property of the controller, since the order of its entries depend on the disturbance types (measured disturbances followed by unmeasured disturbances).

Create an updated disturbance variable structure array. To do so, move the third element to be the second element.

```
DV = MPCObj.DisturbanceVariables;  
DV = [DV(1) DV(3) DV(2)];  
DV(2).Name = 'MD2';
```

To set the internal plant model signal types, obtain the `Model` property from the controller, and modify the signal types of its `Plant` element.

```
model = MPCObj.Model;  
model.Plant = setmpcsignals(model.Plant, 'MV', [1 2], 'MD', [3 5], 'UD', 4);
```

Set the model and disturbance variable properties of the controller to their updated values.

```
set(MPCObj, 'Model', model, 'DisturbanceVariables', DV);
```

In general, it is best practice to not modify the signal types after controller creation. Instead, create and configure a new controller object with the new signal configuration.

See Also

get | mpc | mpcprops

Introduced before R2006a

setconstraint

Set mixed input/output constraints for model predictive controller

Syntax

```
setconstraint(MPCobj,E,F,G)
setconstraint(MPCobj,E,F,G,V)
setconstraint(MPCobj,E,F,G,V,S)

setconstraint(MPCobj)
```

Description

`setconstraint(MPCobj,E,F,G)` specifies mixed input/output constraints of the following form for the MPC controller, `MPCobj`:

$$Eu(k) + j|k) + Fy(k) + j|k) \leq G + \varepsilon$$

For more information, see “Mixed Input/Output Constraints” on page 2-172.

`setconstraint(MPCobj,E,F,G,V)` adds constraints of the following form:

$$Eu(k) + j|k) + Fy(k) + j|k) \leq G + \varepsilon V$$

Use this syntax to specify hard custom constraints or to change the default constraint softening.

`setconstraint(MPCobj,E,F,G,V,S)` adds constraints of the following form:

$$Eu(k) + j|k) + Fy(k) + j|k) + Sv(k) + j|k) \leq G + \varepsilon V$$

Use this syntax if your mixed input/output constraints include measured disturbances.

`setconstraint(MPCobj)` removes all mixed input/output constraints from the MPC controller.

Examples

Specify Custom Constraints on Linear Combination of Inputs and Outputs

Specify a constraint of the form $0 \leq u_2 - 2u_3 + y_2 \leq 15$ on an MPC controller.

Create a third-order plant model with three manipulated variables and two measured outputs.

```
plant = rss(3,2,3);
plant.D = 0;
```

Create an MPC controller for this plant.

```
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
```

-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
 -->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
 -->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.

Formulate the constraint in the required form:

$$\begin{bmatrix} 0 & -1 & 2 \\ 0 & 1 & -2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} + \begin{bmatrix} 0 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \leq \begin{bmatrix} 0 \\ 15 \end{bmatrix} + \varepsilon \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Specify the constraint matrices.

```
E = [0 -1 2; 0 1 -2];
F = [0 -1; 0 1];
G = [0; 15];
```

Set the constraints in the MPC controller.

```
setconstraint(MPCobj,E,F,G)
```

Specify Custom Hard Constraints for MPC Controller

Create a third-order plant model with two manipulated variables and two measured outputs.

```
plant = rss(3,2,2);
plant.D = 0;
```

Create an MPC controller for this plant.

```
MPCobj = mpc(plant,0.1);
```

-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
 -->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
 -->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
 -->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
 -->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.

Assume that you have two hard constraints.

$$u_1 + u_2 \leq 5$$

$$y_1 + y_2 \leq 10$$

Specify the constraint matrices.

```
E = [1 1; 0 0];
F = [0 0; 1 1];
G = [5; 10];
```

Specify the constraints as hard by setting V to zero for both constraints.

```
V = [0; 0];
```

Set the constraints in the MPC controller.

```
setconstraint(MPCobj,E,F,G,V)
```

Specify Custom Constraints for MPC Controller with Measured Disturbances

Create a third-order plant model with two manipulated variables, two measured disturbances, and two measured outputs.

```
plant = rss(3,2,4);
plant.D = 0;
plant = setmpcsignals(plant, 'mv', [1 2], 'md', [3 4]);
```

Create an MPC controller for this plant.

```
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Assume that you have three soft constraints.

$$u_1 + u_2 \leq 5$$

$$y_1 + v_1 \leq 10$$

$$y_2 + v_2 \leq 12$$

Specify the constraint matrices.

```
E = [1 1; 0 0; 0 0];
F = [0 0; 1 0; 0 1];
G = [5;10;12];
S = [0 0; 1 0; 0 1];
```

Set the constraints in the MPC controller using the default value for V.

```
setconstraint(MPCobj,E,F,G,[],S)
```

Remove All Custom Constraints from MPC Controller

Define a plant model and create an MPC controller.

```
plant = rss(3,2,2);
plant.D = 0;
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Define controller custom constraints.

```
E = [-1 2; 1 -2];
F = [0 1; 0 -1];
G = [0; 10];
setconstraint(MPCobj,E,F,G)
```

Remove the custom constraints.

```
setconstraint(MPCobj)
```

-->Removing mixed input/output constraints.

Input Arguments

MPCobj — Model predictive controller

MPC controller object

Model predictive controller, specified as an MPC controller object. To create an MPC controller, use `mpc`.

E — Manipulated variable constraint constant

array of zeros (default) | N_c -by- N_{mv} array

Manipulated variable constraint constant, specified as an N_c -by- N_{mv} array, where N_c is the number of constraints, and N_{mv} is the number of manipulated variables.

F — Controlled output constraint constant

array of zeros (default) | N_c -by- N_y array

Controlled output constraint constant, specified as an N_c -by- N_y array, where N_y is the number of controlled outputs (measured and unmeasured).

G — Mixed input/output constraint constant

column vector of zeros (default) | column vector of length N_c

Mixed input/output constraint constant, specified as a column vector of length N_c .

V — Constraint softening constant

column vector of ones (default) | specified as a column vector of length N_c

Constraint softening constant representing the equal concern for the relaxation (ECR), specified as a column vector of length N_c .

If V is not specified, a default value of 1 is applied to all constraint inequalities and all constraints are soft. This behavior is the same as the default behavior for output bounds, as described in “Standard Cost Function”.

To make the i^{th} constraint hard, specify $V(i) = 0$.

To make the i^{th} constraint soft, specify $V(i) > 0$ in keeping with the constraint violation magnitude you can tolerate. The magnitude violation depends on the numerical scale of the variables involved in the constraint.

In general, as $V(i)$ decreases, the controller hardens the constraints by decreasing the constraint violation that is allowed.

Note If a constraint is difficult to satisfy, reducing its $V(i)$ value to make it harder can be counterproductive. Doing so can lead to erratic control actions, instability, or failure of the QP solver that determines the control action.

S — Measured disturbance constraint constant

array of zeros (default) | N_c -by- N_{md} array

Measured disturbance constraint constant, specified as an N_c -by- N_{md} array, where N_{md} is the number of measured disturbances.

Tips

- The outputs, y , are being predicted using a model. If the model is imperfect, there is no guarantee that a constraint can be satisfied.
- Since the MPC controller does not optimize $u(k + p|k)$, the last constraint at time $k + p$ assumes that $u(k+p|k) = u(k+p-1|k)$.
- When simulating an MPC controller, you can update the E, F, G, and S constraint arrays at run time. For more information, see “Update Constraints at Run Time”.

Algorithms

Mixed Input/Output Constraints

The general form of the mixed input/output constraints is:

$$Eu(k + j) + Fy(k + j) + Sv(k + j) \leq G + \varepsilon V$$

Here, $j = 0, \dots, p$, and:

- p is the prediction horizon.
- k is the current time index.
- u is a column vector manipulated variables.
- y is a column vector of all plant output variables.
- v is a column vector of measured disturbance variables.
- ε is a scalar slack variable used for constraint softening (as in “Standard Cost Function”).
- E, F, G, V , and S are constant matrices.

See Also

getconstraint | setterminal

Topics

“Constraints on Linear Combinations of Inputs and Outputs”
 “Update Constraints at Run Time”

Introduced in R2011a

setEstimator

Modify a model predictive controller's state estimator

Syntax

```
setEstimator(MPCobj,L,M)
setEstimator(MPCobj,'default')
setEstimator(MPCobj,'custom')
```

Description

`setEstimator(MPCobj,L,M)` sets the gain matrices used for estimation of the states of an MPC controller. For more information, see "State Estimator Equations" on page 2-175.

`setEstimator(MPCobj,'default')` restores the gain matrices L and M to their default values. The default values are the optimal static gains calculated using `kalmd` for the plant, disturbance, and measurement noise models specified in `MPCobj`.

`setEstimator(MPCobj,'custom')` specifies that controller state estimation will be performed by a user-supplied procedure. This option suppresses calculation of L and M . When the controller is operating in this way, the procedure must supply the state estimate $x[n|n]$ to the controller at the beginning of each control interval.

Examples

Design State Estimator by Pole Placement

Design an estimator using pole placement, assuming the linear system $AM = L$ is solvable.

Create a plant model.

```
G = tf({1,1,1},{[1 .5 1],[1 1],[.7 .5 1]});
```

To improve the clarity of this example, call `mpcverbosity` to suppress messages related to working with an MPC controller.

```
old_status = mpcverbosity('off');
```

Create a model predictive controller for the plant. Specify the controller sample time as 0.2 seconds.

```
MPCobj = mpc(G, 0.2);
```

Obtain the default state estimator gain.

```
[~,M,A1,Cm1] = getEstimator(MPCobj);
```

Calculate the default observer poles.

```
e = eig(A1-A1*M*Cm1);
abs(e)
```

```
ans = 6×1
    0.9402
    0.9402
    0.8816
    0.8816
    0.7430
    0.9020
```

Specify faster observer poles.

```
new_poles = [.8 .75 .7 .85 .6 .81];
```

Compute a state-gain matrix that places the observer poles at `new_poles`.

```
L = place(A1', Cm1', new_poles)';
```

`place` returns the controller-gain matrix, whereas you want to compute the observer-gain matrix. Using the principle of duality, which relates controllability to observability, you specify the transpose of `A1` and `Cm1` as the inputs to `place`. This function call yields the observer gain transpose.

Obtain the estimator gain from the state-gain matrix.

```
M = A1\L;
```

Specify `M` as the estimator for `MPCobj`.

```
setEstimator(MPCobj, L, M)
```

The pair, (A_1, C_{m1}) , describing the overall state-space realization of the combination of plant and disturbance models must be observable for the state estimation design to succeed. Observability is checked in Model Predictive Control Toolbox software at two levels: (1) observability of the plant model is checked *at construction* of the MPC object, provided that the model of the plant is given in state-space form; (2) observability of the overall extended model is checked *at initialization* of the MPC object, after all models have been converted to discrete-time, delay-free, state-space form and combined together.

Restore `mpcverbosity`.

```
mpcverbosity(old_status);
```

Input Arguments

MPCobj — MPC controller

MPC controller object

MPC controller, specified as an MPC controller object. Use the `mpc` command to create the MPC controller.

L — Kalman gain matrix for time update

A^*M (default) | matrix

Kalman gain matrix for the time update, specified as a matrix. The dimensions of `L` are n_x -by- n_{ym} , where n_x is the total number of controller states, and n_{ym} is the number of measured outputs.

If L is empty, it defaults to $L = A*M$, where A is the state-transition matrix.

M — Kalman gain matrix for measurement update

0 (default) | matrix

Kalman gain matrix for the measurement update, specified as a matrix. The dimensions of L are n_x -by- n_{ym} , where n_x is the total number of controller states, and n_{ym} is the number of measured outputs.

If M is omitted or empty, it defaults to a zero matrix, and the state estimator becomes a Luenberger observer.

Algorithms

State Estimator Equations

In general, the controller states are unmeasured and must be estimated. By default, the controller uses a steady-state Kalman filter that derives from the state observer. For more information, see “Controller State Estimation”.

At the beginning of the k th control interval, the controller state is estimated with the following steps:

1 Obtain the following data:

- $x_c(k|k-1)$ — Controller state estimate from previous control interval, $k-1$
- $u^{act}(k-1)$ — Manipulated variable (MV) actually used in the plant from $k-1$ to k (assumed constant)
- $u^{opt}(k-1)$ — Optimal MV recommended by MPC and assumed to be used in the plant from $k-1$ to k
- $v(k)$ — Current measured disturbances
- $y_m(k)$ — Current measured plant outputs
- B_u, B_v — Columns of observer parameter B corresponding to $u(k)$ and $v(k)$ inputs
- C_m — Rows of observer parameter C corresponding to measured plant outputs
- D_{mv} — Rows and columns of observer parameter D corresponding to measured plant outputs and measured disturbance inputs
- L, M — Constant Kalman gain matrices

Plant input and output signals are scaled to be dimensionless prior to use in calculations.

2 Revise $x_c(k|k-1)$ when $u^{act}(k-1)$ and $u^{opt}(k-1)$ are different.

$$x_c^{rev}(k|k-1) = x_c(k|k-1) + B_u[u^{act}(k-1) - u^{opt}(k-1)]$$

3 Compute the innovation.

$$e(k) = y_m(k) - [C_m x_c^{rev}(k|k-1) + D_{mv} v(k)]$$

4 Update the controller state estimate to account for the latest measurements.

$$x_c(k|k) = x_c^{rev}(k|k-1) + M e(k)$$

Then, the software uses the current state estimate $x_c(k|k)$ to solve the quadratic program at interval k . The solution is $u^{opt}(k)$, the MPC-recommended manipulated-variable value to be used between control intervals k and $k+1$.

Finally, the software prepares for the next control interval assuming that the unknown inputs, $w_{id}(k)$, $w_{od}(k)$, and $w_n(k)$ assume their mean value (zero) between times k and $k+1$. The software predicts the impact of the known inputs and the innovation as follows:

$$x_c(k+1|k) = Ax_c^{rev}(k|k-1) + B_u u^{opt}(k) + B_v v(k) + Le(k)$$

See Also

`getEstimator` | `kalman` | `mpc` | `mpcstate`

Topics

“Controller State Estimation”

“MPC Modeling”

Introduced in R2014b

setindist

Modify unmeasured input disturbance model

Syntax

```
setindist(MPCobj, 'model', model)
setindist(MPCobj, 'integrators')
```

Description

`setindist(MPCobj, 'model', model)` sets the input disturbance model used by the model predictive controller, `MPCobj`, to a custom model.

`setindist(MPCobj, 'integrators')` sets the input disturbance model to its default value. Use this syntax if you previously set a custom input disturbance model and you want to change back to the default model. For more information on the default input disturbance model, see “MPC Modeling”.

Examples

Specify Input Disturbance Model Using Transfer Functions

Define a plant model with no direct feedthrough.

```
plant = rss(3,4,4);
plant.D = 0;
```

Set the first input signal as a manipulated variable and the remaining inputs as input disturbances.

```
plant = setmpcsignals(plant, 'MV', 1, 'UD', [2 3 4]);
```

Create an MPC controller for the defined plant.

```
MPCobj = mpc(plant, 0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
    for output(s) y1 and zero weight for output(s) y2 y3 y4
```

Define disturbance models such that:

- Input disturbance 1 is random white noise with a magnitude of 2.
- Input disturbance 2 is random step-like noise with a magnitude of 0.5.
- Input disturbance 3 is random ramp-like noise with a magnitude of 1.

```
mod1 = tf(2,1);
mod2 = tf(0.5,[1 0]);
mod3 = tf(1,[1 0 0]);
```

Construct the input disturbance model using the above transfer functions. Use a separate noise input for each input disturbance.

```
indist = [mod1 0 0; 0 mod2 0; 0 0 mod3];
```

Set the input disturbance model in the MPC controller.

```
setindist(MPCobj, 'model', indist)
```

View the controller input disturbance model.

```
getindist(MPCobj)
```

```
ans =
```

```
A =
```

	x1	x2	x3
x1	1	0	0
x2	0	1	0
x3	0	0.1	1

```
B =
```

	Noise#1	Noise#2	Noise#3
x1	0	0.05	0
x2	0	0	0.1
x3	0	0	0.005

```
C =
```

	x1	x2	x3
UD1	0	0	0
UD2	1	0	0
UD3	0	0	1

```
D =
```

	Noise#1	Noise#2	Noise#3
UD1	2	0	0
UD2	0	0	0
UD3	0	0	0

```
Sample time: 0.1 seconds
Discrete-time state-space model.
```

The controller converts the continuous-time transfer function model, `indist`, into a discrete-time state-space model.

Remove Input Disturbance for Particular Channel

Define a plant model with no direct feedthrough.

```
plant = rss(3,4,4);
plant.D = 0;
```

Set the first input signal as a manipulated variable and the remaining inputs as input disturbances.

```
plant = setmpcsignals(plant, 'MV', 1, 'UD', [2 3 4]);
```

Create an MPC controller for the defined plant.

```
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
    for output(s) y1 and zero weight for output(s) y2 y3 y4
```

Retrieve the default input disturbance model from the controller.

```
distMod = getindist(MPCobj);
```

```
-->Converting model to discrete time.
-->The "Model.Disturbance" property of "mpc" object is empty:
    Assuming unmeasured input disturbance #2 is integrated white noise.
    Assuming unmeasured input disturbance #3 is integrated white noise.
    Assuming unmeasured input disturbance #4 is integrated white noise.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
    Assuming no disturbance added to measured output channel #2.
    Assuming no disturbance added to measured output channel #3.
    Assuming no disturbance added to measured output channel #4.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Remove the integrator from the second input disturbance. Construct the new input disturbance model by removing the second input channel and setting the effect on the second output by the other two inputs to zero.

```
distMod = sminreal([distMod(1,1) distMod(1,3); 0 0; distMod(3,1) distMod(3,3)]);
setindist(MPCobj,'model',distMod)
```

When removing an integrator from the input disturbance model in this way, use `sminreal` to make the custom model structurally minimal.

View the input disturbance model.

```
tf(getindist(MPCobj))
```

```
ans =
```

```
From input "UD1-wn" to output...
      0.1
UD1:  ----
      z - 1

UD2:  0

UD3:  0

From input "UD3-wn" to output...
UD1:  0

UD2:  0

      0.1
UD3:  ----
      z - 1
```

```
Sample time: 0.1 seconds
Discrete-time transfer function.
```

The integrator has been removed from the second channel. The first and third channels of the input disturbance model remain at their default values as discrete-time integrators.

Set Input Disturbance Model to Default Value

Define a plant model with no direct feedthrough.

```
plant = rss(2,2,3);
plant.D = 0;
```

Set the second and third input signals as input disturbances.

```
plant = setmpcsignals(plant, 'MV', 1, 'UD', [2 3]);
```

Create an MPC controller for the defined plant.

```
MPCobj = mpc(plant, 0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
    for output(s) y1 and zero weight for output(s) y2
```

Set the input disturbance model to unity gain for both channels.

```
setindist(MPCobj, 'model', tf(eye(2)))
```

Restore the default input disturbance model.

```
setindist(MPCobj, 'integrators')
```

Input Arguments

MPCobj — Model predictive controller

MPC controller object

Model predictive controller, specified as an MPC controller object. To create an MPC controller, use `mpc`.

model — Custom input disturbance model

[] (default) | ss object | tf object | zpk object

Custom input disturbance model, specified as a state-space (`ss`), transfer function (`tf`), or zero-pole-gain (`zpk`) model. The MPC controller converts the model to a discrete-time, delay-free, state-space model. Omitting `model` or specifying `model` as [] is equivalent to using `setindist(MPCobj, 'integrators')`.

The input disturbance model has:

- Unit-variance white noise input signals. For custom input disturbance models, the number of inputs is your choice.
- n_d outputs, where n_d is the number of unmeasured disturbance inputs defined in `MPCobj.Model.Plant`. Each disturbance model output is sent to the corresponding plant unmeasured disturbance input.

This model, in combination with the output disturbance model (if any), governs how well the controller compensates for unmeasured disturbances and prediction errors. For more information on the disturbance modeling in MPC and about the model used during state estimation, see “MPC Modeling” and “Controller State Estimation”.

`setindist` does not check custom input disturbance models for violations of state observability. This check is performed later in the MPC design process when the internal state estimator is constructed using commands such as `sim` or `mpcmove`. If the controller states are not fully observable, these commands generate an error.

This syntax is equivalent to `MPCobj.Model.Disturbance = model`.

Tips

- To view the current input disturbance model, use the `getindist` command.

See Also

`getEstimator` | `getindist` | `getoutdist` | `mpc` | `setEstimator` | `setoutdist`

Topics

“MPC Modeling”

“Controller State Estimation”

“Adjust Disturbance and Noise Models”

Introduced before R2006a

setmpcsignals

Set signal types in MPC plant model

Syntax

```
outPlant = setmpcsignals(inPlant)
outPlant = setmpcsignals(inPlant,Name,Value)
```

Description

`outPlant = setmpcsignals(inPlant)` sets the MPC signal types of `inPlant` to their default values, returning the result in `outPlant`. By default, all inputs are manipulated variables, and all outputs are measured outputs.

`outPlant = setmpcsignals(inPlant,Name,Value)` sets the MPC signal types for the input and output signals of the LTI system `inPlant`, returning the result in `outPlant`. Specify the signal types and indices using one or more name-value pair arguments. If you do not specify the type for input or output channels, they are configured as manipulated variables and output variables, respectively.

Examples

Set MPC Signal Types and Create MPC Controller

Create a four-input, two output state-space plant model. By default all input signals are manipulated variables and all outputs are measured outputs.

```
plant = rss(3,2,4);
plant.D = 0;
```

Configure the plant input/output channels such that:

- The second and third inputs are measured disturbances.
- The fourth input is an unmeasured disturbance.
- The second output is unmeasured.

```
plant = setmpcsignals(plant,'MD',[2 3],'UD',4,'UO',2);
```

```
-->Assuming unspecified input signals are manipulated variables.
-->Assuming unspecified output signals are measured outputs.
```

Create an MPC controller.

```
MPCobj = mpc(plant,1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
    for output(s) y1 and zero weight for output(s) y2
```


Change Signal Types of Existing Controller

To modify the signal types for an existing MPC controller, you must simultaneously modify any controller properties that depend on the signal type configuration.

Create a plant model with two outputs, one manipulated variable, one measured disturbance, and two unmeasured disturbances.

```
plant = rss(3,2,5);
plant.D = 0;
plant = setmpcsignals(plant, 'MV', [1 2], 'MD', 3, 'UD', [4 5]);
```

Create an MPC controller using this plant.

```
MPCobj = mpc(plant, 0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
```

Configure the controller properties. For example, set the scaling factors for the disturbance signals.

```
MPCobj.DisturbanceVariables(1).ScaleFactor = 10;
MPCobj.DisturbanceVariables(2).ScaleFactor = 5;
MPCobj.DisturbanceVariables(3).ScaleFactor = 20;
```

Suppose you want to change the second unmeasured disturbance to be a measured disturbance. To do so, you must simultaneously update the `DisturbanceVariables` property of the controller, since the order of its entries depend on the disturbance types (measured disturbances followed by unmeasured disturbances).

Create an updated disturbance variable structure array. To do so, move the third element to be the second element.

```
DV = MPCobj.DisturbanceVariables;
DV = [DV(1) DV(3) DV(2)];
DV(2).Name = 'MD2';
```

To set the internal plant model signal types, obtain the `Model` property from the controller, and modify the signal types of its `Plant` element.

```
model = MPCobj.Model;
model.Plant = setmpcsignals(model.Plant, 'MV', [1 2], 'MD', [3 5], 'UD', 4);
```

Set the model and disturbance variable properties of the controller to their updated values.

```
set(MPCobj, 'Model', model, 'DisturbanceVariables', DV);
```

In general, it is best practice to not modify the signal types after controller creation. Instead, create and configure a new controller object with the new signal configuration.

Input Arguments

inPlant — Input plant model

LTI model | identified linear model

Input plant model, specified as either an LTI model or a linear System Identification Toolbox model.

Name-Value Pair Arguments

Specify optional comma-separated pairs of **Name**, **Value** arguments. **Name** is the argument name and **Value** is the corresponding value. **Name** must appear inside quotes. You can specify several name and value pair arguments in any order as **Name1**, **Value1**, ..., **NameN**, **ValueN**.

Example: `'UnmeasuredDisturbances', [2 3]` configures the second and third input arguments as measured disturbances

ManipulatedVariables — Manipulated variable indices

vector of positive integers

Manipulated variable indices, specified as the comma-separated pair `'ManipulatedVariables'` followed by a vector of positive integers. The maximum index value must not exceed the number of input channels in `inPlant`. The indices specified using `ManipulatedVariables`, `MeasuredDisturbances`, and `UnmeasuredDisturbances` must not overlap.

Instead of `'ManipulatedVariables'`, you can use the abbreviation `'MV'`.

MeasuredDisturbances — Measured disturbance indices

vector of positive integers

Measured disturbance indices, specified as the comma-separated pair `'MeasuredDisturbances'` followed by a vector of positive integers. The maximum index value must not exceed the number of input channels in `inPlant`. The indices specified using `ManipulatedVariables`, `MeasuredDisturbances`, and `UnmeasuredDisturbances` must not overlap.

Instead of `'MeasuredDisturbances'`, you can use the abbreviation `'MD'`.

UnmeasuredDisturbances — Unmeasured disturbance indices

vector of positive integers

Unmeasured disturbance indices, specified as the comma-separated pair `'UnmeasuredDisturbances'` followed by a vector of positive integers. The maximum index value must not exceed the number of input channels in `inPlant`. The indices specified using `ManipulatedVariables`, `MeasuredDisturbances`, and `UnmeasuredDisturbances` must not overlap.

Instead of `'UnmeasuredDisturbances'`, you can use the abbreviation `'UD'`.

MeasuredOutputs — Measured output indices

vector of positive integers

Measured output indices, specified as the comma-separated pair `'MeasuredOutputs'` followed by a vector of positive integers. The maximum index value must not exceed the number of output channels in `inPlant`. The indices specified using `MeasuredOutputs` and `UnmeasuredOutputs` must not overlap.

Instead of `'MeasuredOutputs'`, you can use the abbreviation `'MO'`.

UnmeasuredOutputs — Unmeasured output indices

vector of positive integers

Unmeasured output indices, specified as the comma-separated pair 'UnmeasuredOutputs' followed by a vector of positive integers. The maximum index value must not exceed the number of output channels in `inPlant`. The indices specified using `MeasuredOutputs` and `UnmeasuredOutputs` must not overlap.

Instead of 'UnmeasuredOutputs', you can use the abbreviation 'UO'.

Output Arguments

outPlant — Output plant model

linear dynamic model

Output plant model, returned as a linear dynamic model. `outPlant` has the specified input and output channel types. Otherwise, `outPlant` is identical to `inPlant`.

Tips

In general, set the plant signal types using `setmpcsignals` before creating your controller object.

If you modify the signal types of the internal plant model of an existing controller, you must ensure that the new input/output channel types are consistent with the following controller properties:

- `Weights`
- `ManipulatedVariables`
- `OutputVariables`
- `DisturbanceVariables`
- `Model.Noise`

See Also

`mpc` | `set`

Topics

"MPC Modeling"

Introduced before R2006a

setname

Set I/O signal names in MPC prediction model

Syntax

```
setname(MPCobj, 'input', I, name)  
setname(MPCobj, 'output', I, name)
```

Description

`setname(MPCobj, 'input', I, name)` changes the name of the *I*th input signal to `name`. This is equivalent to `MPCobj.Model.Plant.InputName{I}=name`. Specify `name` as a character vector or string. Note that `setname` also updates the read-only `Name` fields of `MPCobj.DisturbanceVariables` and `MPCobj.ManipulatedVariables`.

`setname(MPCobj, 'output', I, name)` changes the name of the *I*th output signal to `name`. This is equivalent to `MPCobj.Model.Plant.OutputName{I} =name`. Specify `name` as a character vector or string. Note that `setname` also updates the read-only `Name` field of `MPCobj.OutputVariables`.

Note The `Name` properties of `ManipulatedVariables`, `OutputVariables`, and `DisturbanceVariables` are read-only. You must use `setname` to assign signal names, or equivalently modify the `Model.Plant.InputName` and `Model.Plant.OutputName` properties of the MPC object.

See Also

`getname` | `mpc` | `set`

Introduced before R2006a

setoutdist

Modify unmeasured output disturbance model

Syntax

```
setoutdist(MPCobj, 'model', model)
setoutdist(MPCobj, 'integrators')
```

Description

`setoutdist(MPCobj, 'model', model)` sets the output disturbance model used by the model predictive controller, `MPCobj`, to a custom model.

`setoutdist(MPCobj, 'integrators')` sets the output disturbance model to its default value. Use this syntax if you previously set a custom output disturbance model and you want to change back to the default model. For more information on the default output disturbance model, see “MPC Modeling”.

Examples

Specify Output Disturbance Model Using Transfer Functions

Define a plant model with no direct feedthrough, and create an MPC controller for that plant.

```
plant = rss(3,3,3);
plant.D = 0;
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
```

Define disturbance models for each output such that the output disturbance for:

- Channel 1 is random white noise with a magnitude of 2.
- Channel 2 is random step-like noise with a magnitude of 0.5.
- Channel 3 is random ramp-like noise with a magnitude of 1.

```
mod1 = tf(2,1);
mod2 = tf(0.5,[1 0]);
mod3 = tf(1,[1 0 0]);
```

Construct the output disturbance model using these transfer functions. Use a separate noise input for each output disturbance.

```
outdist = [mod1 0 0; 0 mod2 0; 0 0 mod3];
```

Set the output disturbance model in the MPC controller.

```
setoutdist(MPCobj, 'model', outdist)
```

View the controller output disturbance model.

```
getoutdist(MPCobj)
```

```
ans =
```

```
A =
      x1    x2    x3
x1     1     0     0
x2     0     1     0
x3     0    0.1     1
```

```
B =
      Noise#1  Noise#2  Noise#3
x1           0      0.05      0
x2           0       0      0.1
x3           0       0     0.005
```

```
C =
      x1    x2    x3
M01    0     0     0
M02    1     0     0
M03    0     0     1
```

```
D =
      Noise#1  Noise#2  Noise#3
M01         2       0       0
M02         0       0       0
M03         0       0       0
```

```
Sample time: 0.1 seconds
Discrete-time state-space model.
```

The controller converts the continuous-time transfer function model, `outdist`, into a discrete-time state-space model.

Remove Output Disturbance from Particular Output Channel

Define a plant model with no direct feedthrough, and create an MPC controller for that plant.

```
plant = rss(3,3,3);
plant.D = 0;
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.0000.
```

Retrieve the default output disturbance model from the controller.

```
distMod = getoutdist(MPCobj);
```

```
-->Converting model to discrete time.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->Assuming output disturbance added to measured output channel #2 is integrated white noise.
-->Assuming output disturbance added to measured output channel #3 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Remove the integrator from the second output channel. Construct the new output disturbance model by removing the second input channel and setting the effect on the second output by the other two inputs to zero.

```
distMod = sminreal([distMod(1,1) distMod(1,3); 0 0; distMod(3,1) distMod(3,3)]);
setoutdist(MPCobj, 'model', distMod)
```

When removing an integrator from the output disturbance model in this way, use `sminreal` to make the custom model structurally minimal.

View the output disturbance model.

```
tf(getoutdist(MPCobj))
```

```
ans =
```

```
From input "Noise#1" to output...
      0.1
M01:  ----
      z - 1
```

```
M02:  0
```

```
M03:  0
```

```
From input "Noise#2" to output...
M01:  0
```

```
M02:  0
```

```
      0.1
M03:  ----
      z - 1
```

```
Sample time: 0.1 seconds
Discrete-time transfer function.
```

The integrator has been removed from the second channel. The disturbance models for channels 1 and 3 remain at their default values as discrete-time integrators.

Remove Output Disturbances from All Output Channels

Define a plant model with no direct feedthrough and create an MPC controller for that plant.

```
plant = rss(3,3,3);
plant.D = 0;
MPCobj = mpc(plant,1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.  
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.  
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Set the output disturbance model to zero for all three output channels.

```
setoutdist(MPCobj, 'model', tf(zeros(3,1)))
```

View the output disturbance model.

```
getoutdist(MPCobj)
```

```
ans =
```

```
D =  
      Noise#1  
MO1      0  
MO2      0  
MO3      0
```

Static gain.

A static gain of 0 for all output channels indicates that the output disturbances were removed.

Set Output Disturbance Model to Default Value

Define a plant model with no direct feedthrough and create an MPC controller for that plant.

```
plant = rss(2,2,2);  
plant.D = 0;  
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.  
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.  
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.  
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.  
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Remove the output disturbances for all channels.

```
setoutdist(MPCobj, 'model', tf(zeros(2,1)))
```

Restore the default output disturbance model.

```
setoutdist(MPCobj, 'integrators')
```

Input Arguments

MPCobj — Model predictive controller

MPC controller object

Model predictive controller, specified as an MPC controller object. To create an MPC controller, use `mpc`.

model — Custom output disturbance model

[] (default) | ss object | tf object | zpk object

Custom output disturbance model, specified as a state-space (ss), transfer function (tf), or zero-pole-gain (zpk) model. The MPC controller converts the model to a discrete-time, delay-free, state-space model. Omitting `model` or specifying `model` as [] is equivalent to using `setoutdist(MPCobj, 'integrators')`.

The output disturbance model has:

- Unit-variance white noise input signals. For custom output disturbance models, the number of inputs is your choice.
- n_y outputs, where n_y is the number of plant outputs defined in `MPCobj.Model.Plant`. Each disturbance model output is added to the corresponding plant output.

This model, along with the input disturbance model (if any), governs how well the controller compensates for unmeasured disturbances and modeling errors. For more information on the disturbance modeling in MPC and about the model used during state estimation, see “MPC Modeling” and “Controller State Estimation”.

`setoutdist` does not check custom output disturbance models for violations of state observability. This check is performed later in the MPC design process when the internal state estimator is constructed using commands such as `sim` or `mpcmove`. If the controller states are not fully observable, these commands will generate an error.

Tips

- To view the current output disturbance model, use the `getoutdist` command.

See Also`getEstimator` | `getoutdist` | `mpc` | `setEstimator` | `setindist`**Topics**

“MPC Modeling”

“Controller State Estimation”

“Adjust Disturbance and Noise Models”

Introduced in R2006a

setterminal

Terminal weights and constraints

Syntax

```
setterminal(MPCobj,Y,U)
setterminal(MPCobj,Y,U,Pt)
```

Description

`setterminal(MPCobj,Y,U)` specifies diagonal quadratic penalty weights and constraints at the last step in the prediction horizon. The weights and constraints are on the terminal output $y(t+p)$ and terminal input $u(t+p-1)$, where p is the prediction horizon of the MPC controller `MPCobj`.

`setterminal(MPCobj,Y,U,Pt)` specifies diagonal quadratic penalty weights and constraints from step Pt to the horizon end. By default, Pt is the last step in the horizon.

Input Arguments

MPCobj

MPC controller, specified as an MPC controller object on page 3-6

Default:

Y

Terminal weights and constraints for the output variables, specified as a structure with the following fields:

Weight	1-by- n_y vector of nonnegative weights
Min	1-by- n_y vector of lower bounds
Max	1-by- n_y vector of upper bounds
MinECR	1-by- n_y vector of constraint-softening Equal Concern for the Relaxation (ECR) values for the lower bounds
MaxECR	1-by- n_y vector of constraint-softening ECR values for the upper bounds

n_y is the number of controlled outputs of the MPC controller.

If the `Weight`, `Min` or `Max` field is empty, the values in `MPCobj` are used at all prediction horizon steps including the last. For the standard bounds, if any element of the `Min` or `Max` field is infinite, the corresponding variable is unconstrained at the terminal step.

Off-diagonal weights are zero (as described in “Standard Cost Function”). To apply nonzero off-diagonal terminal weights, you must augment the plant model. See “Provide LQR Performance Using Terminal Penalty Weights”.

By default, `Y.MinECR = Y.MaxECR = 1` (soft output constraints).

Choose the ECR magnitudes carefully, accounting for the importance of each constraint and the numerical magnitude of a typical violation.

Default:

U

Terminal weights and constraints for the manipulated variables, specified as a structure with the following fields:

Weight	1-by- n_u vector of nonnegative weights
Min	1-by- n_u vector of lower bounds
Max	1-by- n_u vector of upper bounds
MinECR	1-by- n_u vector of constraint-softening Equal Concern for the Relaxation (ECR) values for the lower bounds
MaxECR	1-by- n_u vector of constraint-softening ECR values for the upper bounds

n_u is the number of manipulated variables of the MPC controller.

If the `Weight`, `Min` or `Max` field is empty, the values in `MPCobj` are used at all prediction horizon steps including the last. For the standard bounds, if individual elements of the `Min` or `Max` fields are infinite, the corresponding variable is unconstrained at the terminal step.

Off-diagonal weights are zero (as described in “Standard Cost Function”). To apply nonzero off-diagonal terminal weights, you must augment the plant model. See “Provide LQR Performance Using Terminal Penalty Weights”.

By default, `U.MinECR = U.MaxECR = 0` (hard manipulated variable constraints)

Choose the ECR magnitudes carefully, accounting for the importance of each constraint and the numerical magnitude of a typical violation.

Default:

Pt

Step in the prediction horizon, specified as an integer between 1 and p , where p is the prediction horizon. The terminal values are applied to `Y` and `U` from prediction step `Pt` to the end.

Default: Prediction horizon p

Examples

Specify Constraints and Penalty Weights at Last Prediction Horizon Step

Create an MPC controller for a plant with three output variables and two manipulated variables.

```
plant = rss(3,3,2);
plant.D = 0;
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
    for output(s) y1 y2 and zero weight for output(s) y3
```

Specify a prediction horizon of 8.

```
MPCobj.PredictionHorizon = 8;
```

Define the following penalty weights and constraints:

- Diagonal penalty weights of 1 and 10 on the first two output variables
- Lower bounds of 0 and -1 on the first and third outputs respectively
- Upper bound of 2 on the second output
- Lower bound of 1 on the first manipulated variable

```
Y = struct('Weight',[1,10,0], 'Min',[0,-Inf,-1], 'Max',[Inf,2,Inf]);
U = struct('Min',[1,-Inf]);
```

Specify the constraints and penalty weights at the last step of the prediction horizon.

```
setterminal(MPCobj,Y,U)
```

Specify Terminal Constraints For Final Prediction Horizon Range

Create an MPC controller for a plant with three output variables and two manipulated variables.

```
plant = rss(3,3,2);
plant.D = 0;
MPCobj = mpc(plant,0.1);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
    for output(s) y1 y2 and zero weight for output(s) y3
```

Specify a prediction horizon of 10.

```
MPCobj.PredictionHorizon = 10;
```

Define the following terminal constraints:

- Lower bounds of 0 and -1 on the first and third outputs respectively
- Upper bound of 2 on the second output
- Lower bound of 1 on the first manipulated variable

```
Y = struct('Min',[0,-Inf,-1], 'Max',[Inf,2,Inf]);
U = struct('Min',[1,-Inf]);
```

Specify the constraints beginning at step 5 and ending at the last step of the prediction horizon.

```
setterminal(MPCobj,Y,U,5)
```

Tips

- Advanced users can impose terminal polyhedral state constraints:

$$K_1 \leq Hx \leq K_2.$$

First, augment the plant model with additional artificial (unmeasured) outputs, $y = Hx$. Then specify bounds K_1 and K_2 on these y outputs.

See Also

[mpc](#) | [mpcprops](#) | [setconstraint](#)

Topics

[“Terminal Weights and Constraints”](#)

[“Provide LQR Performance Using Terminal Penalty Weights”](#)

Introduced in R2011a

sim

Simulate closed-loop/open-loop response to arbitrary reference and disturbance signals for implicit or explicit MPC

Syntax

```
sim(MPCobj,T,r)
sim(MPCobj,T,r,v)
sim(___,SimOptions)
[y,t,u,xp,xmpc,SimOptions] = sim(___)
```

Description

Use `sim` to simulate the implicit (traditional) or explicit MPC controller in closed loop with a linear time-invariant model, which, by default, is the plant model contained in `MPCobj.Model.Plant`. As an alternative, `sim` can simulate the open-loop behavior of the model of the plant, or the closed-loop behavior in the presence of a model mismatch, when the controller's prediction model differs from the actual plant model.

`sim(MPCobj,T,r)` simulates the closed-loop system formed by the plant model specified in `MPCobj.Model.Plant` and by the MPC controller specified by the MPC controller `MPCobj`, in response to the specified reference signal, `r`. The MPC controller can be either a traditional MPC controller (`mpc`) or explicit MPC controller (`explicitMPC`). The simulation runs for the specified number of simulation steps, `T`. `sim` plots the simulation results.

`sim(MPCobj,T,r,v)` also specifies the measured disturbance signal `v`.

`sim(___,SimOptions)` specifies additional simulation options. This syntax allows you to alter the default simulation options, such as initial states, input/output noise and unmeasured disturbances, plant mismatch, etc. You can use `SimOptions` with any of the previous input combinations.

`[y,t,u,xp,xmpc,SimOptions] = sim(___)` suppresses plotting and instead returns the sequence of plant outputs `y`, the time sequence `t` (equally spaced by `MPCobj.Ts`), the manipulated variables `u` generated by the MPC controller, the sequence `xp` of states of the model of the plant used for simulation, the sequence `xmpc` of states of the MPC controller (provided by the state observer), and the simulation options, `SimOptions`. You can use this syntax with any of the allowed input argument combinations.

Input Arguments

MPCobj

MPC controller containing the parameters of the Model Predictive Control law to simulate, specified as either an implicit MPC controller (`mpc`) or an explicit MPC controller (`explicitMPC`).

T

Number of simulation steps, specified as a positive integer.

If you omit T , the default value is the row size of whichever of the following arrays has the largest row size:

- The input argument r
- The input argument v
- The `UnmeasuredDisturbance` property of `SimOptions`, if specified
- The `OutputNoise` property of `SimOptions`, if specified

Default: The largest row size of r , v , `UnmeasuredDisturbance`, and `OutputNoise`

r

Reference signal, specified as an array. This array has n_y columns, where n_y is the number of plant outputs. r can have anywhere from 1 to T rows. If the number of rows is less than T , the missing rows are set equal to the last row.

Default: `MPCobj.Model.Nominal.Y`

v

Measured disturbance signal, specified as an array. This array has n_v columns, where n_v is the number of measured input disturbances. v can have anywhere from 1 to T rows. If the number of rows is less than T , the missing rows are set equal to the last row.

Default: Corresponding entries from `MPCobj.Model.Nominal.U`

SimOptions

Simulation options, specified as an `mpcsimopt` object.

Default: `[]`

Output Arguments

y

Sequence of controlled plant outputs, returned as a T -by- N_y array, where T is the number of simulation steps and N_y is the number of plant outputs. The values in y include neither additive output disturbances nor additive measurement noise (if any).

t

Time sequence, returned as a T -by-1 array, where T is the number of simulation steps. The values in t are equally spaced by `MPCobj.Ts`.

u

Sequence of manipulated variables generated by the MPC controller, returned as a T -by- N_u array, where T is the number of simulation steps and N_u is the number of manipulated variables.

xp

Sequence of plant model states, T-by-Nxp array, where T is the number of simulation steps and Nxp is the number of states in the plant model. The plant model is either `MPCobj.Model` or `SimOptions.Model`, if the latter is specified.

xmpc

Sequence of MPC controller state estimates, returned as a T-by-1 structure array. Each entry in the structure array has the same fields as an `mpcstate` object. The state estimates include plant, disturbance, and noise model states at each time step.

SimOptions

Simulation options used, returned as an `mpcsimopt` object.

Examples**Simulate MPC Control of MISO Plant**

Simulate the MPC control of a MISO system. The system has one manipulated variable, one measured disturbance, one unmeasured disturbance, and one output.

Create the continuous-time plant model. This plant will be used as the prediction model for the MPC controller.

```
sys = ss(tf({1,1,1},{[1 .5 1],[1 1],[.7 .5 1]}));
```

Discretize the plant model using a sampling time of 0.2 units.

```
Ts = 0.2;
sysd = c2d(sys,Ts);
```

Specify the MPC signal type for the plant input signals.

```
sysd = setmpcsignals(sysd, 'MV',1, 'MD',2, 'UD',3);
```

Create an MPC controller for the `sysd` plant model. Use default values for the weights and horizons.

```
MPCobj = mpc(sysd);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Constrain the manipulated variable to the [0 1] range.

```
MPCobj.MV = struct('Min',0, 'Max',1);
```

Specify the simulation stop time.

```
Tstop = 30;
```

Define the reference signal and the measured disturbance signal.


```
num_sim_steps = round(Tstop/Ts);  
r = ones(num_sim_steps,1);  
v = [zeros(num_sim_steps/3,1); ones(2*num_sim_steps/3,1)];
```

The reference signal, r , is a unit step. The measured disturbance signal, v , is a unit step, with a 10 unit delay.

Simulate the controller.

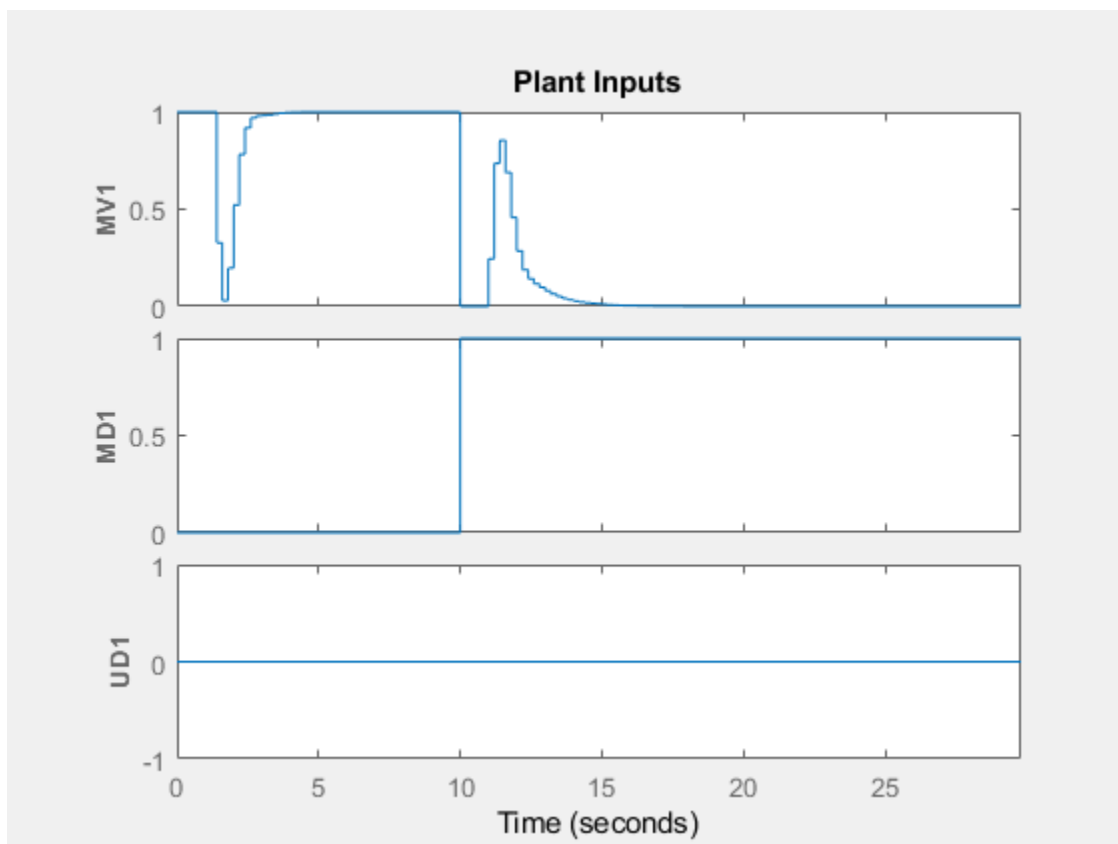
```
sim(MPCobj,num_sim_steps,r,v)
```

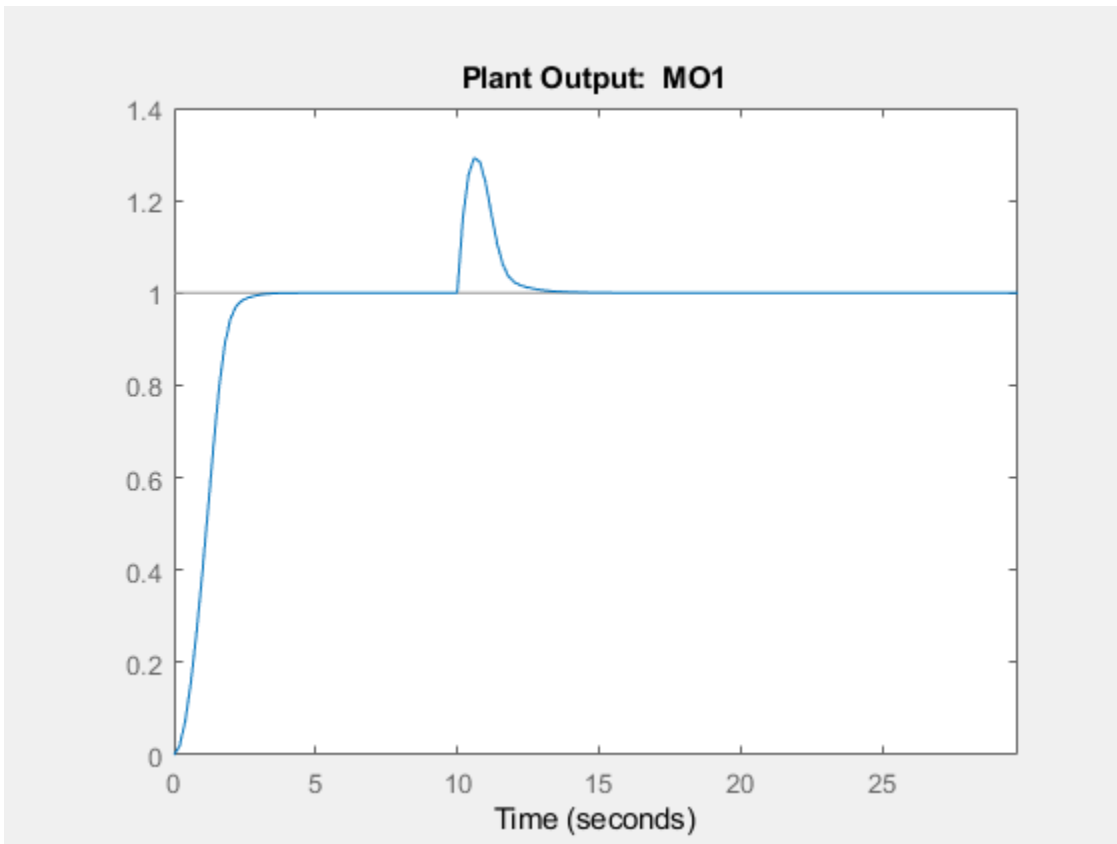
-->The "Model.Disturbance" property of "mpc" object is empty:

Assuming unmeasured input disturbance #3 is integrated white noise.

Assuming no disturbance added to measured output channel #1.

-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured





See Also

`mpc` | `mpcmove` | `mpcsimopt`

Introduced before R2006a

simplify

Reduce explicit MPC controller complexity and memory requirements

Syntax

```
EMPCreduced = simplify(EMPCobj, 'exact')
EMPCreduced = simplify(EMPCobj, 'exact', uniteeps)
EMPCreduced = simplify(EMPCobj, 'radius', r)
EMPCreduced = simplify(EMPCobj, 'sequence', index)
simplify(EMPCobj, ___)
```

Description

`EMPCreduced = simplify(EMPCobj, 'exact')` attempts to reduce the number of piecewise affine (PWA) regions in an explicit MPC controller by merging regions that have identical controller gains and whose union is a convex set. Reducing the number of PWA regions reduces memory requirements of the controller. This command returns a reduced controller, `EMPCreduced`.

`EMPCreduced = simplify(EMPCobj, 'exact', uniteeps)` specifies the tolerance for identifying regions that can be merged.

`EMPCreduced = simplify(EMPCobj, 'radius', r)` retains only regions whose Chebyshev radius (the radius of the largest ball contained in the region) is larger than r .

`EMPCreduced = simplify(EMPCobj, 'sequence', index)` eliminates all regions except those specified in an index vector.

`simplify(EMPCobj, ___)` applies the reduction to the explicit MPC controller `EMPCobj`, rather than returning a new controller object. You can use this syntax with any of the previous reduction options.

Input Arguments

EMPCobj — Explicit MPC controller

explicit MPC controller object

Explicit MPC controller to reduce, specified as an Explicit MPC controller object. Use `generateExplicitMPC` to create an explicit MPC controller.

uniteeps — Tolerance for joining regions

0.001 (default) | positive scalar

Tolerance for joining PWA regions, specified as a positive scalar.

r — Minimum Chebyshev radius

0 (default) | nonnegative scalar

Minimum Chebyshev radius for retaining PWA regions, specified as a nonnegative scalar. When you use the `'radius'` option, `simplify` keeps only the regions whose Chebyshev radius is larger than r . The default value is 0, which causes all regions to be retained.

index — Indices of PWA regions to retain`1:nr (default) | vector`

Indices of PWA regions to retain, specified as a vector. The default value is `[1:nr]`, where `nr` is the number of PWA regions in `EMPCobj`. Thus, by default, all regions are retained. You can obtain a sequence of regions to retain by performing simulations using `EMPCobj` and recording the indices of regions actually encountered.

Output Arguments**EMPCreduced — Reduced MPC controller**`explicit MPC controller object`

Reduced MPC controller, returned as an Explicit MPC controller object.

See Also`generateExplicitMPC`**Introduced in R2014b**

size

Size and order of MPC Controller

Syntax

```
mpc_obj_size = size(MPCobj)
mpc_obj_size = size(MPCobj,signal_type)
size(MPCobj)
```

Description

`mpc_obj_size = size(MPCobj)` returns a row vector specifying the number of manipulated inputs and measured controlled outputs of an MPC controller. This row vector contains the elements $[n_u, n_{ym}]$, where n_u is the number of manipulated inputs and n_{ym} is the number of measured controlled outputs.

`mpc_obj_size = size(MPCobj,signal_type)` returns the number of signals of the specified type that are associated with the MPC controller.

You can specify `signal_type` as one of the following:

- 'uo' — Unmeasured controlled outputs
- 'md' — Measured disturbances
- 'ud' — Unmeasured disturbances
- 'mv' — Manipulated variables
- 'mo' — Measured controlled outputs

`size(MPCobj)` displays the size information for all the signal types of the MPC controller.

See Also

`mpc` | `set`

Introduced before R2006a

SS

Convert unconstrained MPC controller to state-space linear system

Syntax

```
sys = ss(MPCobj)
sys = ss(MPCobj,signals)
sys = ss(MPCobj,signals,ref_preview,md_preview)
[sys,ut] = ss(MPCobj)
```

Description

The `ss` command returns a linear controller in the state-space form. The controller is equivalent to the traditional (implicit) MPC controller `MPCobj` when no constraints are active. You can then use Control System Toolbox™ software for sensitivity analysis and other diagnostic calculations.

`sys = ss(MPCobj)` returns the linear discrete-time dynamic controller `sys`.

$$x(k+1) = Ax(k) + By_m(k)$$

$$u(k) = Cx(k) + Dy_m(k)$$

where y_m is the vector of measured outputs of the plant, and u is the vector of manipulated variables. The sampling time of controller `sys` is `MPCobj.Ts`.

Note Vector x includes the states of the observer (plant + disturbance + noise model states) and the previous manipulated variable $u(k-1)$.

`sys = ss(MPCobj,signals)` returns the linearized MPC controller in its full form and allows you to specify the signals that you want to include as inputs for `sys`.

The full form of the MPC controller has the following structure:

$$x(k+1) = Ax(k) + By_m(k) + B_r r(k) + B_v v(k) + B_{ut} u_{target}(k) + B_{off}$$

$$u(k) = Cx(k) + Dy_m(k) + D_r r(k) + D_v v(k) + D_{ut} u_{target}(k) + D_{off}$$

Here:

- r is the vector of setpoints for both measured and unmeasured plant outputs
- v is the vector of measured disturbances.
- u_{target} is the vector of preferred values for manipulated variables.

Specify `signals` as a character vector or string with any combination that contains one or more of the following characters:

- 'r' — Output references

- 'v' — Measured disturbances
- 'o' — Offset terms
- 't' — Input targets

For example, to obtain a controller that maps $[y_m; r; v]$ to u , use:

```
sys = ss(MPCobj, 'rv');
```

In the general case of nonzero offsets, y_m , r , v , and u_{target} must be interpreted as the difference between the vector and the corresponding offset. Offsets can be nonzero if `MPCobj.Model.Nominal.Y` or `MPCobj.Model.Nominal.U` are nonzero.

Vectors B_{off} and D_{off} are constant terms. They are nonzero if and only if `MPCobj.Model.Nominal.DX` is nonzero (continuous-time prediction models), or `MPCobj.Model.Nominal.Dx-MPCobj.Model.Nominal.X` is nonzero (discrete-time prediction models). In other words, when `Nominal.X` represents an equilibrium state, B_{off} , D_{off} are zero.

Only the following fields of `MPCobj` are used when computing the state-space model: `Model`, `PredictionHorizon`, `ControlHorizon`, `Ts`, `Weights`.

`sys = ss(MPCobj, signals, ref_preview, md_preview)` specifies if the MPC controller has preview actions on the reference and measured disturbance signals. If the flag `ref_preview = 'on'`, then matrices B_r and D_r multiply the whole reference sequence:

$$x(k+1) = Ax(k) + By_m(k) + B_r[r(k);r(k+1);...;r(k+p-1)] + \dots$$

$$u(k) = Cx(k) + Dy_m(k) + D_r[r(k);r(k+1);...;r(k+p-1)] + \dots$$

Similarly if the flag `md_preview = 'on'`, then matrices B_v and D_v multiply the whole measured disturbance sequence:

$$x(k+1) = Ax(k) + \dots + B_v[v(k);v(k+1);...;v(k+p)] + \dots$$

$$u(k) = Cx(k) + \dots + D_v[v(k);v(k+1);...;v(k+p)] + \dots$$

`[sys, ut] = ss(MPCobj)` also returns the input target values for the full form of the controller.

`ut` is returned as a vector of doubles, `[utarget(k); utarget(k+1); ... utarget(k+h)]`.

Here:

- h — Maximum length of previewed inputs; that is, $h = \max(\text{length}(\text{MPCobj.ManipulatedVariables}(:).\text{Target}))$
- `utarget` — Difference between the input target and corresponding input offsets; that is, `MPCobj.ManipulatedVariables(:).Targets - MPCobj.Model.Nominal.U`

Examples

Convert Unconstrained MPC Controller to State-Space Model

To improve the clarity of the example, suppress messages about working with an MPC controller.

```
old_status = mpcverbosity('off');
```

Create the plant model.

```
G = rss(5,2,3);  
G.D = 0;  
G = setmpcsignals(G, 'mv',1, 'md',2, 'ud',3, 'mo',1, 'uo',2);
```

Configure the MPC controller with nonzero nominal values, weights, and input targets.

```
C = mpc(G,0.1);  
C.Model.Nominal.U = [0.7 0.8 0];  
C.Model.Nominal.Y = [0.5 0.6];  
C.Model.Nominal.DX = rand(5,1);  
C.Weights.MV = 2;  
C.Weights.OV = [3 4];  
C.MV.Target = [0.1 0.2 0.3];
```

C is an unconstrained MPC controller. Specifying `C.Model.Nominal.DX` as nonzero means that the nominal values are not at steady state. `C.MV.Target` specifies three preview steps.

Convert C to a state-space model.

```
sys = ss(C);
```

The output, `sys`, is a seventh-order SISO state-space model. The seven states include the five plant model states, one state from the default input disturbance model, and one state from the previous move, $u(k-1)$.

Restore `mpcverbosity`.

```
mpcverbosity(old_status);
```

See Also

`mpc` | `set` | `tf` | `zpk`

Introduced before R2006a

tf

Convert unconstrained MPC controller to linear transfer function

Syntax

```
sys = tf(MPCobj)
```

Description

The `tf` function computes the transfer function of the linear controller `ss(MPCobj)` as an LTI system in `tf` form corresponding to the MPC controller when the constraints are not active. The purpose is to use the linear equivalent control in Control System Toolbox software for sensitivity and other linear analysis.

See Also

`ss` | `zpk`

Introduced before R2006a

trim

Compute steady-state value of MPC controller state for given inputs and outputs

Syntax

```
x = trim(MPCobj,y,u)
```

Description

The `trim` function finds a steady-state value for the plant state or the best approximation in a least squares sense such that:

$$x - x_{off} = A(x - x_{off}) + B(u - u_{off})$$

$$y - y_{off} = C(x - x_{off}) + D(u - u_{off})$$

Here, x_{off} , u_{off} , and y_{off} are the nominal values of the extended state x , input u , and output y respectively.

x is returned as an `mpcstate` object. Specify y and u as doubles. y specifies the measured and unmeasured output values. u specifies the manipulated variable, measured disturbance, and unmeasured disturbance values. The values for unmeasured disturbances must be $\mathbf{0}$.

`trim` assumes the disturbance model and measurement noise model to be zero when computing the steady-state value. The software uses the extended state vector to perform the calculation.

See Also

`mpc` | `mpcstate`

Introduced before R2006a

validateFcns

Examine prediction model and custom functions of `nltmpc` object for potential problems

Syntax

```
validateFcns(nltmpcobj,x,mv)
validateFcns(nltmpcobj,x,mv,md)
validateFcns(nltmpcobj,x,mv,md,parameters)
validateFcns(nltmpcobj,x,mv,md,parameters,ref)
validateFcns(nltmpcobj,x,mv,md,parameters,ref,mvtarget)
```

Description

`validateFunctions` tests the prediction model, custom cost, custom constraint, and Jacobian functions of a nonlinear MPC controller for potential problems. When you first design your nonlinear MPC controller, or when you make significant changes to an existing controller, it is best practice to validate your controller functions.

`validateFcns(nltmpcobj,x,mv)` tests the functions of nonlinear MPC controller `nltmpcobj` for potential problems. The functions are tested using specified nominal state values, `x`, and manipulated variable values, `mv`. Use this syntax if your controller has no measured disturbances and no parameters.

`validateFcns(nltmpcobj,x,mv,md)` specifies nominal measured disturbance values. If your controller has measured disturbance channels, you must specify `md`.

`validateFcns(nltmpcobj,x,mv,md,parameters)` specifies nominal parameter values. If your controller has parameters, you must specify `parameters`.

`validateFcns(nltmpcobj,x,mv,md,parameters,ref)` specifies nominal output references.

`validateFcns(nltmpcobj,x,mv,md,parameters,ref,mvtarget)` specifies nominal manipulated variable targets.

Examples

Validate Nonlinear MPC Prediction Model and Custom Functions

Create nonlinear MPC controller with six states, six outputs, and four inputs.

```
nx = 6;
ny = 6;
nu = 4;
nlobj = nltmpc(nx,ny,nu);
```

In standard cost function, zero weights are applied by default to one or more OVs because there a

Specify the controller sample time and horizons.

```
Ts = 0.4;
p = 30;
```

```
c = 4;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = p;
nlobj.ControlHorizon = c;
```

Specify the prediction model state function and the Jacobian of the state function. For this example, use a model of a flying robot.

```
nlobj.Model.StateFcn = "FlyingRobotStateFcn";
nlobj.Jacobian.StateFcn = "FlyingRobotStateJacobianFcn";
```

Specify a custom cost function for the controller that replaces the standard cost function.

```
nlobj.Optimization.CustomCostFcn = @(X,U,e,data) Ts*sum(sum(U(1:p,:)));
nlobj.Optimization.ReplaceStandardCost = true;
```

Specify a custom constraint function for the controller.

```
nlobj.Optimization.CustomEqConFcn = @(X,U,data) X(end,:)';
```

Validate the prediction model and custom functions at the initial states (x_0) and initial inputs (u_0) of the robot.

```
x0 = [-10;-10;pi/2;0;0;0];
u0 = zeros(nu,1);
validateFcns(nlobj,x0,u0);
```

```
Model.StateFcn is OK.
Jacobian.StateFcn is OK.
No output function specified. Assuming "y = x" in the prediction model.
Optimization.CustomCostFcn is OK.
Optimization.CustomEqConFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Create Nonlinear MPC Controller with Discrete-Time Prediction Model

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nx = 4;
ny = 2;
nu = 1;
nlobj = nlmpc(nx,ny,nu);
```

In standard cost function, zero weights are applied by default to one or more OVs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The discrete-time state function uses an optional parameter, the sample time T_s , to integrate the continuous-time model. Therefore, you must specify the number of optional parameters as 1.

```
nlobj.Model.NumberOfParameters = 1;
```

Specify the output function for the controller. In this case, define the first and third states as outputs. Even though this output function does not use the optional sample time parameter, you must specify the parameter as an input argument (T_s).

```
nlobj.Model.OutputFcn = @(x,u,Ts) [x(1); x(3)];
```

Validate the prediction model functions for nominal states x_0 and nominal inputs u_0 . Since the prediction model uses a custom parameter, you must pass this parameter to `validateFcns`.

```
x0 = [0.1;0.2;-pi/2;0.3];
u0 = 0.4;
validateFcns(nlobj, x0, u0, [], {Ts});
```

```
Model.StateFcn is OK.
Model.OutputFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Create Nonlinear MPC Controller with Measured and Unmeasured Disturbances

Create a nonlinear MPC controller with three states, one output, and four inputs. The first two inputs are measured disturbances, the third input is the manipulated variable, and the fourth input is an unmeasured disturbance.

```
nlobj = nlmpc(3,1,'MV',3,'MD',[1 2],'UD',4);
```

To view the controller state, output, and input dimensions and indices, use the `Dimensions` property of the controller.

```
nlobj.Dimensions
ans = struct with fields:
    NumberOfStates: 3
    NumberOfOutputs: 1
    NumberOfInputs: 4
        MVIndex: 3
        MDIndex: [1 2]
        UDIndex: 4
```

Specify the controller sample time and horizons.

```
nlobj.Ts = 0.5;
nlobj.PredictionHorizon = 6;
nlobj.ControlHorizon = 3;
```

Specify the prediction model state function, which is in the file `exocstrStateFcnCT.m`.

```
nlobj.Model.StateFcn = 'exocstrStateFcnCT';
```

Specify the prediction model output function, which is in the file `exocstrOutputFcn.m`.

```
nlobj.Model.OutputFcn = 'exocstrOutputFcn';
```

Validate the prediction model functions using the initial operating point as the nominal condition for testing and setting the unmeasured disturbance state, $x_0(3)$, to 0. Since the model has measured disturbances, you must pass them to `validateFcns`.

```
x0 = [311.2639; 8.5698; 0];
u0 = [10; 298.15; 298.15];
validateFcns(nlobj,x0,u0(3),u0(1:2)');
```

```
Model.StateFcn is OK.
Model.OutputFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Input Arguments

nmpcobj — Nonlinear MPC controller

nmpc object

Nonlinear MPC controller, specified as an nmpc object.

x — Nominal state values

vector

Nominal state values, specified as a vector of length N_x , N_x is equal to `nmpcobj.Dimensions.NumberOfStates`

mv — Nominal manipulated variable values

vector

Nominal manipulated variable values, specified as a vector of length N_{mv} , where N_{mv} is equal to the length of `nmpcobj.Dimensions.MVIndex`.

md — Nominal measured disturbance values

[] (default) | vector

Nominal measured disturbance values, specified as a vector of length N_{md} , where N_{md} is equal to the length of `nmpcobj.Dimensions.MDIndex`. If your controller has measured disturbance channels, you must specify `md`. If your controller does not have measured disturbance channels, specify `md` as `[]`.

parameters — Nominal parameter values

[] (default) | cell array

Nominal parameter values used by the prediction model, custom cost function, and custom constraints, specified as a cell array of length N_p , where N_p is equal to `nmpcobj.Model.NumberOfParameters`. The order of the parameters must match the order specified in the model functions, and each parameter must be a numeric parameter with the correct dimensions.

If your controller has parameters, you must specify `parameters`. If your controller does not have parameters, specify `parameters` as `[]`.

ref — Nominal output reference values

[] (default) | vector

Nominal output reference values, specified as a vector of length N_y , where N_y is equal to `nlpmpcobj.Dimensions.NumberOfOutputs`. `ref` is passed to the custom cost and constraint function. If you do not specify `ref`, the controller passes a vector of zeros to the custom functions.

mvtarget — Nominal manipulated variable targets

[] (default) | vector

Nominal manipulated variable targets, specified as a vector of length N_{mv} , where N_{mv} is equal to the length of `nlpmpcobj.Dimensions.MVIndex`. `mvtarget` is passed to the custom cost and constraint function. If you do not specify `mvtarget`, the controller passes a vector of zeros to the custom functions.

Tips

- When you provide your own analytical Jacobian functions, it is especially important that these functions return valid Jacobian values. If `validateFunctions` detects large differences between the values returned by your user-defined Jacobian functions and the finite-difference approximation, verify the code in your Jacobian implementations.

Algorithms

For each controller function, `validateFunctions` checks whether the function:

- Exists on the MATLAB path
- Has the required number of input arguments
- Can be executed successfully without errors
- Returns the output arguments with the correct size and dimensions
- Returns valid numerical data; that is, it does not return `Inf` or `NaN` values

For Jacobian functions, `validateFunctions` checks whether the returned values are comparable to a finite-difference approximation of the Jacobian values. These finite-difference values are computed using numerical perturbation.

See Also`nlpmpc`**Topics**

"Specify Prediction Model for Nonlinear MPC"

"Specify Cost Function for Nonlinear MPC"

"Specify Constraints for Nonlinear MPC"

Introduced in R2018b

zpk

Convert unconstrained MPC controller to zero/pole/gain form

Syntax

```
sys = zpk(MPCobj)
```

Description

The `zpk` function computes the zero-pole-gain form of the linear controller `ss(MPCobj)` as an LTI system in `zpk` form corresponding to the MPC controller when the constraints are not active. The purpose is to use the linear equivalent control in Control System Toolbox software for sensitivity and other linear analysis.

See Also

`ss` | `tf`

Introduced before R2006a

Objects

explicitMPC

Explicit model predictive controller

Description

Explicit model predictive control uses offline computations to determine all operating regions in which the optimal control moves are determined by evaluating a linear function. Explicit MPC controllers require fewer run-time computations than traditional (implicit) model predictive controllers and are therefore useful for applications that require small sample times.

To implement explicit MPC, first design a traditional (implicit) model predictive controller for your application, and then use this controller to generate an explicit MPC controller for use in real-time control. For more information, see “Design Workflow for Explicit MPC”.

Creation

To create an `explicitMPC` object:

- 1 Create an implicit MPC controller using an `mpc` object.
- 2 Define the operating range for the explicit MPC controller by creating a range structure using the `generateExplicitRange` function and specifying the bounds using dot notation.
- 3 Define the optimization options for converting the implicit controller into an explicit controller using the `generateExplicitOptions` function.
- 4 Create the explicit MPC controller based on the implicit controller, operating range, and optimization options using the `generateExplicitMPC` function.

Properties

MPC — Implicit MPC controller

`mpc` object

Implicit MPC controller, specified as an `mpc` object.

Range — Parameter bounds

structure

Parameter bounds that define the controller operating range, specified as a structure with the following fields.

Field	Description
State	Bounds on controller state values
Reference	Bounds on controller reference signal values
MeasuredDisturbance	Bounds on measured disturbance values
ManipulatedVariable	Bounds on manipulated variable values

Define this property using the `range` input argument to the `generateExplicitMPC` function, which you create using the `generateExplicitRange` function and modify using dot notation. For detailed descriptions of the range parameters, see `generateExplicitRange`.

OptimizationOptions – Optimization options

structure

Optimization options for the conversion computation, specified as a structure with the following fields.

Field	Description
<code>zerotol</code>	Zero-detection tolerance
<code>removetol</code>	Redundant-inequality-constraint detection tolerance
<code>flattol</code>	Flat region detection tolerance
<code>normalizetol</code>	Constraint normalization tolerance
<code>maxiterNLS</code>	Maximum number of NLS solver iterations
<code>maxiterQP</code>	Maximum number of QP solver iterations
<code>maxiterBS</code>	Maximum number of bisection method iterations
<code>polyreduction</code>	Method for removing redundant inequalities

Define this property using the `opt` input argument to the `generateExplicitMPC` function, which you create using the `generateExplicitOptions` function. For detailed descriptions of these options, see `generateExplicitOptions`.

PiecewiseAffineSolution – Piecewise affine solution

structure array

Piecewise affine solution for the different operating regions, specified as a structure array with N_r elements, where N_r is the number of operating regions.

Each structure element contains fields defining the inequality constraints and control law for each region. For more information on the control law and constraints, see “Design Workflow for Explicit MPC”.

Field	Dimensions
<code>F</code>	Row vector of length N_x -by- N_{mv} .
<code>G</code>	Column vector of length N_{mv}
<code>H</code>	N_c -by- N_x array
<code>K</code>	Column vector of length N_c

Here:

- N_x is the number of independent variables.
- N_{mv} is the number of manipulated variables.
- N_c is the number of inequality constraints for the region.

IsSimplified – Flag indicating whether the explicit control law has been simplified

false (default) | true

Flag indicating whether the explicit control law has been simplified using the `simplify` command. If the control law is simplified, it approximates the implicit MPC controller behavior. If the control law is not simplified, it should reproduce the implicit controller behavior exactly, provided both operate within the bounds described by the `Range` property.

Object Functions

<code>simplify</code>	Reduce explicit MPC controller complexity and memory requirements
<code>plotSection</code>	Visualize explicit MPC control law as 2-D sectional plot
<code>mpcmoveExplicit</code>	Compute optimal control using explicit MPC
<code>sim</code>	Simulate closed-loop/open-loop response to arbitrary reference and disturbance signals for implicit or explicit MPC
<code>mpcstate</code>	MPC controller state
<code>getCodeGenerationData</code>	Create data structures for <code>mpcmoveCodeGeneration</code>

Examples

Generate Explicit MPC Controller

Generate an explicit MPC controller based upon a traditional MPC controller for a double-integrator plant.

Define the double-integrator plant.

```
plant = tf(1,[1 0 0]);
```

Create a traditional (implicit) MPC controller for this plant, with sample time 0.1, a prediction horizon of 10, and a control horizon of 3.

```
Ts = 0.1;
p = 10;
m = 3;
MPCobj = mpc(plant,Ts,p,m);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

To generate an explicit MPC controller, you must specify the ranges of parameters such as state values and manipulated variables. To do so, generate a range structure. Then, modify values within the structure to the desired parameter ranges.

```
range = generateExplicitRange(MPCobj);
```

```
-->Converting the "Model.Plant" property of "mpc" object to state-space.
-->Converting model to discrete time.
    Assuming no disturbance added to measured output channel #1.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
range.State.Min(:) = [-10;-10];
range.State.Max(:) = [10;10];
range.Reference.Min = -2;
range.Reference.Max = 2;
range.ManipulatedVariable.Min = -1.1;
range.ManipulatedVariable.Max = 1.1;
```

Use the more robust reduction method for the computation. Use `generateExplicitOptions` to create a default options set, and then modify the `polyreduction` option.

```
opt = generateExplicitOptions(MPCobj);
opt.polyreduction = 1;
```

Generate the explicit MPC controller.

```
EMPCobj = generateExplicitMPC(MPCobj,range,opt)
```

```
Explicit MPC Controller
```

```
-----
Controller sample time:    0.1 (seconds)
Polyhedral regions:       1
Number of parameters:     4
Is solution simplified:    No
State Estimation:         Default Kalman gain
-----
```

Type 'EMPCobj.MPC' for the original implicit MPC design.

Type 'EMPCobj.Range' for the valid range of parameters.

Type 'EMPCobj.OptimizationOptions' for the options used in multi-parametric QP computation.

Type 'EMPCobj.PiecewiseAffineSolution' for regions and gain in each solution.

See Also

Explicit MPC Controller | Multiple Explicit MPC Controllers

Topics

“Explicit MPC Control of a Single-Input-Single-Output Plant”

“Explicit MPC Control of an Aircraft with Unstable Poles”

“Explicit MPC Control of DC Servomotor with Constraint on Unmeasured Output”

“Explicit MPC”

“Design Workflow for Explicit MPC”

Introduced in R2014b

mpc

Model predictive controller

Description

A model predictive controller uses linear plant, disturbance, and noise models to estimate the controller state and predict future plant outputs. Using the predicted plant outputs, the controller solves a quadratic programming optimization problem to determine control moves.

For more information on the structure of model predictive controllers, see “MPC Modeling”.

Creation

Syntax

```
mpcobj = mpc(plant)
mpcobj = mpc(plant,ts)
mpcobj = mpc(plant,ts,P,M,W,MV,OV,DV)

mpcobj = mpc(model)
mpcobj = mpc(model,ts)
mpcobj = mpc(model,Ts,P,M,W,MV,OV,DV)
```

Description

`mpcobj = mpc(plant)` creates a model predictive controller object based on the discrete-time prediction model `plant`. The controller, `mpcobj`, inherits its control interval from `plant.Ts`, and its time unit from `plant.TimeUnit`. All other controller properties are default values. After you create the MPC controller, you can set its properties using dot notation.

If `plant.Ts = -1`, you must set the `Ts` property of the controller to a positive value before designing and simulating your controller.

`mpcobj = mpc(plant,ts)` creates a model predictive controller based on the specified plant model and sets the controller sample time to `ts`, which corresponds to the `Ts` property of the controller. If `plant` is a:

- Continuous-time model, then the controller discretizes the model for prediction using sample time `ts`
- A discrete-time model with a specified sample time, the controller resamples the plant for prediction using sample time `ts`
- A discrete-time model with an unspecified sample time (`plant.Ts = -1`), it inherits sample time `ts` when used for predictions

`mpcobj = mpc(plant,ts,P,M,W,MV,OV,DV)` specifies the following controller properties. If any of these values are omitted or empty, the default values apply.

- `P` sets the `PredictionHorizon` property.
- `M` sets the `ControlHorizon` property.
- `W` sets the `Weights` property.
- `MV` sets the `ManipulatedVariables` property.
- `OV` sets the `OutputVariables` property.
- `DV` sets the `DisturbanceVariables` property.

`mpcobj = mpc(model)` creates a model predictive controller object based on the specified prediction model set, which includes the plant, input disturbance, and measurement noise models along with the nominal conditions at which the models were obtained. When you do not specify a sample time, the plant model, `model.Plant`, must be a discrete-time model. This syntax sets the `Model` property of the controller.

`mpcobj = mpc(model, ts)` creates a model predictive controller based on the specified plant model and sets the controller sample time to `ts`. If `model.Plant` is a discrete-time LTI model with an unspecified sample time (`model.Plant.Ts = -1`), it inherits sample time `ts` when used for predictions.

`mpcobj = mpc(model, Ts, P, M, W, MV, OV, DV)` specifies additional controller properties. If any of these values are omitted or empty, the default values apply.

Input Arguments

plant — Plant prediction model

LTI model | identified linear model

Plant prediction model, specified as either an LTI model or a linear System Identification Toolbox model. The specified plant corresponds to the `Model.Plant` property of the controller.

If you do not specify a sample time when creating your controller, `plant` must be a discrete-time model.

For more information on MPC prediction models, see “MPC Modeling”.

Note Direct feedthrough from manipulated variables to any output in `plant` is not supported.

model — Prediction model

structure

Prediction model, specified as a structure with the same format as the `Model` property of the controller. If you do not specify a sample time when creating your controller, `model.Plant` must be a discrete-time model.

For more information on MPC prediction models, see “MPC Modeling”.

Properties

Ts — Controller sample time

positive scalar

Controller sample time, specified as a positive finite scalar. The controller uses a discrete-time model with sample time `Ts` for prediction.

PredictionHorizon — Prediction horizon

positive integer

Prediction horizon steps, specified as a positive integer. The product of `PredictionHorizon` and `Ts` is the prediction time; that is, how far the controller looks into the future.

ControlHorizon — Control horizon

2 (default) | positive integer | vector of positive integers

Control horizon, specified as one of the following:

- Positive integer, m , between 1 and p , inclusive, where p is equal to `PredictionHorizon`. In this case, the controller computes m free control moves occurring at times k through $k+m-1$, and holds the controller output constant for the remaining prediction horizon steps from $k+m$ through $k+p-1$. Here, k is the current control interval.
- Vector of positive integers $[m_1, m_2, \dots]$, specifying the lengths of blocking intervals. By default the controller computes M blocks of free moves, where M is the number of blocking intervals. The first free move applies to times k through $k+m_1-1$, the second free move applies from time $k+m_1$ through $k+m_1+m_2-1$, and so on. Using block moves can improve the robustness of your controller. The sum of the values in `ControlHorizon` must match the prediction horizon p . If you specify a vector whose sum is:
 - Less than the prediction horizon, then the controller adds a blocking interval. The length of this interval is such that the sum of the interval lengths is p . For example, if $p=10$ and you specify a control horizon of `ControlHorizon=[1 2 3]`, then the controller uses four intervals with lengths `[1 2 3 4]`.
 - Greater than the prediction horizon, then the intervals are truncated until the sum of the interval lengths is equal to p . For example, if $p=10$ and you specify a control horizon of `ControlHorizon=[1 2 3 6 7]`, then the controller uses four intervals with lengths `[1 2 3 4]`.

For more information on manipulated variable blocking, see “Manipulated Variable Blocking”.

Model — Prediction model and nominal conditions

structure

Prediction model and nominal conditions, specified as a structure with the following fields. For more information on the MPC prediction model, see “MPC Modeling” and “Controller State Estimation”.

Plant — Plant prediction model

LTI model | identified linear model

Plant prediction model, specified as either an LTI model or a linear System Identification Toolbox model.

Note Direct feedthrough from manipulated variables to any output in `plant` is not supported.

Disturbance — Model describing expected unmeasured disturbances

LTI model

Model describing expected unmeasured disturbances, specified as an LTI model. This model is required only when the plant has unmeasured disturbances. You can set this disturbance model directly using dot notation or using the `setindist` function.

By default, input disturbances are expected to be integrated white noise. To model the signal, an integrator with dimensionless unity gain is added for each unmeasured input disturbance, unless the addition causes the controller to lose state observability. In that case, the disturbance is expected to be white noise, and so, a dimensionless unity gain is added to that channel instead.

Noise — Model describing expected output measurement noise

LTI model

Model describing expected output measurement noise, specified as an LTI model.

By default, measurement noise is expected to be white noise with unit variance. To model the signal, a dimensionless unity gain is added for each measured channel.

Nominal — Nominal operating point at which plant model is linearized

structure

Nominal operating point at which plant model is linearized, specified as a structure with the following fields.

Field	Description	Default
X	Plant state at operating point, specified as a column vector with length equal to the number of states in <code>Model.Plant</code> .	zero vector
U	Plant input at operating point, including manipulated variables and measured and unmeasured disturbances, specified as a column vector with length equal to the number of inputs in <code>Model.Plant</code> .	zero vector
Y	Plant output at operating point, including measured and unmeasured outputs, specified as a column vector with length equal to the number of outputs in <code>Model.Plant</code> .	zero vector
DX	For continuous-time models, DX is the state derivative at operating point: $DX=f(X,U)$. For discrete-time models, $DX=x(k+1)-x(k)=f(X,U)-X$. Specify DX as a column vector with length equal to the number of states in <code>Model.Plant</code> .	zero vector

ManipulatedVariables — Manipulated variable information, bounds, and scale factors

structure array

Manipulated Variable (MV) information, bounds, and scale factors, specified as a structure array with N_{mv} elements, where N_{mv} is the number of manipulated variables. To access this property, you can use the alias `MV` instead of `ManipulatedVariables`.

Note Rates refer to the difference $\Delta u(k)=u(k)-u(k-1)$. Constraints and weights based on derivatives du/dt of continuous-time input signals must be properly reformulated for the discrete-time difference $\Delta u(k)$, using the approximation $du/dt \cong \Delta u(k)/T_s$.

Each structure element has the following fields.

Min – MV lower bound

-Inf (default) | scalar | vector

MV lower bound, specified as a scalar or vector. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

Max – MV upper bound

Inf (default) | scalar | vector

MV upper bound, specified as a scalar or vector. By default, this upper bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

MinECR – MV lower bound softness

0 (default) | nonnegative scalar | vector

MV lower bound softness, where a larger equal concern for relaxation (ECR) value indicates a softer constraint, specified as a nonnegative scalar or vector. By default, MV lower bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

MaxECR – MV upper bound

0 (default) | nonnegative scalar | vector

MV upper bound softness, where a larger equal concern for relaxation (ECR) value indicates a softer constraint, specified as a nonnegative scalar or vector. By default, MV upper bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

RateMin – MV rate of change lower bound

-Inf (default) | nonpositive scalar | vector

MV rate of change lower bound, specified as a nonpositive scalar or vector. The MV rate of change is defined as $MV(k) - MV(k-1)$, where k is the current time. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

RateMax — MV rate of change upper bound

Inf (default) | nonnegative scalar | vector

MV rate of change upper bound, specified as a nonnegative scalar or vector. The MV rate of change is defined as $MV(k) - MV(k-1)$, where k is the current time. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

RateMinECR — MV rate of change lower bound softness

0 (default) | nonnegative finite scalar | vector

MV rate of change lower bound softness, where a larger equal concern for relaxation (ECR) value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, MV rate of change lower bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR values over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR values are used for the remaining steps of the prediction horizon.

RateMaxECR — MV rate of change upper bound softness

0 (default) | nonnegative finite scalar | vector

MV rate of change upper bound softness, where a larger equal concern for relaxation (ECR) value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, MV rate of change upper bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR values over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR values are used for the remaining steps of the prediction horizon.

Name — MV name

string | character vector

MV name, specified as a string or character vector.

Units — MV units

" " (default) | string | character vector

MV units, specified as a string or character vector.

ScaleFactor — MV scale factor

1 (default) | positive finite scalar

MV scale factor, specified as a positive finite scalar. In general, use the operating range of the manipulated variable. Specifying the proper scale factor can improve numerical conditioning for optimization. For more information, see “Specify Scale Factors”.

OutputVariables – Output variable information, bounds, and scale factors

structure array

Output variable (OV) information, bounds, and scale factors, specified as a structure array with N_y elements, where N_y is the number of output variables. To access this property, you can use the alias `OV` instead of `OutputVariables`.

Each structure element has the following fields.

Min – OV lower bound

- Inf (default) | scalar | vector

OV lower bound, specified as a scalar or vector. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

Max – OV upper bound

Inf (default) | scalar | vector

OV upper bound, specified as a scalar or vector. By default, this upper bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

MinECR – OV lower bound softness

1 (default) | nonnegative finite scalar | vector

OV lower bound softness, where a larger equal concern for relaxation (ECR) value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, OV upper bounds are soft constraints.

To avoid creating an infeasible optimization problem at run time, it is best practice to use soft OV bounds.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

MaxECR – OV upper bound softness

1 (default) | nonnegative finite scalar | vector

OV upper bound softness, where a larger equal concern for relaxation (ECR) value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, OV lower bounds are soft constraints.

To avoid creating an infeasible optimization problem at run time, it is best practice to use soft OV bounds.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

Name — OV name

string | character vector

OV name, specified as a string or character vector.

Units — OV units

" " (default) | string | character vector

OV units, specified as a string or character vector.

ScaleFactor — OV scale factor

1 (default) | positive finite scalar

OV scale factor, specified as a positive finite scalar. In general, use the operating range of the output variable. Specifying the proper scale factor can improve numerical conditioning for optimization. For more information, see “Specify Scale Factors”.

DisturbanceVariables — Input disturbance variable information and scale factors

structure array

Disturbance variable (DV) information and scale factors, specified as a structure array with N_d elements, where N_d is the total number of measured and unmeasured disturbance inputs. The order of the disturbance signals within `DisturbanceVariables` is the following: the first N_{md} entries relate to measured input disturbances, the last N_{ud} entries relate to unmeasured input disturbances.

To access this property, you can use the alias `DV` instead of `DisturbanceVariables`.

Each structure element has the following fields.

Name — DV name

string | character vector

DV name, specified as a string or character vector.

Units — DV units

" " (default) | string | character vector

DV units, specified as a string or character vector.

ScaleFactor — DV scale factor

1 (default) | positive finite scalar

DV scale factor, specified as a positive finite scalar. Specifying the proper scale factor can improve numerical conditioning for optimization. For more information, see “Specify Scale Factors”.

Weights — Standard cost function tuning weights

structure

Standard cost function tuning weights, specified as a structure. The controller applies these weights to the scaled variables. Therefore, the tuning weights are dimensionless values.

The format of `OutputWeights` must match the format of the `Weights.OutputVariables` property of the controller object. For example, you cannot specify constant weights across the prediction horizon in the controller object, and then specify time-varying weights using `mpcmoveopt`.

`Weights` has the following fields. The values of these fields depend on whether you use the standard or alternative cost function. For more information on these cost functions, see “Optimization Problem”.

ManipulatedVariables — Manipulated variable tuning weights

row vector | array

Manipulated variable tuning weights, which penalize deviations from MV targets, specified as a row vector or array of nonnegative values. The default weight for all manipulated variables is θ .

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

If you use the alternative cost function, specify `Weights.ManipulatedVariables` as a cell array that contains the N_{mv} -by- N_{mv} R_u matrix. For example, `mpcobj.Weights.ManipulatedVariables = {Ru}`. R_u must be a positive semidefinite matrix. Varying the R_u matrix across the prediction horizon is not supported. For more information, see “Alternative Cost Function”.

ManipulatedVariablesRate — Manipulated variable rate tuning weights

row vector | array | cell array

Manipulated variable rate tuning weights, which penalize large changes in control moves, specified as a row vector or array of nonnegative values. The default weight for all manipulated variable rates is $\theta \cdot 1$.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable rate tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

Note It is best practice to use nonzero manipulated variable rate weights.

To improve the numerical robustness of the optimization problem, the software adds the quantity $10 \cdot \sqrt{\text{eps}}$ to each zero-valued weight.

Note It is best practice to use nonzero manipulated variable rate weights. If all manipulated variable rate weights are strictly positive, the resulting QP problem is strictly convex. If some weights are zero, the QP Hessian could be positive semidefinite. To keep the QP problem strictly convex, when the condition number of the Hessian matrix $K_{\Delta U}$ is larger than 10^{12} , the quantity $10 \cdot \sqrt{\text{eps}}$ is added to each diagonal term. See “Cost Function”.

If you use the alternative cost function, specify `Weights.ManipulatedVariablesRate` as a cell array that contains the N_{mv} -by- N_{mv} $R_{\Delta u}$ matrix. For example, `mpcobj.Weights.ManipulatedVariablesRate = {Rdu}`. $R_{\Delta u}$ must be a positive semidefinite matrix. Varying the $R_{\Delta u}$ matrix across the prediction horizon is not supported. For more information, see “Alternative Cost Function”.

OutputVariables – Output variable tuning weights

vector | array

Output variable tuning weights, which penalize deviation from output references, specified as a row vector or array of nonnegative values. The default weight for all output variables is 1.

To use the same weights across the prediction horizon, specify a row vector of length N_y , where N_y is the number of output variables.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the output variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

If you use the alternative cost function, specify `Weights.OutputVariables` as a cell array that contains the N_y -by- N_y Q matrix. For example, `mpcobj.Weights.OutputVariables = {Q}`. Q must be a positive semidefinite matrix. Varying the Q matrix across the prediction horizon is not supported. For more information, see “Alternative Cost Function”.

ECR – Slack variable tuning weight

1e5 (default) | positive scalar

Slack variable tuning weight, specified as a positive scalar. Increase or decrease the equal concern for relaxation (ECR) weight to make all soft constraints harder or softer, respectively.

Optimizer – QP optimization parameters

structure

QP optimization parameters, specified as a structure with the following fields. For more information on the supported QP solvers, see “QP Solvers”.

Algorithm – QP solver algorithm

'active-set' (default) | 'interior-point'

QP solver algorithm, specified as one of the following:

- 'active-set' — Solve the QP problem using the KWIK active-set algorithm.

- `'interior-point'` — Solve the QP problem using a primal-dual interior-point algorithm with Mehrotra predictor-corrector.

ActiveSetOptions — Active-set QP solver settings

structure

Active-set QP solver settings, specified as a structure. These settings apply only when `Algorithm` is `'active-set'`.

If `CustomSolver` or `CustomSolverGodeGen` is `true`, the controller does not require the custom solver to honor these settings.

You can specify the following active-set optimizer settings.

MaxIterations — Maximum number of iterations

`'default'` (default) | positive integer

Maximum number of iterations allowed when computing the QP solution, specified as one of the following:

- `'default'` — The MPC controller automatically computes the maximum number of QP solver iterations as $4(n_c + n_v)$, where:
 - n_c is the total number of constraints across the prediction horizon.
 - n_v is the total number of optimization variables across the control horizon.

The default `MaxIterations` value has a lower bound of 120.

- Positive integer — The QP solver stops after the specified number of iterations. If the solver fails to converge in the final iteration, the controller:
 - Freezes the controller movement if `UseSuboptimalSolution` is `false`.
 - Applies the suboptimal solution reached after the final iteration if `UseSuboptimalSolution` is `true`.

Note The default `MaxIterations` value can be very large for some controller configurations, such as those with large prediction and control horizons. When simulating such controllers, if the QP solver cannot find a feasible solution, the simulation can appear to stop responding, since the solver continues searching for `MaxIterations` iterations.

ConstraintTolerance — Tolerance used to verify that inequality constraints are satisfied

`1e-6` (default) | positive scalar

Tolerance used to verify that inequality constraints are satisfied by the optimal solution, specified as a positive scalar. A larger `ConstraintTolerance` value allows for larger constraint violations.

UseWarmStart — Flag indicating whether to warm start each QP solver iteration

`true` (default) | `false`

Flag indicating whether to *warm start* each QP solver iteration by passing in a list of active inequalities from the previous iteration, specified as a logical value. Inequalities are active when their equal portion is `true`.

InteriorPointOptions — Interior-point QP solver settings

structure

Interior-point QP solver settings, specified as a structure. These settings apply only when `Algorithm` is 'interior-point'.

If `CustomSolver` or `CustomSolverGodeGen` is `true`, the controller does not require the custom solver to honor these settings.

You can specify the following interior-point optimizer settings.

MaxIterations — Maximum number of iterations

50 (default) | positive integer

Maximum number of iterations allowed when computing the QP solution, specified as a positive integer. The QP solver stops after the specified number of iterations. If the solver fails to converge in the final iteration, the controller:

- Freezes the controller movement if `UseSuboptimalSolution` is `false`.
- Applies the suboptimal solution reached after the final iteration if `UseSuboptimalSolution` is `true`.

ConstraintTolerance — Tolerance used to verify that equality and inequality constraints are satisfied

1e-6 (default) | positive scalar

Tolerance used to verify that equality and inequality constraints are satisfied by the optimal solution, specified as a positive scalar. A larger `ConstraintTolerance` value allows for larger constraint violations.

OptimalityTolerance — Termination tolerance for first-order optimality (KKT dual residual)

1e-6 (default) | positive scalar

Termination tolerance for first-order optimality (KKT dual residual), specified as a positive scalar.

ComplementarityTolerance — Termination tolerance for first-order optimality (KKT average complementarity residual)

1e-8 (default) | positive scalar

Termination tolerance for first-order optimality (KKT average complementarity residual), specified as a positive scalar. Increasing this value improves robustness, while decreasing this value increases accuracy.

StepTolerance — Termination tolerance for decision variables

1e-8 (default) | positive scalar

Termination tolerance for decision variables, specified as a positive scalar.

MinOutputECR — Minimum value allowed for output constraint ECR values

0 (default) | nonnegative scalar

Minimum value allowed for output constraint equal concern for relaxation (ECR) values, specified as a nonnegative scalar. A value of 0 indicates that hard output constraints are allowed. If either of the `OutputVariables.MinECR` or `OutputVariables.MaxECR` properties of an MPC controller are less

than `MinOutputECR`, a warning is displayed and the value is raised to `MinOutputECR` during computation.

UseSuboptimalSolution — Flag indicating whether a suboptimal solution is acceptable

`false` (default) | `true`

Flag indicating whether a suboptimal solution is acceptable, specified as a logical value. When the QP solver reaches the maximum number of iterations without finding a solution (the exit flag is 0), the controller:

- Freezes the MV values if `UseSuboptimalSolution` is `false`
- Applies the suboptimal solution found by the solver after the final iteration if `UseSuboptimalSolution` is `true`

To specify the maximum number of iterations, depending on the value of `Algorithm`, use either `ActiveSetOptions.MaxIterations` or `InteriorPointOptions.MaxIterations`.

CustomSolver — Flag indicating whether to use a custom QP solver for simulation

`false` (default) | `true`

Flag indicating whether to use a custom QP solver for simulation, specified as a logical value. If `CustomSolver` is `true`, the user must provide an `mpcCustomSolver` function on the MATLAB path.

This custom solver is not used for code generation. To generate code for a controller with a custom solver, use `CustomSolverCodeGen`.

If `CustomSolver` is `true`, the controller does not require the custom solver to honor the settings in either `ActiveSetOptions` or `InteriorPointOptions`.

For more information on using a custom QP solver see, “Custom QP Solver”.

CustomSolverCodeGen — Flag indicating whether to use a custom QP solver for code generation

`false` (default) | `true`

Flag indicating whether to use a custom QP solver for code generation, specified as a logical value. If `CustomSolverCodeGen` is `true`, the user must provide an `mpcCustomSolverCodeGen` function on the MATLAB path.

This custom solver is not used for simulation. To simulate a controller with a custom solver, use `CustomSolver`.

If `CustomSolverCodeGen` is `true`, the controller does not require the custom solver to honor the settings in either `ActiveSetOptions` or `InteriorPointOptions`.

For more information on using a custom QP solver see, “Custom QP Solver”.

Notes — User notes

`{}` (default) | cell array of character vectors

User notes associated with the MPC controller, specified as a cell array of character vectors.

UserData — User data

`[]` (default) | any MATLAB data

User data associated with the MPC controller, specified as any MATLAB data, such as a cell array or structure.

History — Controller creation date and time

vector

This property is read-only.

Controller creation date and time, specified as a vector with the following elements:

- History(1) — Year
- History(2) — Month
- History(3) — Day
- History(4) — Hours
- History(5) — Minutes
- History(6) — Seconds

Object Functions

review	Examine MPC controller for design errors and stability problems at run time
mpcmove	Compute optimal control action
sim	Simulate closed-loop/open-loop response to arbitrary reference and disturbance signals for implicit or explicit MPC
mpcstate	MPC controller state
getCodeGenerationData	Create data structures for mpcmoveCodeGeneration
generateExplicitMPC	Convert implicit MPC controller to explicit MPC controller

Examples

Create MPC Controller with Specified Prediction and Control Horizons

Create a plant model with the transfer function $(s + 1)/(s^2 + 2s)$.

```
Plant = tf([1 1],[1 2 0]);
```

The plant is SISO, so its input must be a manipulated variable and its output must be measured. In general, it is good practice to designate all plant signal types using either the `setmpcsignals` command, or the LTI `InputGroup` and `OutputGroup` properties.

Specify a sample time for the controller.

```
Ts = 0.1;
```

Define bounds on the manipulated variable, u , such that $-1 \leq u \leq 1$.

```
MV = struct('Min',-1,'Max',1);
```

MV contains only the upper and lower bounds on the manipulated variable. In general, you can specify additional MV properties. When you do not specify other properties, their default values apply.

Specify a 20-interval prediction horizon and a 3-interval control horizon.

```
p = 20;  
m = 3;
```

Create an MPC controller using the specified values. The fifth input argument is empty, so default tuning weights apply.

```
MPCobj = mpc(Plant,Ts,p,m,[],MV);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.  
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.  
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Algorithms

To minimize computational overhead, model predictive controller creation occurs in two phases. The first happens at creation when you use the `mpc` function, or when you change a controller property. Creation includes basic validity and consistency checks, such as signal dimensions and nonnegativity of weights.

The second phase is initialization, which occurs when you use the object for the first time in a simulation or analytical procedure. Initialization computes all constant properties required for efficient numerical performance, such as matrices defining the optimal control problem and state estimator gains. Additional, diagnostic checks occur during initialization, such as verification that the controller states are observable.

By default, both phases display informative messages in the command window. You can turn these messages on or off using the `mpcverbosity` function.

Alternative Functionality

You can also create model predictive controllers using the **MPC Designer** app.

Compatibility Considerations

Support for implementing economic MPC using a linear MPC controller has been removed

Errors starting in R2018b

Support for implementing economic MPC using a linear MPC controller has been removed. Implement economic MPC using a nonlinear MPC controller instead. For more information on nonlinear MPC controllers, see “Nonlinear MPC”.

Update Code

If you previously saved a linear MPC object configured with custom cost or constraint functions, the software generates a warning when the object is loaded and an error if it is simulated. To suppress the error and warning messages and continue using your linear MPC controller, `mpcobj`, without the custom costs and constraints, set the `IsEconomicMPC` flag to `false`.

```
mpcobj.IsEconomicMPC = false;
```

To implement your economic MPC controller using a nonlinear MPC object:

- 1 Create an `nmpc` object.

- 2 Convert your custom cost function to the format required for nonlinear MPC. For more information on nonlinear MPC cost functions, see “Specify Cost Function for Nonlinear MPC”.
- 3 Convert your custom constraint function to the format required for nonlinear MPC. For more information on nonlinear MPC constraints, see “Specify Constraints for Nonlinear MPC”.
- 4 Implement your linear prediction model using state and output functions. For more information on nonlinear MPC prediction models, see “Specify Prediction Model for Nonlinear MPC”.

See Also

get | mpcprops | mpcverbosity | set | setmpcsignals

Topics

“MPC Modeling”

“Design MPC Controller at the Command Line”

Introduced before R2006a

mpcmoveopt

Option set for mpcmove function

Description

To specify options for the `mpcmove`, `mpcmoveAdaptive`, and `mpcmoveMultiple` functions, use an `mpcmoveopt` object.

Using this object, you can specify run-time values for a subset of controller properties, such as tuning weights and constraints. If you do not specify a value for one of the `mpcmoveopt` properties, the value of the corresponding controller option is used instead.

Creation

Syntax

```
options = mpcmoveopt
```

Description

`options = mpcmoveopt` creates a default set of options for the `mpcmove` function. To modify the property values, use dot notation.

Properties

OutputWeights — Output variable tuning weights

[] (default) | vector | array

Output variable tuning weights that replace the `Weights.OutputVariables` property of the controller at run time, specified as a vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_y , where N_y is the number of output variables.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the output variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

The format of `OutputWeights` must match the format of the `Weights.OutputVariables` property of the controller object. For example, you cannot specify constant weights across the prediction horizon in the controller object, and then specify time-varying weights using `mpcmoveopt`.

MVWeights — Manipulated variable tuning weights

[] (default) | vector | array

Manipulated variable tuning weights that replace the `Weights.ManipulatedVariables` property of the controller at run time, specified as a vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

The format of `MVWeights` must match the format of the `Weights.ManipulatedVariables` property of the controller object. For example, you cannot specify constant weights across the prediction horizon in the controller object, and then specify time-varying weights using `mpcmoveopt`.

MVRateWeights — Manipulated variable rate tuning weights

[] (default) | vector | array

Manipulated variable rate tuning weights that replace the `Weights.ManipulatedVariablesRate` property of the controller at run time, specified as a vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable rate tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

The format of `MVRateWeights` must match the format of the `Weights.ManipulatedVariablesRate` property of the controller object. For example, you cannot specify constant weights across the prediction horizon in the controller object, and then specify time-varying weights using `mpcmoveopt`.

ECRWeight — Slack variable tuning weight

[] (default) | positive scalar

Slack variable tuning weight that replaces the `Weights.ECR` property of the controller at run time, specified as a positive scalar.

OutputMin — Output variable lower bounds

[] (default) | row vector

Output variable lower bounds, specified as a row vector of length N_y , where N_y is the number of output variables. `OutputMin(i)` replaces the `OutputVariables(i).Min` property of the controller at run time.

If the `OutputVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), `OutputMin(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

OutputMax — Output variable upper bounds

[] (default) | row vector

Output variable upper bounds, specified as a row vector of length N_y , where N_y is the number of output variables. `OutputMax(i)` replaces the `OutputVariables(i).Max` property of the controller at run time.

If the `OutputVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), `OutputMax(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

MVMin — Manipulated variable lower bounds

`[]` (default) | row vector

Manipulated variable lower bounds, specified as a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables. `MVMin(i)` replaces the `ManipulatedVariables(i).Min` property of the controller at run time.

If the `ManipulatedVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), `MVMin(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

MVMax — Manipulated variable upper bounds

`[]` (default) | row vector

Manipulated variable upper bounds, specified as a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables. `MVMax(i)` replaces the `ManipulatedVariables(i).Max` property of the controller at run time.

If the `ManipulatedVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), `MVMax(i)` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

CustomConstraint — Custom mixed input/output constraints

`[]` (default) | structure

Custom mixed input/output constraints, specified as a structure with the following fields. These constraints replace the mixed input/output constraints previously set using `setconstraint`.

E — Manipulated variable constraint constant

array of zeros (default) | N_c -by- N_{mv} array

Manipulated variable constraint constant, specified as an N_c -by- N_{mv} array, where N_c is the number of constraints, and N_{mv} is the number of manipulated variables.

F — Controlled output constraint constant

array of zeros (default) | N_c -by- N_y array

Controlled output constraint constant, specified as an N_c -by- N_y array, where N_y is the number of controlled outputs (measured and unmeasured).

G — Mixed input/output constraint constant

column vector of zeros (default) | column vector of length N_c

Mixed input/output constraint constant, specified as a column vector of length N_c .

S — Measured disturbance constraint constant

array of zeros (default) | N_c -by- N_{md} array

Measured disturbance constraint constant, specified as an N_c -by- N_{md} array, where N_{md} is the number of measured disturbances.

OnlyComputeCost — Flag indicating whether to calculate the optimal control sequence

0 (default) | 1

Flag indicating whether to calculate the optimal control sequence, specified as one of the following:

- 0 — Controller returns the predicted optimal control moves in addition to the objective function cost value.
- 1 — Controller returns the objective function cost only, which saves computational effort.

MVused — Manipulated variable values used in the plant during the previous control interval

[] (default) | row vector

Manipulated variable values used in the plant during the previous control interval, specified as a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables. If you do not specify **MVused**, the `mpcmove` uses the `LastMove` property of its current controller state input argument, `x`.

MVtarget — Manipulated variable targets

[] (default) | row vector

Manipulated variable targets, specified as a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables. `MVtarget(i)` replaces the `ManipulatedVariables(i).Target` property of the controller at run time.

PredictionHorizon — Prediction horizon

[] (default) | positive integer

Prediction horizon, which replaces the `PredictionHorizon` property of the controller at run time, specified as a positive integer. If you specify `PredictionHorizon`, you must also specify `ControlHorizon`.

Specifying `PredictionHorizon` changes the:

- Number of rows in the optimal sequences returned by the `mpcmove` and `mpcmoveAdaptive` functions
- Maximum dimensions of the `Plant` and `Nominal` input arguments of `mpcmoveAdaptive`

This parameter is ignored by the `mpcmoveMultiple` function.

ControlHorizon — Control horizon

[] (default) | positive integer | vector of positive integers

Control horizon, which replaces the `ControlHorizon` property of the controller at run time, specified as one of the following:

- Positive integer, m , between 1 and p , inclusive, where p is equal to `PredictionHorizon`. In this case, the controller computes m free control moves occurring at times k through $k+m-1$, and holds the controller output constant for the remaining prediction horizon steps from $k+m$ through $k+p-1$. Here, k is the current control interval. For optimal trajectory planning set m equal to p .
- Vector of positive integers, $[m_1, m_2, \dots]$, where the sum of the integers equals the prediction horizon, p . In this case, the controller computes M blocks of free moves, where M is the length of

the `ControlHorizon` vector. The first free move applies to times k through $k+m_1-1$, the second free move applies from time $k+m_1$ through $k+m_1+m_2-1$, and so on. Using block moves can improve the robustness of your controller compared to the default case.

If you specify `ControlHorizon`, you must also specify `PredictionHorizon`.

This parameter is ignored by the `mpcmoveMultiple` function.

Object Functions

<code>mpcmove</code>	Compute optimal control action
<code>mpcmoveAdaptive</code>	Compute optimal control with prediction model updating
<code>mpcmoveMultiple</code>	Compute gain-scheduling MPC control action at a single time instant

Examples

Simulation with Varying Controller Property

Vary a manipulated variable upper bound during a simulation.

Define the plant, which includes a 4-second input delay. Convert to a delay-free, discrete, state-space model using a 2-second control interval. Create the corresponding default controller, and specify MV bounds at ± 2 .

```
Ts = 2;
Plant = absorbDelay(c2d(ss(tf(0.8,[5 1], 'InputDelay',4)),Ts));
MPCobj = mpc(Plant,Ts);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

```
MPCobj.MV(1).Min = -2;
MPCobj.MV(1).Max = 2;
```

Create an empty `mpcmoveopt` object. During simulation, you can set properties of the object to specify controller parameters.

```
options = mpcmoveopt;
```

Pre-allocate storage and initialize the controller state.

```
v = [];
t = [0:Ts:20];
N = length(t);
y = zeros(N,1);
u = zeros(N,1);
x = mpcstate(MPCobj);
```

```
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

Use `mpcmove` to simulate the following:

- Reference (setpoint) step change from initial condition $r = 0$ to $r = 1$ (servo response)
- MV upper bound step decrease from 2 to 1, occurring at $t = 10$

```

r = 1;
for i = 1:N
    y(i) = Plant.C*x.Plant;
    if t(i) >= 10
        options.MVMax = 1;
    end
    [u(i),Info] = mpcmove(MPCobj,x,y(i),r,v,options);
end

```

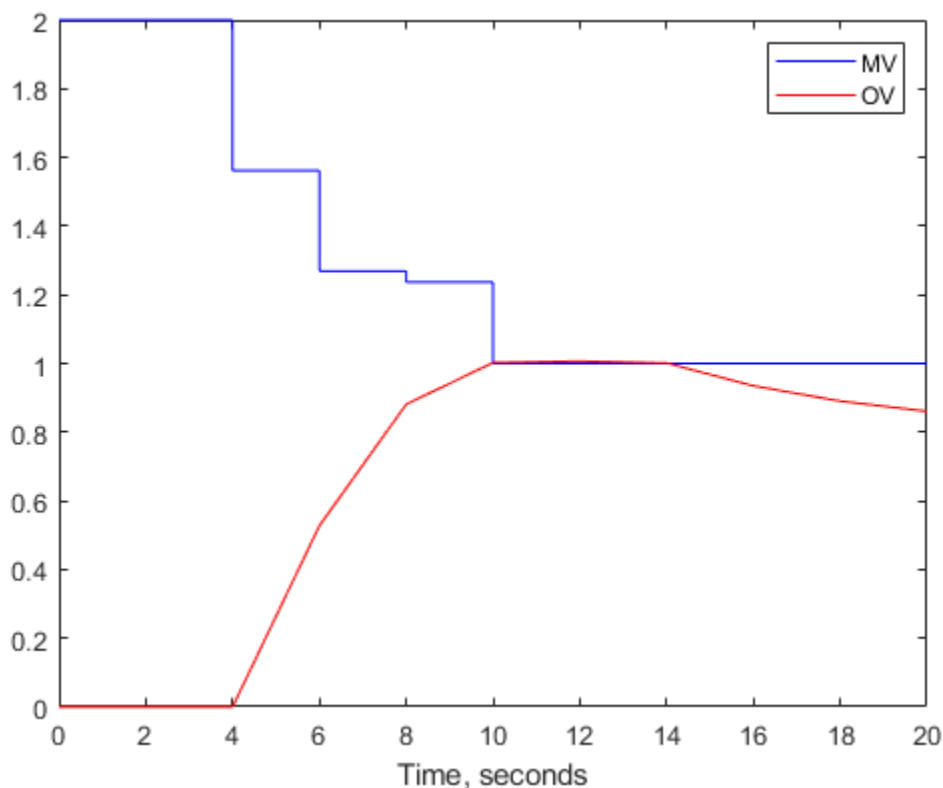
As the loop executes, the value of `options.MVMax` is reset to 1 for all iterations that occur after $t = 10$. Prior to that iteration, `options.MVMax` is empty. Therefore, the controller's value for `MVMax` is used, `MPCobj.MV(1).Max = 2`.

Plot the results of the simulation.

```

[Ts,us] = stairs(t,u);
plot(Ts,us,'b-',t,y,'r-')
legend('MV','OV')
xlabel(sprintf('Time, %s',Plant.TimeUnit))

```



From the plot, you can observe that the original MV upper bound is active until $t = 4$. After the input delay of 4 seconds, the output variable (OV) moves smoothly to its new target of $r = 1$, reaching the target at $t = 10$. The new MV bound imposed at $t = 10$ becomes active immediately. This forces the OV below its target, after the input delay elapses.

Now assume that you want to impose an OV upper bound at a specified location relative to the OV target. Consider the following constraint design command:

```
MPCobj.OV(1).Max = [Inf, Inf, 0.4, 0.3, 0.2];
```

This is a horizon-varying constraint. The known input delay makes it impossible for the controller to satisfy an OV constraint prior to the third prediction-horizon step. Therefore, a finite constraint during the first two steps would be poor practice. For illustrative purposes, the previous constraint also decreases from 0.4 at step 3 to 0.2 at step 5 and thereafter.

The following commands produce the same results shown in the previous plot. The OV constraint is never active because it is being varied in concert with the setpoint, r .

```
x = mpcstate(MPCobj);
```

```
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.  
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
```

```
OPTobj = mpcmoveopt;
```

```
for i = 1:N  
    y(i) = Plant.C*x.Plant;  
    if t(i) >= 10  
        OPTobj.MVMax = 1;  
    end  
    OPTobj.OutputMax = r + 0.4;  
    [u(i), Info] = mpcmove(MPCobj, x, y(i), r, v, OPTobj);  
end
```

The scalar value $r + 0.4$ replaces the first finite value in the `MPCobj.OV(1).Max` vector, and the remaining finite values adjust to maintain the original profile, that is, the numerical difference between these values is unchanged. $r = 1$ for the simulation, so the previous use of the `mpcmoveopt` object is equivalent to the command

```
MPCobj.OV(1).Max = [Inf, Inf, 1.4, 1.3, 1.2];
```

However, using the `mpcmoveopt` object involves much less computational overhead.

Tips

- If a variable is unconstrained in the initial controller design, you cannot constrain it using `mpcmoveopt`. The controller ignores any such specifications.
- You cannot remove a constraint from a variable that is constrained in the initial controller design. However, you can change it to a large (or small) value such that it is unlikely to become active.

See Also

`mpc` | `mpcmove` | `setconstraint` | `setterminal`

Introduced in R2018b

mpcsimopt

MPC simulation options

Description

When simulating an implicit or explicit MPC controller using the `sim` function, you can specify additional simulation options using an `mpcsimopt` object.

Creation

Syntax

```
options = mpcsimopt(mpcobj)
```

Description

`options = mpcsimopt(mpcobj)` creates a default set of options for specifying additional parameters for simulating the MPC controller `mpcobj` with the `sim` function. To specify nondefault values for the properties on page 3-29, use dot notation.

Input Arguments

mpcobj — MPC controller object

`mpc object` | `explicitMPC object`

MPC controller object, specified as either an `mpc` or `explicitMPC` object.

Properties

PlantInitialState — Simulation plant model initial state

`[]` (default) | `vector`

Simulation plant model initial state, specified as a vector with length equal to the number states in the plant model used for the simulation. To use the default nominal state of the simulation plant model, set `PlantInitialState` to `[]`.

If you do not specify the `Model` option, then the plant model used for the simulation is the internal plant model from the controller. In this case, the default initial controller state is equal to `mpcobj.Model.Nominal.X`.

If you specify the `Model` option, then the plant model used for simulation is `Model.Plant`. In this case, the default initial controller state is equal to `Model.Nominal.X`.

ControllerInitialState — MPC controller initial condition

`[]` (default) | `mpcstate object`

MPC controller initial condition, specified as an `mpcstate` object. Setting `ControllerInitialState = []` is equivalent to setting `ControllerInitialState = mpcstate(mpcobj)`.

UnmeasuredDisturbance — Unmeasured disturbance signal

`[]` (default) | array

Unmeasured disturbance signal for simulating disturbances occurring at the unmeasured disturbance inputs of the simulation plant model, specified as an array with N_{ud} columns and up to N_t rows, where N_{ud} is the number of unmeasured disturbances, and N_t is the number of simulation steps. If you specify fewer than N_t rows, then the values in the final row of the array are extended to the end of the simulation.

InputNoise — Manipulated variable noise signal

`[]` (default) | array

Manipulated variable noise signal for simulating load disturbances occurring at the manipulated variable inputs to the simulation plant model, specified as an array with N_{mv} columns and up to N_t rows, where N_{mv} is the number of manipulated variables, and N_t is the number of simulation steps. If you specify fewer than N_t rows, then the values in the final row of the array are extended to the end of the simulation.

OutputNoise — Measured output noise signal

`[]` (default) | array

Measured output noise signal for simulating disturbances occurring at the measured output of the simulation plant model, specified as an array with N_y columns and up to N_t rows, where N_y is the number of measured outputs, and N_t is the number of simulation steps. If you specify fewer than N_t rows, then the values in the final row of the array are extended to the end of the simulation.

RefLookAhead — Flag indicating whether to use reference previewing

'off' (default) | 'on'

Flag indicating whether to use reference previewing during simulation, specified as one of the following:

- 'off' — Do not use reference previewing.
- 'on' — Use reference previewing.

When simulating an explicit MPC controller, you must set `RefLookAhead` to 'off'.

MDLookAhead — Flag indicating whether to use measured disturbance previewing

'off' (default) | 'on'

Flag indicating whether to use measured disturbance previewing during simulation, specified as one of the following:

- 'off' — Do not use measured disturbance previewing.
- 'on' — Use measured disturbance previewing.

When simulating an explicit MPC controller, you must set `MDLookAhead` to 'off'.

Constraints — Flag indicating whether to enable constraints

'on' (default) | 'off'

Flag indicating whether to enable constraints during simulation, specified as one of the following:

- 'on' — Use the constraints defined in the controller during simulation.
- 'off' — Simulate the controller without any constraints.

Model — Plant model to use for simulation

[] (default) | LTI system object | structure

Plant model to use for simulation, specified as one of the following:

- [] — Simulate the controller against its internal plant model (`mpcobj.Model`). In this case, there is no plant-model mismatch.
- LTI system object — Simulate the controller against the specified LTI plant. The specified plant must have the same input and output group configuration as `mpcobj.Model.Plant`. To set this configuration, use `setmpcsignals`.
- Structure with fields `Plant` and `Nominal` — Simulate the controller using the specified plant (`Plant`) and nominal conditions (`Nominal`).

`Model` sets the actual plant that the controller is simulated against (not the internal prediction model of the controller). Use this option to specify a plant that differs from the controller internal plant model (model mismatch).

If you do not specify nominal conditions, `Model.Nominal.U` and `Model.Nominal.Y` are inherited from `mpcobj.Model.Nominal`. `Model.Nominal.X` and `Model.Nominal.DX` are only inherited if both plants are state-space objects with the same state dimension.

To specify the initial state of this simulation plant model, use the `PlantInitialState` option.

StatusBar — Flag indicating whether to display the simulation status bar

'off' (default) | 'on'

Flag indicating whether to display the simulation status bar, specified as one of the following:

- 'off' — Do not display the status bar.
- 'on' — Display the status bar.

MVSignal — Sequence of manipulated variables

[] (default) | array

Sequence of manipulated variables to use during open-loop simulation, specified as an array with N_{mv} columns and up to N_t rows, where N_{mv} is the number of manipulated variables, and N_t is the number of simulation steps. If you specify fewer than N_t rows, then the values in the final row of the array are extended to the end of the simulation. The specified manipulated variable signals must include any manipulated variable offsets.

If you specify `MVSignal`, then the controller does not compute control actions and the simulation reference signal is ignored.

OpenLoop — Flag indicating whether to run an open-loop simulation

'off' (default) | 'on'

Flag indicating whether to run an open-loop simulation, specified as one of the following:

- 'off' — Do not display the status bar.
- 'on' — Display the status bar.

Object Functions

`sim` Simulate closed-loop/open-loop response to arbitrary reference and disturbance signals for implicit or explicit MPC

Examples

Simulate MPC Control with Plant Model Mismatch

Simulate the MPC control of a multi-input, multi-output (MIMO) system with a mismatch between the predicted and actual plant models. The system has two manipulated variables, two unmeasured disturbances, and two measured outputs.

Define the predicted plant model.

```
p1 = tf(1,[1 2 1])*[1 1;0 1];
plantPredict = ss([p1 p1]);
plantPredict.InputName = {'mv1','mv2','umd3','umd4'};
```

Specify the MPC signal types.

```
plantPredict = setmpcsignals(plantPredict,'MV',[1 2],'UD',[3 4]);
```

Create the MPC controller.

```
mpcobj = mpc(plantPredict,1,40,2);
```

```
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.00000.
```

```
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.
```

```
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Define the unmeasured input disturbance model used by the controller.

```
distModel = eye(2,2)*ss(-0.5,1,1,0);
mpcobj.Model.Disturbance = distModel;
```

Define an actual plant model which differs from the predicted model and has unforeseen unmeasured disturbance inputs.

```
p2 = tf(1.5,[0.1 1 2 1])*[1 1;0 1];
plantActual = ss([p2 p2 tf(1,[1 1])*[0;1]]);
plantActual = setmpcsignals(plantActual,'MV',[1 2],'UD',[3 4 5]);
```

Configure the unmeasured disturbance and output reference trajectories.

```
dist = ones(1,3);
refs = [1 2];
```

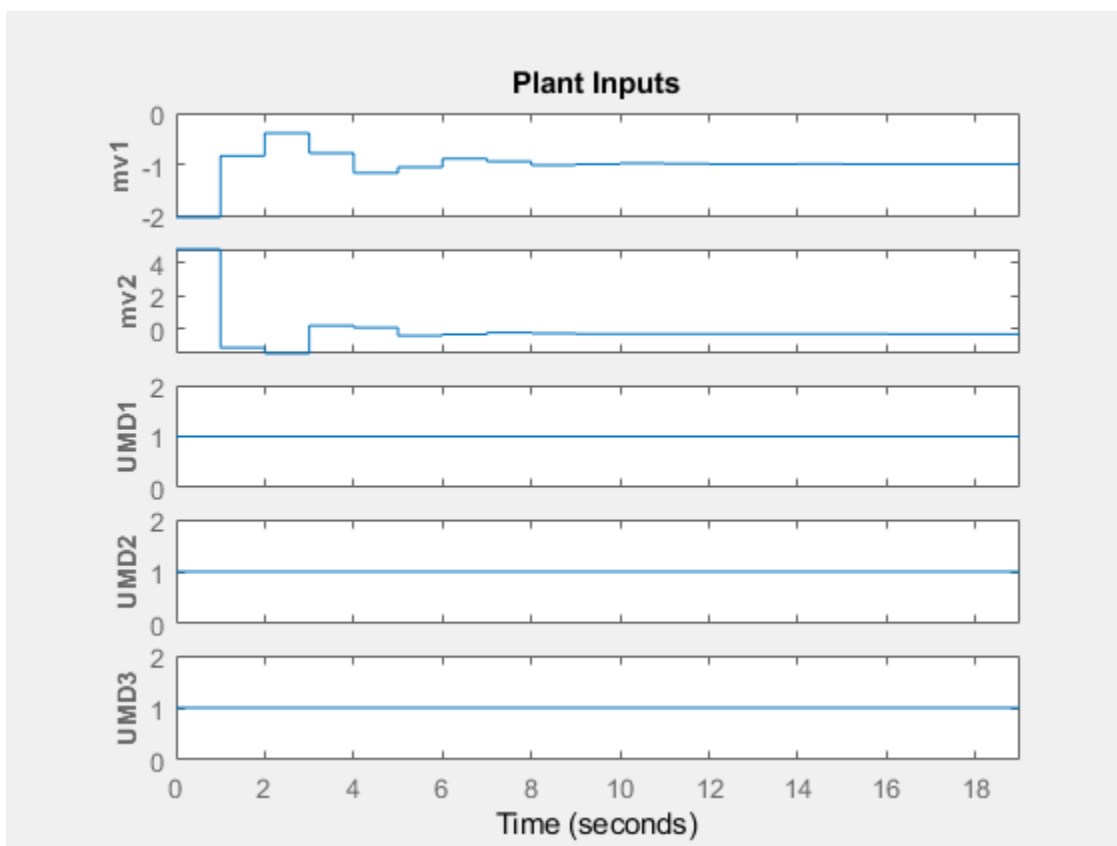
Create and configure a simulation option set.

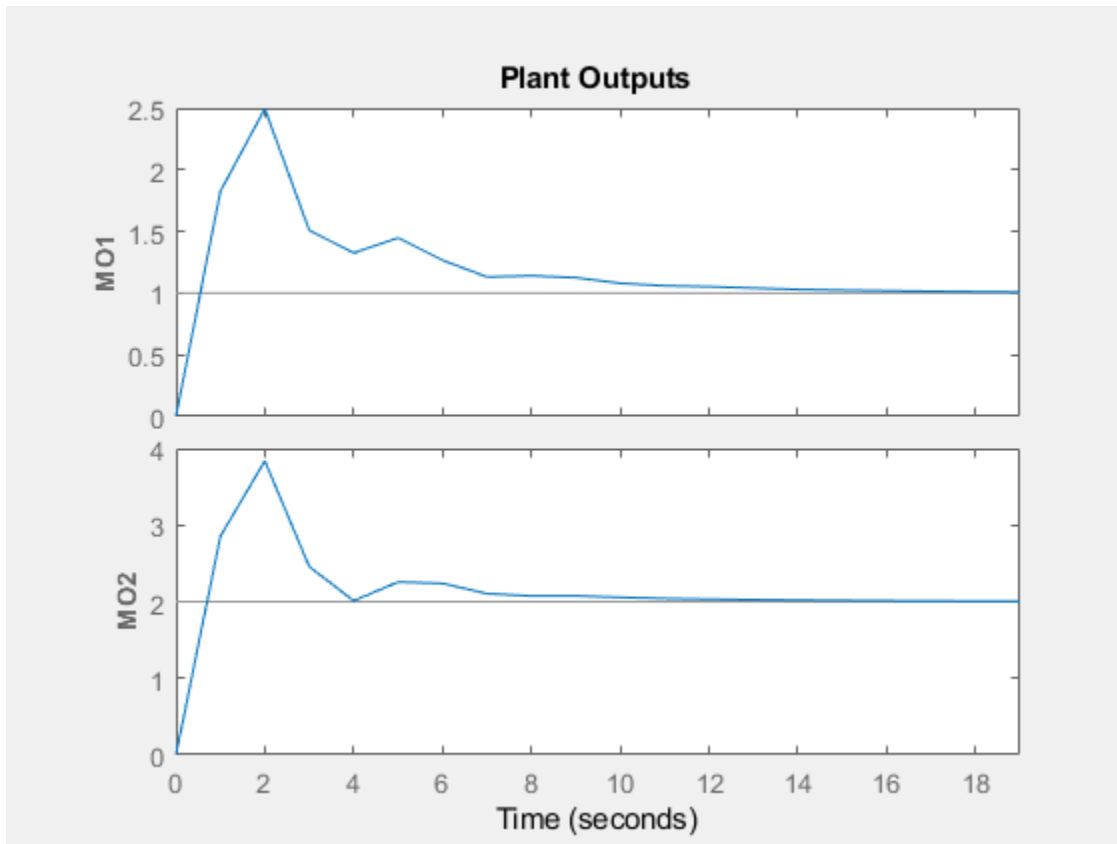
```
options = mpcsimopt(mpcobj);
options.UnmeasuredDisturbance = dist;
options.Model = plantActual;
```


Simulate the system.

```
sim(mpcobj,20,refs,options)
```

```
-->Converting model to discrete time.  
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.  
-->Assuming output disturbance added to measured output channel #2 is integrated white noise.  
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured  
-->Converting model to discrete time.  
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.  
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.  
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.  
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.  
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```





See Also

Topics

“Simulate Controller with Nonlinear Plant”

Introduced before R2006a

mpcstate

MPC controller state

Description

The `mpcstate` object represents the state of an implicit or explicit MPC controller. Use an `mpcstate` object to initialize the controller object before simulation.

The controller state includes the:

- States of the plant, disturbance, and noise models of the controller.
- Manipulated variables used in the previous control interval.
- State covariance matrix for the controller.

`mpcstate` objects are updated during simulation using the internal state observer based on the extended prediction model. The overall state is updated from the measured output $y_m(k)$ by a linear state observer. For more information, see “Controller State Estimation”.

Creation

Syntax

```
x = mpcstate(mpcobj)
x = mpcstate(mpcobj,plant,disturbance,noise,lastMove,covariance)
```

Description

`x = mpcstate(mpcobj)` creates a controller state object for the implicit or explicit MPC controller `mpcobj`, setting the state object properties to their default values.

`x = mpcstate(mpcobj,plant,disturbance,noise,lastMove,covariance)` sets the properties on page 3-35 of the state object to specified nondefault values. To use default values for a given property, set the corresponding input argument to `[]`.

Input Arguments

mpcobj — MPC controller object

mpc object | `explicitMPC` object

MPC controller object, specified as either an `mpc` or `explicitMPC` object.

Properties

Plant — Plant model state estimates

vector

Plant model state estimates, specified as a vector. The plant state estimate values are in engineering units and are absolute; that is, they include state offsets. By default, the `Plant` property is equal to the `Model.Nominal.X` property of the controller used to create the `mpcstate` object.

If the controller plant model includes delays, the `Plant` property includes states that model the delays. Therefore the number of elements in `Plant` is greater than the order of the nondelayed controller plant model.

Disturbance – Disturbance model state estimates

vector

Disturbance model state estimates, specified as a vector. The disturbance state estimates include the states of the input disturbance model followed by the states of the output disturbance model. By default, the `Disturbance` property is a zero vector if the controller has disturbance model states and empty otherwise.

To view the input and output disturbance models of your controller, use the `getindist` and `getoutdist` functions, respectively.

Noise – Output measurement noise model state estimates

vector

Output measurement noise model state estimates, specified as a vector. By default, the `Noise` property is a zero vector if the controller has noise model states and empty otherwise.

LastMove – Optimal manipulated variable control move from previous control interval

vector

Optimal manipulated variable control move from previous control interval, specified as a vector with length equal to the number of manipulated variables. By default, the `LastMove` property is equal to the nominal values of the manipulated variables.

During simulation, the `mpcmove` function automatically sets the value of `LastMove`.

When the actual control signals sent to the plant in the previous control interval do not match the calculated optimal value, do not use `LastMove` to specify the actual control signals. Instead, do so using `mpcmoveopt`.

Covariance – Covariance matrix for controller state estimates

symmetrical matrix

Covariance matrix for controller state estimates, specified as an N_s -by- N_s symmetric matrix, where N_s is the sum of the number states contained in the `Plant`, `Disturbance`, and `Noise` fields. T

If the controller is employing default state estimation the default covariance matrix is the steady-state covariance computed according to the assumptions in “Controller State Estimation”. For more information, see the description of the `P` output argument of the `kalmd` function.

If the controller uses custom state estimation, the `Covariance` property is empty and not used.

During simulation, do not modify `Covariance`. The `mpcmove` function automatically sets the value of `Covariance` at each control interval.

Object Functions

<code>mpcmove</code>	Compute optimal control action
<code>mpcmoveAdaptive</code>	Compute optimal control with prediction model updating
<code>mpcmoveMultiple</code>	Compute gain-scheduling MPC control action at a single time instant
<code>mpcmoveExplicit</code>	Compute optimal control using explicit MPC

Examples

Get Controller State Object

Create a model predictive controller for a single-input-single-output (SISO) plant. For this example, the plant includes an input delay of 0.4 time units, and the control interval to 0.2 time units.

```
H = tf(1,[10 1], 'InputDelay',0.4);
MPCobj = mpc(H,0.2);
```

```
-->The "PredictionHorizon" property of "mpc" object is empty. Trying PredictionHorizon = 10.
-->The "ControlHorizon" property of the "mpc" object is empty. Assuming 2.
-->The "Weights.ManipulatedVariables" property of "mpc" object is empty. Assuming default 0.0000.
-->The "Weights.ManipulatedVariablesRate" property of "mpc" object is empty. Assuming default 0.1.
-->The "Weights.OutputVariables" property of "mpc" object is empty. Assuming default 1.00000.
```

Create the corresponding controller state object in which all states are at their default values.

```
xMPC = mpcstate(MPCobj)
```

```
-->Converting the "Model.Plant" property of "mpc" object to state-space.
-->Converting model to discrete time.
-->Converting delays to states.
-->Assuming output disturbance added to measured output channel #1 is integrated white noise.
-->The "Model.Noise" property of the "mpc" object is empty. Assuming white noise on each measured
MPCSTATE object with fields
    Plant: [0 0 0]
    Disturbance: 0
    Noise: [1x0 double]
    LastMove: 0
    Covariance: [4x4 double]
```

The plant model, `H`, is a first-order, continuous-time transfer function. The `Plant` property of the `mpcstate` object contains two additional states to model the two intervals of delay. By default, the controller contains a first-order output disturbance model (`Disturbance` property is a scalar) and a static gain noise model (`Noise` property is empty).

You can access the properties of the controller state object using dot notation. For example, view the default covariance matrix.

```
xMPC.Covariance
```

```
ans = 4x4
```

```
    0.0624    0.0000    0.0000   -0.0224
    0.0000    1.0000   -0.0000   -0.0000
    0.0000   -0.0000    1.0000    0.0000
   -0.0224   -0.0000    0.0000    0.2301
```

See Also

`getEstimator` | `getindist` | `getoutdist` | `mpcmove` | `setEstimator` | `setindist` | `setoutdist`

Introduced before R2006a

nlmpc

Nonlinear model predictive controller

Description

A nonlinear model predictive controller computes optimal control moves across the prediction horizon using a nonlinear prediction model, a nonlinear cost function, and nonlinear constraints. For more information on nonlinear MPC, see “Nonlinear MPC”.

Creation

Syntax

```
nlobj = nlmpc(nx,ny,nu)
```

```
nlobj = nlmpc(nx,ny,'MV',mvIndex,'MD',mdIndex)
```

```
nlobj = nlmpc(nx,ny,'MV',mvIndex,'UD',udIndex)
```

```
nlobj = nlmpc(nx,ny,'MV',mvIndex,'MD',mdIndex,'UD',udIndex)
```

Description

`nlobj = nlmpc(nx,ny,nu)` creates an `nlmpc` object whose prediction model has `nx` states, `ny` outputs, and `nu` inputs, where all inputs are manipulated variables. Use this syntax if your model has no measured or unmeasured disturbance inputs.

`nlobj = nlmpc(nx,ny,'MV',mvIndex,'MD',mdIndex)` creates an `nlmpc` object whose prediction model has measured disturbance inputs. Specify the input indices for the manipulated variables, `mvIndex`, and measured disturbances, `mdIndex`.

`nlobj = nlmpc(nx,ny,'MV',mvIndex,'UD',udIndex)` creates an `nlmpc` object whose prediction model has unmeasured disturbance inputs. Specify the input indices for the manipulated variables and unmeasured disturbances, `udIndex`.

`nlobj = nlmpc(nx,ny,'MV',mvIndex,'MD',mdIndex,'UD',udIndex)` creates an `nlmpc` object whose prediction model has both measured and unmeasured disturbance inputs. Specify the input indices for the manipulated variables, measured disturbances, and unmeasured disturbances.

Input Arguments

nx — Number of prediction model states

positive integer

Number of prediction model states, specified as a positive integer. You cannot change the number of states after creating the controller object.

ny — Number of prediction model outputs

positive integer

Number of prediction model outputs, specified as a positive integer. You cannot change the number of outputs after creating the controller object.

nu — Number of prediction model inputs

positive integer

Number of prediction model inputs, which are all manipulated variables, specified as a positive integer. You cannot change the number of manipulated variables after creating the controller object.

mvIndex — Manipulated variable indices

vector of positive integers

Manipulated variable indices, specified as a vector of positive integers. You cannot change these indices after creating the controller object. This value is stored in the `Dimensions.MVIndex` controller property.

The combined set of indices from `mvIndex`, `mdIndex`, and `udIndex` must contain all integers from 1 through N_u , where N_u is the number of prediction model inputs.

mdIndex — Measured disturbance indices

vector of positive integers

Measured disturbance indices, specified as a vector of positive integers. You cannot change these indices after creating the controller object. This value is stored in the `Dimensions.MDIndex` controller property.

The combined set of indices from `mvIndex`, `mdIndex`, and `udIndex` must contain all integers from 1 through N_u , where N_u is the number of prediction model inputs.

udIndex — Unmeasured disturbance indices

vector of positive integers

Unmeasured disturbance indices, specified as a vector of positive integers. You cannot change these indices after creating the controller object. This value is stored in the `Dimensions.UDIndex` controller property.

The combined set of indices from `mvIndex`, `mdIndex`, and `udIndex` must contain all integers from 1 through N_u , where N_u is the number of prediction model inputs.

Properties

Ts — Prediction model sample time

1 (default) | positive finite scalar

Prediction model sample time, specified as a positive finite scalar. The controller uses a discrete-time model with sample time `Ts` for prediction. If you specify a continuous-time prediction model (`Model.IsContinuousTime` is `true`), then the controller discretizes the model using the built-in implicit trapezoidal rule with a sample time of `Ts`.

PredictionHorizon — Prediction horizon

10 (default) | positive integer

Prediction horizon steps, specified as a positive integer. The product of `PredictionHorizon` and `Ts` is the prediction time; that is, how far the controller looks into the future.

ControlHorizon — Control horizon

2 (default) | positive integer | vector of positive integers

Control horizon, specified as one of the following:

- Positive integer, m , between 1 and p , inclusive, where p is equal to `PredictionHorizon`. In this case, the controller computes m free control moves occurring at times k through $k+m-1$, and holds the controller output constant for the remaining prediction horizon steps from $k+m$ through $k+p-1$. Here, k is the current control interval.
- Vector of positive integers $[m_1, m_2, \dots]$, specifying the lengths of blocking intervals. By default the controller computes M blocks of free moves, where M is the number of blocking intervals. The first free move applies to times k through $k+m_1-1$, the second free move applies from time $k+m_1$ through $k+m_1+m_2-1$, and so on. Using block moves can improve the robustness of your controller. The sum of the values in `ControlHorizon` must match the prediction horizon p . If you specify a vector whose sum is:
 - Less than the prediction horizon, then the controller adds a blocking interval. The length of this interval is such that the sum of the interval lengths is p . For example, if $p=10$ and you specify a control horizon of `ControlHorizon=[1 2 3]`, then the controller uses four intervals with lengths `[1 2 3 4]`.
 - Greater than the prediction horizon, then the intervals are truncated until the sum of the interval lengths is equal to p . For example, if $p=10$ and you specify a control horizon of `ControlHorizon=[1 2 3 6 7]`, then the controller uses four intervals with lengths `[1 2 3 4]`.

Piecewise constant blocking moves are often too restrictive for optimal path planning applications. To produce a less-restrictive, better-conditioned nonlinear programming problem, you can specify piecewise linear manipulated variable blocking intervals. To do so, set the `Optimization.MVInterpolationOrder` property of your `nlmpc` controller object to 1.

For more information on how manipulated variable blocking works with different interpolation methods, see “Manipulated Variable Blocking”.

Dimensions — Prediction model dimensional information

structure

This property is read-only.

Prediction model dimensional information, specified when the controller is created and stored as a structure with the following fields.

NumberOfStates — Number of states

positive integer

Number of states in the prediction model, specified as a positive integer. This value corresponds to n_x .

NumberOfOutputs — Number of outputs

positive integer

Number of outputs in the prediction model, specified as a positive integer. This value corresponds to n_y .

NumberOfInputs — Number of states

positive integer

Number of inputs in the prediction model, specified as a positive integer. This value corresponds to either `nmv` or the sum of the lengths of `mvIndex`, `mdIndex`, and `udIndex`.

MVIndex — Manipulated variable indices

vector of positive integers

Manipulated variable indices for the prediction model, specified as a vector of positive integers. This value corresponds to `mvIndex`.

MDIndex — Measured disturbance indices

vector of positive integers

Measured disturbance indices for the prediction model, specified as a vector of positive integers. This value corresponds to `mdIndex`.

UDIndex — Unmeasured disturbance indices

vector of positive integers

Unmeasured disturbance indices for the prediction model, specified as a vector of positive integers. This value corresponds to `udIndex`.

Model — Prediction model

structure

Prediction model, specified as a structure with the following fields.

StateFcn — State function

string | character vector | function handle

State function, specified as a string, character vector, or function handle. For a continuous-time prediction model, `StateFcn` is the state derivative function. For a discrete-time prediction model, `StateFcn` is the state update function.

If your state function is continuous-time, the controller automatically discretizes the model using the implicit trapezoidal rule. This method can handle moderately stiff models, and its prediction accuracy depends on the controller sample time `Ts`; that is, a large sample time leads to inaccurate prediction.

If the default discretization method does not provide satisfactory prediction for your application, you can specify your own discrete-time prediction model that uses a different method, such as the multistep forward Euler rule.

You can specify your state function in one of the following ways:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Model.StateFcn = "myStateFunction";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Model.StateFcn = @myStateFunction;
```

- Anonymous function

```
Model.StateFcn = @(x,u,params) myStateFunction(x,u,params)
```

For more information, see “Specify Prediction Model for Nonlinear MPC”.

OutputFcn — Output function

[] (default) | string | character vector | function handle

Output function, specified as a string, character vector, or function handle. If the number of states and outputs of the prediction model are the same, you can omit `OutputFcn`, which implies that all states are measurable; that is, each output corresponds to one state.

Note Your output function cannot have direct feedthrough from any manipulated variable to any output at any time.

You can specify your output function in one of the following ways:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Model.OutputFcn = "myOutputFunction";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Model.OutputFcn = @myOutputFunction;
```

- Anonymous function

```
Model.OutputFcn = @(x,u,params) myOutputFunction(x,u,params)
```

For more information, see “Specify Prediction Model for Nonlinear MPC”.

IsContinuousTime — Flag indicating prediction model time domain

true (default) | false

Flag indicating prediction model time domain, specified as one of the following:

- `true` — Continuous-time prediction model. In this case, the controller automatically discretizes the model during prediction using `Ts`.
- `false` — Discrete-time prediction model. In this case, `Ts` is the sample time of the model.

Note `IsContinuousTime` must be consistent with the functions specified in `Model.StateFcn` and `Model.OutputFcn`.

NumberOfParameters — Number of optional model parameters

0 (default) | nonnegative integer

Number of optional model parameters used by the prediction model, custom cost function, and custom constraint functions, specified as a nonnegative integer. The number of parameters includes all the parameters used by these functions. For example, if the state function uses only parameter `p1`, the constraint functions use only parameter `p2`, and the cost function uses only parameter `p3`, then `NumberOfParameters` is 3.

States — State information, bounds, and scale factors

structure array

State information, bounds, and scale factors, specified as a structure array with N_x elements, where N_x is the number of states. Each structure element has the following fields.

Min — State lower bound

-Inf (default) | scalar | vector

State lower bound, specified as a scalar or vector. By default, the lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

State bounds are always hard constraints.

Max — State upper bound

Inf (default) | scalar | vector

State upper bound, specified as a scalar or vector. By default, the upper bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

State bounds are always hard constraints.

Name — State name

string | character vector

State name, specified as a string or character vector. The default state name is "x#", where # is its state index.

Units — State units

" " (default) | string | character vector

State units, specified as a string or character vector.

ScaleFactor — State scale factor

1 (default) | positive finite scalar

State scale factor, specified as a positive finite scalar. In general, use the operating range of the state. Specifying the proper scale factor can improve numerical conditioning for optimization.

OutputVariables — Output variable information, bounds, and scale factors

structure array

Output variable (OV) information, bounds, and scale factors, specified as a structure array with N_y elements, where N_y is the number of output variables. To access this property, you can use the alias `OV` instead of `OutputVariables`.

Each structure element has the following fields.

Min — OV lower bound

-Inf (default) | scalar | vector

OV lower bound, specified as a scalar or vector. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

Max — OV upper bound

Inf (default) | scalar | vector

OV upper bound, specified as a scalar or vector. By default, this upper bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

MinECR — OV lower bound softness

1 (default) | nonnegative finite scalar | vector

OV lower bound softness, where a larger ECR value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, OV upper bounds are soft constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

MaxECR — OV upper bound softness

1 (default) | nonnegative finite scalar | vector

OV upper bound softness, where a larger ECR value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, OV lower bounds are soft constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time $k+1$ to time $k+p$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

Name — OV name

string | character vector

OV name, specified as a string or character vector. The default OV name is "y#", where # is its output index.

Units — OV units

" " (default) | string | character vector

OV units, specified as a string or character vector.

ScaleFactor — OV scale factor

1 (default) | positive finite scalar

OV scale factor, specified as a positive finite scalar. In general, use the operating range of the output variable. Specifying the proper scale factor can improve numerical conditioning for optimization.

ManipulatedVariables — Manipulated variable information, bounds, and scale factors

structure array

Manipulated Variable (MV) information, bounds, and scale factors, specified as a structure array with N_{mv} elements, where N_{mv} is the number of manipulated variables. To access this property, you can use the alias `MV` instead of `ManipulatedVariables`.

Each structure element has the following fields.

Min — MV lower bound

-Inf (default) | scalar | vector

MV lower bound, specified as a scalar or vector. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

Max — MV upper bound

Inf (default) | scalar | vector

MV upper bound, specified as a scalar or vector. By default, this upper bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

MinECR — MV lower bound softness

0 (default) | nonnegative scalar | vector

MV lower bound softness, where a larger ECR value indicates a softer constraint, specified as a nonnegative scalar or vector. By default, MV lower bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

MaxECR — MV upper bound

0 (default) | nonnegative scalar | vector

MV upper bound softness, where a larger ECR value indicates a softer constraint, specified as a nonnegative scalar or vector. By default, MV upper bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR value over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR value is used for the remaining steps of the prediction horizon.

RateMin — MV rate of change lower bound

-Inf (default) | nonpositive scalar | vector

MV rate of change lower bound, specified as a nonpositive scalar or vector. The MV rate of change is defined as $MV(k) - MV(k-1)$, where k is the current time. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

RateMax — MV rate of change upper bound

Inf (default) | nonnegative scalar | vector

MV rate of change upper bound, specified as a nonnegative scalar or vector. The MV rate of change is defined as $MV(k) - MV(k-1)$, where k is the current time. By default, this lower bound is unconstrained.

To use the same bound across the prediction horizon, specify a scalar value.

To vary the bound over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final bound is used for the remaining steps of the prediction horizon.

RateMinECR — MV rate of change lower bound softness

0 (default) | nonnegative finite scalar | vector

MV rate of change lower bound softness, where a larger ECR value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, MV rate of change lower bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR values over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR values are used for the remaining steps of the prediction horizon.

RateMaxECR — MV rate of change upper bound softness

0 (default) | nonnegative finite scalar | vector

MV rate of change upper bound softness, where a larger ECR value indicates a softer constraint, specified as a nonnegative finite scalar or vector. By default, MV rate of change upper bounds are hard constraints.

To use the same ECR value across the prediction horizon, specify a scalar value.

To vary the ECR values over the prediction horizon from time k to time $k+p-1$, specify a vector of up to p values. Here, k is the current time and p is the prediction horizon. If you specify fewer than p values, the final ECR values are used for the remaining steps of the prediction horizon.

Name — MV name

string | character vector

MV name, specified as a string or character vector. The default MV name is "u#", where # is its input index.

Units — MV units

"" (default) | string | character vector

MV units, specified as a string or character vector.

ScaleFactor — MV scale factor

1 (default) | positive finite scalar

MV scale factor, specified as a positive finite scalar. In general, use the operating range of the manipulated variable. Specifying the proper scale factor can improve numerical conditioning for optimization.

MeasuredDisturbances — Measured disturbance information and scale factors

structure array

Measured disturbance (MD) information and scale factors, specified as a structure array with N_{md} elements, where N_{md} is the number of measured disturbances. If your model does not have measured disturbances, then `MeasuredDisturbances` is []. To access this property, you can use the alias `MD` instead of `MeasuredDisturbances`.

Each structure element has the following fields.

Name — MD name

string | character vector

MD name, specified as a string or character vector. The default MD name is "u#", where # is its input index.

Units — MD units

"" (default) | string | character vector

MD units, specified as a string or character vector.

ScaleFactor — MD scale factor

1 (default) | positive finite scalar

MD scale factor, specified as a positive finite scalar. In general, use the operating range of the disturbance. Specifying the proper scale factor can improve numerical conditioning for optimization.

Weights — Standard cost function tuning weights

structure

Standard cost function tuning weights, specified as a structure. The controller applies these weights to the scaled variables. Therefore, the tuning weights are dimensionless values.

Note If you define a custom cost function using `Optimization.CustomCostFcn` and set `Optimization.ReplaceStandardCost` to `true`, then the controller ignores the standard cost function tuning weights in `Weights`.

Weights has the following fields.

ManipulatedVariables — Manipulated variable tuning weights

row vector | array

Manipulated variable tuning weights, which penalize deviations from MV targets, specified as a row vector or array of nonnegative values. The default weight for all manipulated variables is 0.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

To specify MV targets at run time, create an `nlmpcmoveopt` object, and set its `MVTarget` property.

ManipulatedVariablesRate — Manipulated variable rate tuning weights

row vector | array

Manipulated variable rate tuning weights, which penalize large changes in control moves, specified as a row vector or array of nonnegative values. The default weight for all manipulated variable rates is 0.1.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable rate tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

OutputVariables — Output variable tuning weights

vector | array

Output variable tuning weights, which penalize deviation from output references, specified as a row vector or array of nonnegative values. The default weight for all output variables is 1.

To use the same weights across the prediction horizon, specify a row vector of length N_y , where N_y is the number of output variables.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the output variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

ECR — Slack variable tuning weight

1e5 (default) | positive scalar

Slack variable tuning weight, specified as a positive scalar.

Optimization — Custom optimization functions and solver

structure

Custom optimization functions and solver, specified as a structure with the following fields.

CustomCostFcn — Custom cost function

[] | string | character vector | function handle

Custom cost function, specified as one of the following:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Optimization.CustomCostFcn = "myCostFunction";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Optimization.CustomCostFcn = @myCostFunction;
```

- Anonymous function

```
Optimization.CustomCostFcn = @(X,U,e,data,params) myCostFunction(X,U,e,data,params);
```

Your cost function must have the signature:

```
function J = myCostFunction(X,U,e,data,params)
```

For more information, see “Specify Cost Function for Nonlinear MPC”.

ReplaceStandardCost — Flag indicating whether to replace the standard cost function

true (default) | false

Flag indicating whether to replace the standard cost function with the custom cost function, specified as one of the following:

- `true` — The controller uses the custom cost alone as the objective function during optimization. In this case, the `Weights` property of the controller is ignored.
- `false` — The controller uses the sum of the standard cost and custom cost as the objective function during optimization.

If you do not specify a custom cost function using `CustomCostFcn`, then the controller ignores `ReplaceStandardCost`.

For more information, see “Specify Cost Function for Nonlinear MPC”.

CustomEqConFcn — Custom equality constraint function

[] (default) | string | character vector | function handle

Custom equality constraint function, specified as one of the following:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Optimization.CustomEqConFcn = "myEqConFunction";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Optimization.CustomEqConFcn = @myEqConFunction;
```

- Anonymous function

```
Optimization.CustomEqConFcn = @(X,U,data,params) myEqConFunction(X,U,data,params);
```

Your equality constraint function must have the signature:

```
function ceq = myEqConFunction(X,U,data,p1,p2,...)
```

For more information, see “Specify Constraints for Nonlinear MPC”.

CustomIneqConFcn — Custom inequality constraint function

[] (default) | string | character vector | function handle

Custom inequality constraint function, specified as one of the following:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Optimization.CustomIneqConFcn = "myIneqConFunction";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Optimization.CustomIneqConFcn = @myIneqConFunction;
```

- Anonymous function

```
Optimization.CustomIneqConFcn = @(X,U,e,data,params) myIneqConFunction(X,U,e,data,params);
```

Your equality constraint function must have the signature:

```
function cineq = myIneqConFunction(X,U,e,data,params)
```

For more information, see “Specify Constraints for Nonlinear MPC”.

CustomSolverFcn — Custom nonlinear programming solver

[] (default) | string | character vector | function handle

Custom nonlinear programming solver function, specified as a string, character vector, or function handle. If you do not have Optimization Toolbox™ software, you must specify your own custom nonlinear programming solver. You can specify your custom solver function in one of the following ways:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Optimization.CustomSolverFcn = "myNLPsolver";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Optimization.CustomSolverFcn = @myNLPsolver;
```

For more information, see “Configure Optimization Solver for Nonlinear MPC”.

SolverOptions — Solver options

options object for fmincon | []

Solver options, specified as an options object for fmincon or [].

If you have Optimization Toolbox software, SolverOptions contains an options object for the fmincon solver.

If you do not have Optimization Toolbox, `SolverOptions` is `[]`.

For more information, see “Configure Optimization Solver for Nonlinear MPC”.

RunAsLinearMPC — Flag indicating whether to simulate as a linear controller

`"off"` (default) | `"Adaptive"` | `"TimeVarying"`

Flag indicating whether to simulate as a linear controller, specified as one of the following:

- `"off"` — Simulate the controller as a nonlinear controller with a nonlinear prediction model.
- `"Adaptive"` — For each control interval, a linear model is obtained from the specified nonlinear state and output functions at the current operating point and used across the prediction horizon. To determine if an adaptive MPC controller provides comparable performance to the nonlinear controller, use this option. For more information on adaptive MPC, see “Adaptive MPC”.
- `"TimeVarying"` — For each control interval, p linear models are obtained from the specified nonlinear state and output functions at the p operating points predicted from the previous interval, one for each prediction horizon step. To determine if a linear time-varying MPC controller provides comparable performance to the nonlinear controller, use this option. For more information on time-varying MPC, see “Time-Varying MPC”.

To use either the `"Adaptive"` or `"TimeVarying"` option, your controller must have no custom constraints and no custom cost function.

For an example that simulates a nonlinear MPC controller as a linear controller, see “Optimization and Control of a Fed-Batch Reactor Using Nonlinear MPC”.

UseSuboptimalSolution — Flag indicating whether a suboptimal solution is acceptable

`false` (default) | `true`

Flag indicating whether a suboptimal solution is acceptable, specified as a logical value. When the nonlinear programming solver reaches the maximum number of iterations without finding a solution (the exit flag is `0`), the controller:

- Freezes the MV values if `UseSuboptimalSolution` is `false`
- Applies the suboptimal solution found by the solver after the final iteration if `UseSuboptimalSolution` is `true`

To specify the maximum number of iterations, use `Optimization.SolverOptions.MaxIter`.

MVInterpolationOrder — Linear interpolation order used for block moves

`0` (default) | `1`

Linear interpolation order used by block moves, specified as one of the following:

- `0` — Use piecewise constant manipulated variable intervals.
- `1` — Use piecewise linear manipulated variable intervals.

If the control horizon is a scalar, then the controller ignores `MVInterpolationOrder`.

For more information on manipulated variable blocking, see “Manipulated Variable Blocking”.

Jacobian — Jacobians of model functions, and custom cost and constraint functions

structure

Jacobians of model functions, and custom cost and constraint functions, specified as a structure. It is best practice to use Jacobians whenever they are available, since they improve optimization efficiency. If you do not specify a Jacobian for a given function, the nonlinear programming solver must numerically compute the Jacobian.

The **Jacobian** structure contains the following fields.

StateFcn — Jacobian of state function

[] (default) | string | character vector | function handle

Jacobian of state function z from `Model.StateFcn`, specified as one of the following

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Model.StateFcn = "myStateJacobian";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Model.StateFcn = @myStateJacobian;
```

- Anonymous function

```
Model.StateFcn = @(x,u,params) myStateJacobian(x,u,params)
```

For more information, see “Specify Prediction Model for Nonlinear MPC”.

OutputFcn — Jacobian of output function

[] (default) | string | character vector | function handle

Jacobian of output function y from `Model.OutputFcn`, specified as one of the following:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Model.StateFcn = "myOutputJacobian";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Model.StateFcn = @myOutputJacobian;
```

- Anonymous function

```
Model.StateFcn = @(x,u,params) myOutputJacobian(x,u,params)
```

For more information, see “Specify Prediction Model for Nonlinear MPC”.

CustomCostFcn — Jacobian of custom cost function

[] | string | character vector | function handle

Jacobian of custom cost function J from `Optimization.CustomCostFcn`, specified as one of the following:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Jacobian.CustomCostFcn = "myCostJacobian";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Jacobian.CustomCostFcn = @myCostJacobian;
```

- Anonymous function

```
Jacobian.CustomCostFcn = @(X,U,e,data,params) myCostJacobian(X,U,e,data,params)
```

Your cost Jacobian function must have the signature:

```
function [G,Gmv,Ge] = myCostJacobian(X,U,e,data,params)
```

For more information, see “Specify Cost Function for Nonlinear MPC”.

CustomEqConFcn — Jacobian of custom equality constraints

[] (default) | string | character vector | function handle

Jacobian of custom equality constraints `ceq` from `Optimization.CustomEqConFcn`, specified as one of the following:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Jacobian.CustomEqConFcn = "myEqConJacobian";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Jacobian.CustomEqConFcn = @myEqConJacobian;
```

- Anonymous function

```
Jacobian.CustomEqConFcn = @(X,U,data,params) myEqConJacobian(X,U,data,params);
```

Your equality constraint Jacobian function must have the signature:

```
function [G,Gmv] = myEqConJacobian(X,U,data,params)
```

For more information, see “Specify Constraints for Nonlinear MPC”.

CustomIneqConFcn — Jacobian of custom inequality constraints

[] (default) | string | character vector | function handle

Jacobian of custom inequality constraints `c` from `Optimization.CustomIneqConFcn`, specified as one of the following:

- Name of a function in the current working folder or on the MATLAB path, specified as a string or character vector

```
Jacobian.CustomEqConFcn = "myIneqConJacobian";
```

- Handle to a function in the current working folder or on the MATLAB path

```
Jacobian.CustomEqConFcn = @myIneqConJacobian;
```

- Anonymous function

```
Jacobian.CustomEqConFcn = @(X,U,data,params) myIneqConJacobian(X,U,data,params);
```

Your inequality constraint Jacobian function must have the signature:

```
function [G,Gmv,Ge] = myIneqConJacobian(X,U,data,params)
```

For more information, see “Specify Constraints for Nonlinear MPC”.

Object Functions

<code>nlmpcmove</code>	Compute optimal control action for nonlinear MPC controller
<code>validateFcns</code>	Examine prediction model and custom functions of <code>nlmpc</code> object for potential problems
<code>convertToMPC</code>	Convert <code>nlmpc</code> object into one or more <code>mpc</code> objects
<code>createParameterBus</code>	Create Simulink bus object and configure Bus Creator block for passing model parameters to Nonlinear MPC Controller block

Examples

Create Nonlinear MPC Controller with Discrete-Time Prediction Model

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nx = 4;
ny = 2;
nu = 1;
nlobj = nlmpc(nx,ny,nu);
```

In standard cost function, zero weights are applied by default to one or more 0Vs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The discrete-time state function uses an optional parameter, the sample time `Ts`, to integrate the continuous-time model. Therefore, you must specify the number of optional parameters as 1.

```
nlobj.Model.NumberOfParameters = 1;
```

Specify the output function for the controller. In this case, define the first and third states as outputs. Even though this output function does not use the optional sample time parameter, you must specify the parameter as an input argument (`Ts`).

```
nlobj.Model.OutputFcn = @(x,u,Ts) [x(1); x(3)];
```

Validate the prediction model functions for nominal states `x0` and nominal inputs `u0`. Since the prediction model uses a custom parameter, you must pass this parameter to `validateFcns`.

```
x0 = [0.1;0.2;-pi/2;0.3];
u0 = 0.4;
validateFcns(nlobj, x0, u0, [], {Ts});
```

```
Model.StateFcn is OK.
Model.OutputFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Create Nonlinear MPC Controller with Measured and Unmeasured Disturbances

Create a nonlinear MPC controller with three states, one output, and four inputs. The first two inputs are measured disturbances, the third input is the manipulated variable, and the fourth input is an unmeasured disturbance.

```
nlobj = nlmpc(3,1,'MV',3,'MD',[1 2],'UD',4);
```

To view the controller state, output, and input dimensions and indices, use the `Dimensions` property of the controller.

```
nlobj.Dimensions
```

```
ans = struct with fields:
    NumberOfStates: 3
    NumberOfOutputs: 1
    NumberOfInputs: 4
        MVIndex: 3
        MDIndex: [1 2]
        UDIndex: 4
```

Specify the controller sample time and horizons.

```
nlobj.Ts = 0.5;
nlobj.PredictionHorizon = 6;
nlobj.ControlHorizon = 3;
```

Specify the prediction model state function, which is in the file `exocstrStateFcnCT.m`.

```
nlobj.Model.StateFcn = 'exocstrStateFcnCT';
```

Specify the prediction model output function, which is in the file `exocstrOutputFcn.m`.

```
nlobj.Model.OutputFcn = 'exocstrOutputFcn';
```

Validate the prediction model functions using the initial operating point as the nominal condition for testing and setting the unmeasured disturbance state, $x_0(3)$, to 0. Since the model has measured disturbances, you must pass them to `validateFcns`.

```
x0 = [311.2639; 8.5698; 0];
u0 = [10; 298.15; 298.15];
validateFcns(nlobj,x0,u0(3),u0(1:2)');
```

```
Model.StateFcn is OK.
Model.OutputFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Validate Nonlinear MPC Prediction Model and Custom Functions

Create nonlinear MPC controller with six states, six outputs, and four inputs.

```
nx = 6;
ny = 6;
```



```
nu = 4;
nlobj = nlmpc(nx,ny,nu);
```

In standard cost function, zero weights are applied by default to one or more OVs because there are

Specify the controller sample time and horizons.

```
Ts = 0.4;
p = 30;
c = 4;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = p;
nlobj.ControlHorizon = c;
```

Specify the prediction model state function and the Jacobian of the state function. For this example, use a model of a flying robot.

```
nlobj.Model.StateFcn = "FlyingRobotStateFcn";
nlobj.Jacobian.StateFcn = "FlyingRobotStateJacobianFcn";
```

Specify a custom cost function for the controller that replaces the standard cost function.

```
nlobj.Optimization.CustomCostFcn = @(X,U,e,data) Ts*sum(sum(U(1:p,:)));
nlobj.Optimization.ReplaceStandardCost = true;
```

Specify a custom constraint function for the controller.

```
nlobj.Optimization.CustomEqConFcn = @(X,U,data) X(end,:)';
```

Validate the prediction model and custom functions at the initial states (x_0) and initial inputs (u_0) of the robot.

```
x0 = [-10;-10;pi/2;0;0;0];
u0 = zeros(nu,1);
validateFcns(nlobj,x0,u0);
```

```
Model.StateFcn is OK.
Jacobian.StateFcn is OK.
No output function specified. Assuming "y = x" in the prediction model.
Optimization.CustomCostFcn is OK.
Optimization.CustomEqConFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Create Linear MPC Controllers from Nonlinear MPC Controller

Create a nonlinear MPC controller with four states, one output variable, one manipulated variable, and one measured disturbance.

```
nlobj = nlmpc(4,1,'MV',1,'MD',2);
```

Specify the controller sample time and horizons.

```
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 3;
```

Specify the state function of the prediction model.

```
nlobj.Model.StateFcn = 'oxidationStateFcn';
```

Specify the prediction model output function and the output variable scale factor.

```
nlobj.Model.OutputFcn = @(x,u) x(3);
nlobj.OutputVariables.ScaleFactor = 0.03;
```

Specify the manipulated variable constraints and scale factor.

```
nlobj.ManipulatedVariables.Min = 0.0704;
nlobj.ManipulatedVariables.Max = 0.7042;
nlobj.ManipulatedVariables.ScaleFactor = 0.6;
```

Specify the measured disturbance scale factor.

```
nlobj.MeasuredDisturbances.ScaleFactor = 0.5;
```

Compute the state and input operating conditions for three linear MPC controllers using the `fsolve` function.

```
options = optimoptions('fsolve','Display','none');

uLow = [0.38 0.5];
xLow = fsolve(@(x) oxidationStateFcn(x,uLow),[1 0.3 0.03 1],options);

uMedium = [0.24 0.5];
xMedium = fsolve(@(x) oxidationStateFcn(x,uMedium),[1 0.3 0.03 1],options);

uHigh = [0.15 0.5];
xHigh = fsolve(@(x) oxidationStateFcn(x,uHigh),[1 0.3 0.03 1],options);
```

Create linear MPC controllers for each of these nominal conditions.

```
mpcobjLow = convertToMPC(nlobj,xLow,uLow);
mpcobjMedium = convertToMPC(nlobj,xMedium,uMedium);
mpcobjHigh = convertToMPC(nlobj,xHigh,uHigh);
```

You can also create multiple controllers using arrays of nominal conditions. The number of rows in the arrays specifies the number controllers to create. The linear controllers are returned as cell array of `mpc` objects.

```
u = [uLow; uMedium; uHigh];
x = [xLow; xMedium; xHigh];
mpcobjs = convertToMPC(nlobj,x,u);
```

View the properties of the `mpcobjLow` controller.

```
mpcobjLow
```

```
MPC object (created on 29-Feb-2020 02:55:58):
```

```
-----
Sampling time:      1 (seconds)
Prediction Horizon: 10
Control Horizon:   3
```

```
Plant Model:
```

```
-----
1 manipulated variable(s)  -->| 4 states |
```

```

1 measured disturbance(s)  --> | 2 inputs | --> 1 measured output(s)
                                |         |
0 unmeasured disturbance(s) --> | 1 outputs | --> 0 unmeasured output(s)
                                |         |
                                -----
Indices:
  (input vector)   Manipulated variables: [1 ]
                   Measured disturbances: [2 ]
  (output vector)   Measured outputs: [1 ]

Disturbance and Noise Models:
  Output disturbance model: default (type "getoutdist(mpcobjLow)" for details)
  Measurement noise model: default (unity gain after scaling)

Weights:
  ManipulatedVariables: 0
  ManipulatedVariablesRate: 0.1000
  OutputVariables: 1
  ECR: 100000

State Estimation: Default Kalman Filter (type "getEstimator(mpcobjLow)" for details)

Constraints:
  0.0704 <= u1 <= 0.7042, u1/rate is unconstrained, y1 is unconstrained

```

Plan Optimal Trajectory Using Nonlinear MPC

Create nonlinear MPC controller with six states, six outputs, and four inputs.

```

nx = 6;
ny = 6;
nu = 4;
nlobj = nlmpc(nx,ny,nu);

```

In standard cost function, zero weights are applied by default to one or more OV's because there are

Specify the controller sample time and horizons.

```

Ts = 0.4;
p = 30;
c = 4;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = p;
nlobj.ControlHorizon = c;

```

Specify the prediction model state function and the Jacobian of the state function. For this example, use a model of a flying robot.

```

nlobj.Model.StateFcn = "FlyingRobotStateFcn";
nlobj.Jacobian.StateFcn = "FlyingRobotStateJacobianFcn";

```

Specify a custom cost function for the controller that replaces the standard cost function.

```

nlobj.Optimization.CustomCostFcn = @(X,U,e,data) Ts*sum(sum(U(1:p,:)));
nlobj.Optimization.ReplaceStandardCost = true;

```

Specify a custom constraint function for the controller.

```
nlobj.Optimization.CustomEqConFcn = @(X,U,data) X(end,:)';
```

Specify linear constraints on the manipulated variables.

```
for ct = 1:nu
    nlobj.MV(ct).Min = 0;
    nlobj.MV(ct).Max = 1;
end
```

Validate the prediction model and custom functions at the initial states (x_0) and initial inputs (u_0) of the robot.

```
x0 = [-10;-10;pi/2;0;0;0];
u0 = zeros(nu,1);
validateFcns(nlobj,x0,u0);
```

```
Model.StateFcn is OK.
Jacobian.StateFcn is OK.
No output function specified. Assuming "y = x" in the prediction model.
Optimization.CustomCostFcn is OK.
Optimization.CustomEqConFcn is OK.
Analysis of user-provided model, cost, and constraint functions complete.
```

Compute the optimal state and manipulated variable trajectories, which are returned in the `info`.

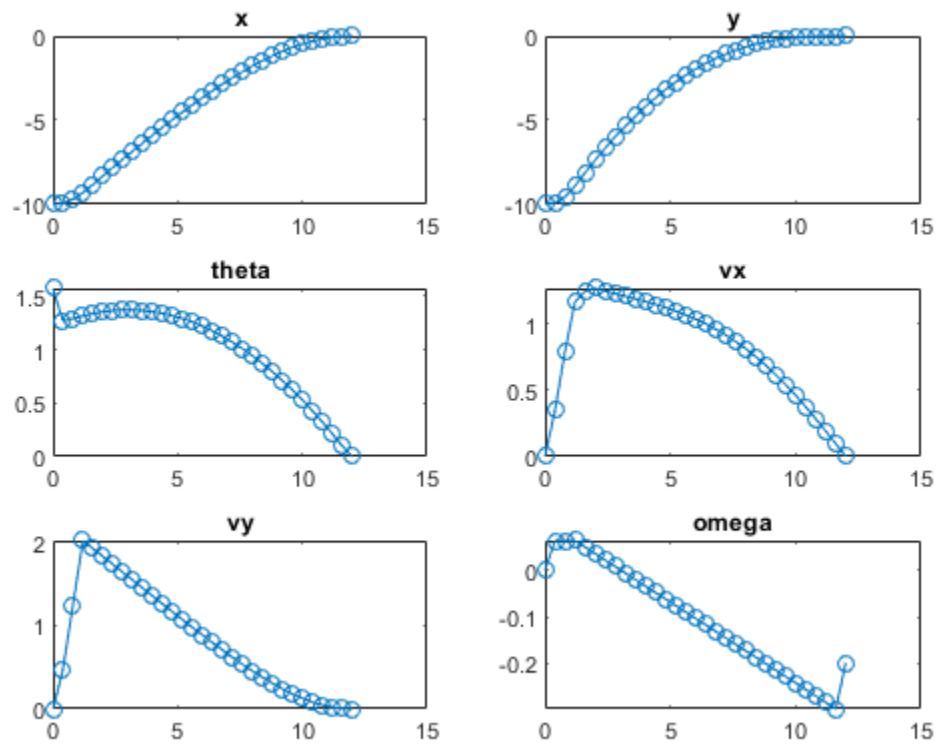
```
[~,~,info] = nlmpcmove(nlobj,x0,u0);
```

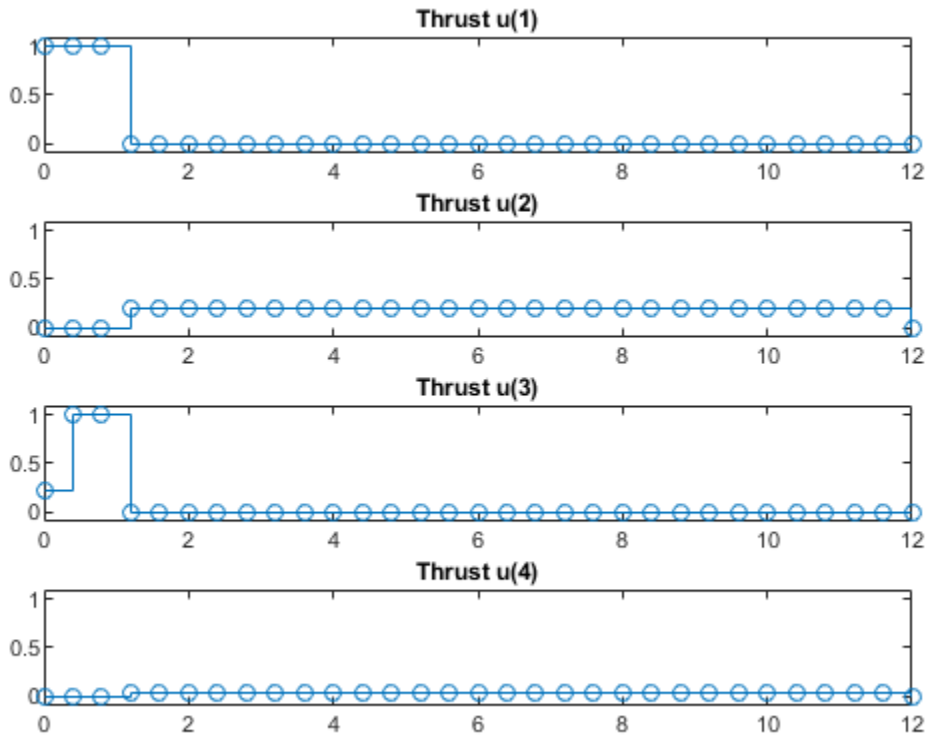
Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard.

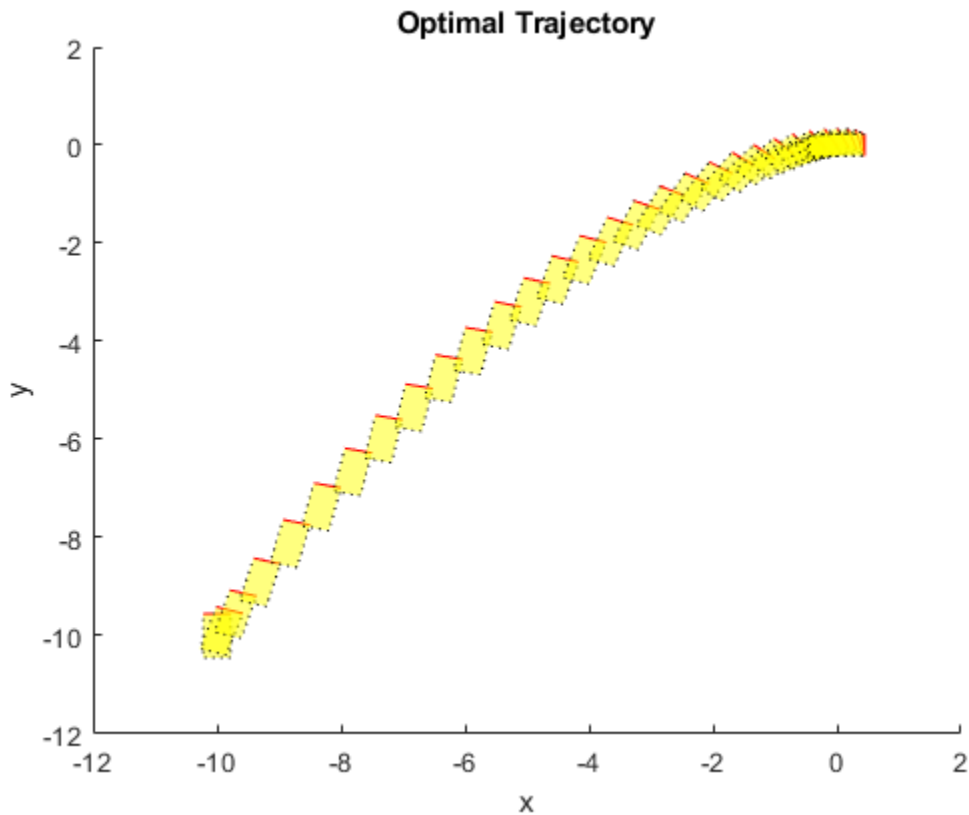
Plot the optimal trajectories.

```
FlyingRobotPlotPlanning(info)
```

```
Optimal fuel consumption = 4.712383
```







Simulate Closed-Loop Control using Nonlinear MPC Controller

Create a nonlinear MPC controller with four states, two outputs, and one input.

```
nlobj = nlmpc(4,2,1);
```

In standard cost function, zero weights are applied by default to one or more OVs because there a

Specify the sample time and horizons of the controller.

```
Ts = 0.1;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 5;
```

Specify the state function for the controller, which is in the file `pendulumDT0.m`. This discrete-time model integrates the continuous time model defined in `pendulumCT0.m` using a multistep forward Euler method.

```
nlobj.Model.StateFcn = "pendulumDT0";
nlobj.Model.IsContinuousTime = false;
```

The prediction model uses an optional parameter, `Ts`, to represent the sample time. Specify the number of parameters.

```
nlobj.Model.NumberOfParameters = 1;
```

Specify the output function of the model, passing the sample time parameter as an input argument.

```
nlobj.Model.OutputFcn = @(x,u,Ts) [x(1); x(3)];
```

Define standard constraints for the controller.

```
nlobj.Weights.OutputVariables = [3 3];  
nlobj.Weights.ManipulatedVariablesRate = 0.1;  
nlobj.OV(1).Min = -10;  
nlobj.OV(1).Max = 10;  
nlobj.MV.Min = -100;  
nlobj.MV.Max = 100;
```

Validate the prediction model functions.

```
x0 = [0.1;0.2;-pi/2;0.3];  
u0 = 0.4;  
validateFcns(nlobj, x0, u0, [], {Ts});
```

```
Model.StateFcn is OK.
```

```
Model.OutputFcn is OK.
```

```
Analysis of user-provided model, cost, and constraint functions complete.
```

Only two of the plant states are measurable. Therefore, create an extended Kalman filter for estimating the four plant states. Its state transition function is defined in `pendulumStateFcn.m` and its measurement function is defined in `pendulumMeasurementFcn.m`.

```
EKF = extendedKalmanFilter(@pendulumStateFcn,@pendulumMeasurementFcn);
```

Define initial conditions for the simulation, initialize the extended Kalman filter state, and specify a zero initial manipulated variable value.

```
x = [0;0;-pi;0];  
y = [x(1);x(3)];  
EKF.State = x;  
mv = 0;
```

Specify the output reference value.

```
yref = [0 0];
```

Create an `nlpmoveopt` object, and specify the sample time parameter.

```
nloptions = nlpmoveopt;  
nloptions.Parameters = {Ts};
```

Run the simulation for 10 seconds. During each control interval:

- 1 Correct the previous prediction using the current measurement.
- 2 Compute optimal control moves using `nlpmove`. This function returns the computed optimal sequences in `nloptions`. Passing the updated options object to `nlpmove` in the next control interval provides initial guesses for the optimal sequences.
- 3 Predict the model states.
- 4 Apply the first computed optimal control move to the plant, updating the plant states.

- 5 Generate sensor data with white noise.
- 6 Save the plant states.

```

Duration = 10;
xHistory = x;
for ct = 1:(Duration/Ts)
    % Correct previous prediction
    xk = correct(EKF,y);
    % Compute optimal control moves
    [mv,nloptions] = nlmpcmove(nlobj,xk,mv,yref,[],nloptions);
    % Predict prediction model states for the next iteration
    predict(EKF,[mv; Ts]);
    % Implement first optimal control move
    x = pendulumDT0(x,mv,Ts);
    % Generate sensor data
    y = x([1 3]) + randn(2,1)*0.01;
    % Save plant states
    xHistory = [xHistory x];
end

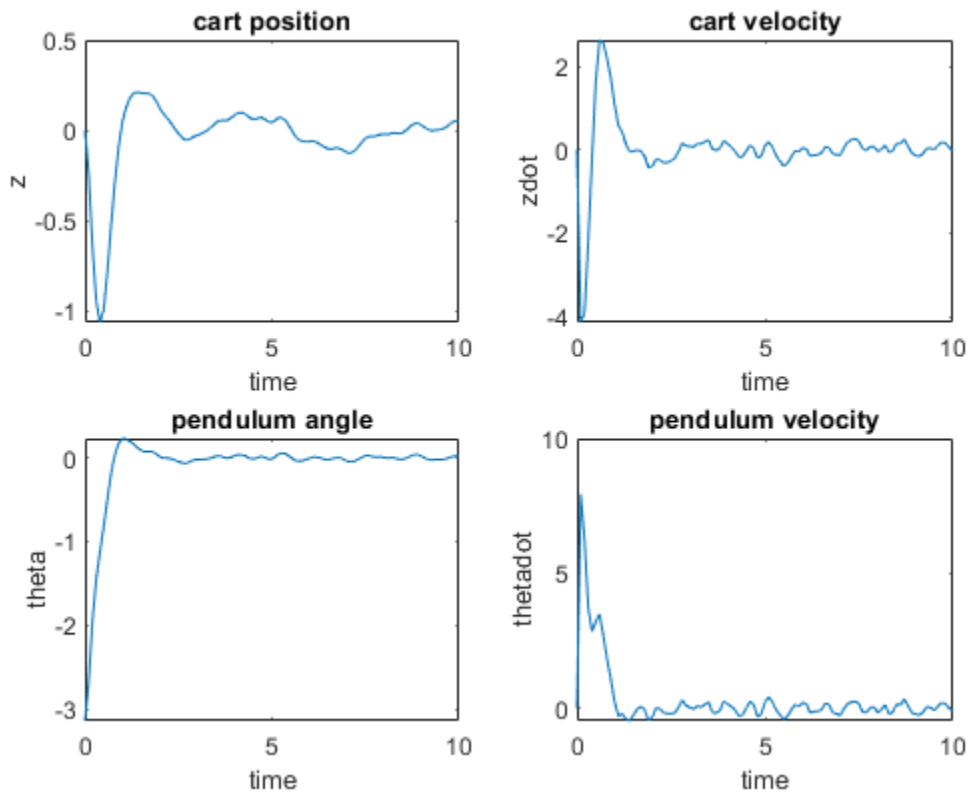
```

Plot the resulting state trajectories.

```

figure
subplot(2,2,1)
plot(0:Ts:Duration,xHistory(1,:))
xlabel('time')
ylabel('z')
title('cart position')
subplot(2,2,2)
plot(0:Ts:Duration,xHistory(2,:))
xlabel('time')
ylabel('zdot')
title('cart velocity')
subplot(2,2,3)
plot(0:Ts:Duration,xHistory(3,:))
xlabel('time')
ylabel('theta')
title('pendulum angle')
subplot(2,2,4)
plot(0:Ts:Duration,xHistory(4,:))
xlabel('time')
ylabel('thetadot')
title('pendulum velocity')

```



See Also

Blocks

Nonlinear MPC Controller

Topics

“Trajectory Optimization and Control of Flying Robot Using Nonlinear MPC”

“Nonlinear Model Predictive Control of an Exothermic Chemical Reactor”

“Swing-up Control of a Pendulum Using Nonlinear Model Predictive Control”

“Nonlinear and Gain-Scheduled MPC Control of an Ethylene Oxidation Plant”

“Plan and Execute Collision-Free Trajectories using KINOVA Gen3 Manipulator” (Robotics System Toolbox)

“Nonlinear MPC”

Introduced in R2018b

nlmpcmoveopt

Option set for nlmpcmove function

Description

To specify options for the nlmpcmove function, use an nlmpcmoveopt option set.

Using this option set, you can specify run-time values for a subset of controller properties, such as tuning weights and constraints. If you do not specify a value for one of the nlmpcmoveopt properties, the corresponding value defined in the nlmpc controller object is used instead.

Creation

Syntax

```
options = nlmpcmoveopt
```

Description

options = nlmpcmoveopt creates a default set of options for the nlmpcmove function. To modify the property values, use dot notation.

Properties

OutputWeights — Output variable tuning weights

[] (default) | row vector | array

Output variable tuning weights that replace the `Weights.OutputVariables` property of the controller at run time, specified as a row vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_y , where N_y is the number of output variables.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, specify an array with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the output variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

MVWeights — Manipulated variable tuning weights

[] (default) | row vector | array

Manipulated variable tuning weights that replace the `Weights.ManipulatedVariables` property of the controller at run time, specified as a row vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each

row contains the manipulated variable tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

MVRateWeights — Manipulated variable rate tuning weights

[] (default) | row vector | array

Manipulated variable rate tuning weights that replace the `Weights.ManipulatedVariablesRate` property of the controller at run time, specified as a row vector or array of nonnegative values.

To use the same weights across the prediction horizon, specify a row vector of length N_{mv} , where N_{mv} is the number of manipulated variables.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, specify an array with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the manipulated variable rate tuning weights for one prediction horizon step. If you specify fewer than p rows, the weights in the final row are used for the remaining steps of the prediction horizon.

ECR Weight — Slack variable tuning weight

[] (default) | positive scalar

Slack variable tuning weight that replaces the `Weights.ECR` property of the controller at run time, specified as a positive scalar.

OutputMin — Output variable lower bounds

[] (default) | row vector | array

Output variable lower bounds, specified as a row vector of length N_y or an array with N_y columns, where N_y is the number of output variables. `OutputMin(:, i)` replaces the `OutputVariables(i).Min` property of the controller at run time.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

OutputMax — Output variable upper bounds

[] (default) | row vector | array

Output variable upper bounds, specified as a row vector of length N_y or an array with N_y columns, where N_y is the number of output variables. `OutputMax(:, i)` replaces the `OutputVariables(i).Max` property of the controller at run time.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVMin — Manipulated variable lower bounds

[] (default) | row vector | array

Manipulated variable lower bounds, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. `MVMin(:, i)` replaces the `ManipulatedVariables(i).Min` property of the controller at run time.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVMax — Manipulated variable upper bounds

[] (default) | row vector | array

Manipulated variable upper bounds, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. `MVMax(:, i)` replaces the `ManipulatedVariables(i).Max` property of the controller at run time.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVRateMin — Manipulated variable rate lower bounds

[] (default) | row vector | array

Manipulated variable rate lower bounds, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. `MVRateMin(:, i)` replaces the `ManipulatedVariables(i).RateMin` property of the controller at run time. `MVRateMin` bounds must be nonpositive.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVRateMax — Manipulated variable rate upper bounds

[] (default) | row vector | array

Manipulated variable rate upper bounds, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables. `MVRateMax(:, i)` replaces the `ManipulatedVariables(i).RateMax` property of the controller at run time. `MVRateMax` bounds must be nonnegative.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

StateMin — State lower bounds

[] (default) | row vector | array

State lower bounds, specified as a row vector of length N_x or an array with N_x columns, where N_x is the number of states. `StateMin(:, i)` replaces the `States(i).Min` property of the controller at run time.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

StateMax — State upper bounds

[] (default) | row vector | array

State upper bounds, specified as a row vector of length N_x or an array with N_x columns, where N_x is the number of states. `StateMax(:, i)` replaces the `States(i).Max` property of the controller at run time.

To use the same bounds across the prediction horizon, specify a row vector.

To vary the bounds over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the final bounds are used for the remaining steps of the prediction horizon.

MVTarget — Manipulated variable targets

[] (default) | row vector | array

Manipulated variable targets, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables.

To use the same manipulated variable targets across the prediction horizon, specify a row vector.

To vary the targets over the prediction horizon (previewing) from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the targets for one prediction horizon step. If you specify fewer than p rows, the final targets are used for the remaining steps of the prediction horizon.

Parameters — Parameter values

{ } (default) | cell vector

Parameter values used by the prediction model, custom cost function, and custom constraints, specified as a cell vector with length equal to the `Model.NumberOfParameters` property of the controller. If the controller has no parameters, then `Parameters` must be `{}`.

The controller, `nlpmpcobj`, passes these parameters to the:

- Model functions in `nlpmpcobj.Model` (`StateFcn` and `OutputFcn`)
- Cost function `nlpmpcobj.Optimization.CustomCostFcn`
- Constraint functions in `nlpmpcobj.Optimization` (`CustomEqConFcn` and `CustomIneqConFcn`)

- Jacobian functions in `nlmpcobj.Jacobian`

The order of the parameters must match the order defined for these functions.

X0 — Initial guesses for the optimal state solutions

[] (default) | vector | array

Initial guesses for the optimal state solutions, specified as a row vector of length N_x or an array with N_x columns, where N_x is the number of states.

To use the same initial guesses across the prediction horizon, specify a row vector.

To vary the initial guesses over the prediction horizon from time $k+1$ to time $k+p$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the initial guesses for one prediction horizon step. If you specify fewer than p rows, the final guesses are used for the remaining steps of the prediction horizon.

If `X0` is [], the default initial guesses are the current states of the prediction model (`x` input argument to `nlmpcmove`).

In general, during closed-loop simulation, you do not specify `X0` yourself. Instead, when calling `nlmpcmove`, return the `opt` output argument, which is an `nlmpcmoveopt` object. `opt.X0` contains the calculated optimal state trajectories as initial guesses. You can then pass `opt` in as the `options` input argument to `nlmpcmove` for the next control interval. These steps are a best practice, even if you do not specify any other run-time options.

MV0 — Initial guesses for the optimal manipulated variable solutions

[] (default) | vector | array

Initial guesses for the optimal manipulated variable solutions, specified as a row vector of length N_{mv} or an array with N_{mv} columns, where N_{mv} is the number of manipulated variables.

To use the same initial guesses across the prediction horizon, specify a row vector.

To vary the initial guesses over the prediction horizon from time k to time $k+p-1$, specify an array with up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the initial guesses for one prediction horizon step. If you specify fewer than p rows, the final guesses are used for the remaining steps of the prediction horizon.

If `MV0` is [], the default initial guesses are the control signals used in the plant at the previous control interval (`lastmv` input argument to `nlmpcmove`).

In general, during closed-loop simulation, you do not specify `MV0` yourself. Instead, when calling `nlmpcmove`, return the `opt` output argument, which is an `nlmpcmoveopt` object. `opt.MV0` contains the calculated optimal manipulated variable trajectories as initial guesses. You can then pass `opt` in as the `options` input argument to `nlmpcmove` for the next control interval. These steps are a best practice, even if you do not specify any other run-time options.

Slack0 — Initial guess for the slack variable at the solution

[] (default) | nonnegative scalar

Initial guess for the slack variable at the solution, specified as a nonnegative scalar. If `Slack0` is [], the default initial guess is 0.

In general, during closed-loop simulation, you do not specify `Slack0` yourself. Instead, when calling `nlmpcmove`, return the `opt` output argument, which is an `nlmpcmoveopt` object. `opt.Slack`

contains the calculated slack variable as an initial guess. You can then pass `opt` in as the `options` input argument to `nlpmove` for the next control interval. These steps are a best practice, even if you do not specify any other run-time options.

Object Functions

`nlpmove` Compute optimal control action for nonlinear MPC controller

Examples

Specify Run-Time Parameters for Nonlinear MPC

Create a default `nlpmoveopt` option set.

```
options = nlpmoveopt;
```

Specify the run-time values for the controller prediction model parameters. For this example, assume that the controller has the following optional parameters, which are input arguments to all the prediction model functions and custom functions of the controller.

- Sample time of the model, specified as a single numeric value. Specify a value of `0.25`.
- Gain factors, specified as a two-element row vector. Specify a value of `[0.7 0.35]`.

The order in which you specify the parameters must match the order specified in the custom function argument lists. Also, the dimensions of the parameters must match the dimensions expected by the custom functions.

```
options.Parameters = {0.25,[0.7 0.35]};
```

To use these parameters when computing optional control actions for a nonlinear MPC controller, pass `options` to the `nlpmove` function.

See Also

`nlpmpc`

Topics

“Trajectory Optimization and Control of Flying Robot Using Nonlinear MPC”

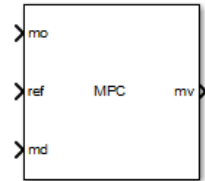
Introduced in R2018b

Blocks

MPC Controller

Simulate model predictive controller

Library: Model Predictive Control Toolbox



Description

The MPC Controller block receives the current measured output signal (**mo**), reference signal (**ref**), and optional measured disturbance signal (**md**). The block computes the optimal manipulated variable (**mv**) by solving a quadratic programming problem using either the default KWIK solver or a custom QP solver. For more information, see “QP Solvers”.

To use the block in simulation and code generation, you must specify an **mpc** object, which defines a model predictive controller. This controller must have already been designed for the plant that it controls.

Because the MPC Controller block uses MATLAB Function blocks, it requires compilation each time you change the MPC object and block. Also, because MATLAB does not allow compiled code to reside in any MATLAB product folder, you must use a non-MATLAB folder to work on your Simulink model when you use MPC blocks.

Ports

Input

Required Inputs

ref — Model output reference values

row vector | matrix

Plant output reference values, specified as a row vector signal or matrix signal.

To use the same reference values across the prediction horizon, connect **ref** to a row vector signal with N_y elements, where N_y is the number of output variables. Each element specifies the reference for an output variable.

To vary the references over the prediction horizon (previewing) from time $k+1$ to time $k+p$, connect **ref** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the references for one prediction horizon step. If you specify fewer than p rows, the final references are used for the remaining steps of the prediction horizon.

mo — Measured output

vector

Measured output signals, specified as a vector signal. The MPC controller uses the measured plant outputs to improve its state estimates. If your controller uses default state estimation, you must

connect the measured plant outputs to the **mo** input port. If your controller uses custom state estimation, you must connect a signal to the **x[k|k]** input port.

Dependencies

To enable this port, clear the **Use custom state estimation instead of using the built-in Kalman filter** parameter.

x[k|k] — Custom state estimate

vector

Custom state estimate, specified as a vector signal. The MPC controller uses the connected state estimates instead of estimating the states using its built-in estimator. If your controller uses custom state estimation, you must connect current state estimates to the **x[k|k]** input port. If your controller uses default state estimation, you must connect a signal to the **mo** input port.

Even though measurement noise states (if any) are not used in MPC optimization, the custom state vector must contain all the states defined in the `mpcstate` object of the controller, including the plant, disturbance, and noise model states.

Use custom state estimates when an alternative estimation technique is considered superior to the built-in estimator or when the states are fully measurable.

Dependencies

To enable this port, select the **Use custom state estimation instead of using the built-in Kalman filter** parameter.

Additional Inputs

md — input

row vector | matrix

If your controller model has measured disturbances, enable this input port, and connect a row vector or matrix signal. If your controller has measured disturbances, you must enable this port.

To use the same measured disturbance values across the prediction horizon, connect **md** to a row vector signal with N_{md} elements, where N_{md} is the number of manipulated variables. Each element specifies the value for a measured disturbance.

To vary the disturbances over the prediction horizon (previewing) from time k to time $k+p$, connect **md** to a matrix signal with N_{md} columns and up to $p+1$ rows. Here, k is the current time and p is the prediction horizon. Each row contains the disturbances for one prediction horizon step. If you specify fewer than $p+1$ rows, the final disturbances are used for the remaining steps of the prediction horizon.

ext.mv — Control signals used in plant at previous control interval

vector

Control signals used in plant at previous control interval, specified as a vector signal of length N_{mv} , where N_{mv} is the number of manipulated variables. Use this input port when:

- You know your controller is not always in control of the plant
- When the actual MV signals applied to the plant can potentially differ from the values generated by the controller, such as control signal saturation

Controller state estimation assumes that the MV is piecewise constant. Therefore, at time t_k , the **ext.mv** value must be the effective MV between times t_{k-1} and t_k . For example, if the MV is actually varying over this interval, you might supply the time-averaged value evaluated at time t_k .

Note

- Connect **ext.mv** to the MV signals actually applied to the plant in the previous control interval. Typically, these MV signals are the values generated by the controller, though this is not always the case. For example, if your controller is offline and running in tracking mode; that is, the controller output is not driving the plant, then feeding the actual control signal to **ext.mv** can help achieve bumpless transfer when the controller is switched back online.
 - Using this option can cause an algebraic loop in the Simulink model, since there is direct feedthrough from the **ext.mv** input to the **mv** output. To prevent such algebraic loops, insert a Memory block or Unit Delay block.
-

For an example that uses the external manipulated variable input port for bumpless transfer, see “Switch Controller Online and Offline with Bumpless Transfer”.

Dependencies

To enable this port, select the **External manipulated variable** parameter.

switch — Enable or disable optimization

scalar

To turn off the controller optimization calculations, connect **switch** to a nonzero signal.

Disabling optimization calculations reduces computational effort when the controller output is not needed, such as when the system is operating manually or another controller has taken over. However, the controller continues to update its internal state estimates in the usual way. Therefore, it is ready to resume optimization calculations whenever the **switch** signal returns to zero. While controller optimization is off, the block passes the current **ext.mv** signal to the controller output. If the **ext.mv** input is not enabled, the controller output is held at the value it had when optimization was disabled.

For an example that uses the external manipulated variable input port for bumpless transfer, see “Switch Controller Online and Offline with Bumpless Transfer”.

Dependencies

To enable this port, select the **Use external signal to enable or disable optimization** parameter.

mv.target — Manipulated variable targets

row vector | array

To specify manipulated variable targets, enable this input port, and connect a row vector or matrix signal. To make a given manipulated variable track its specified target value, you must also specify a nonzero tuning weight for that manipulated variable.

To use the same manipulated variable targets across the prediction horizon, connect **mv.target** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies the target for a manipulated variable.

To vary the targets over the prediction horizon (previewing) from time k to time $k+p-1$, connect **mv.target** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the targets for one prediction horizon step. If you specify fewer than p rows, the final targets are used for the remaining steps of the prediction horizon.

Dependencies

To enable this port, select the **Targets for manipulated variables** parameter.

Online Constraints

ymin — Minimum output variable constraints

row vector

Minimum output variable constraints, specified as a row vector that contains N_y finite values, where N_y is the number of outputs. Each element specifies the lower bound for an output variable. The i th element of **ymin** replaces the `OutputVariables(i).Min` property of the controller at run time.

If an output variable does not have a lower bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `OutputVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **ymin** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Lower OV limits** parameter.

ymax — Maximum output variable constraints

row vector

Maximum output variable constraints, specified as a row vector that contains N_y finite values, where N_y is the number of outputs. Each element specifies the upper bound for an output variable. The i th element of **ymax** replaces the `OutputVariables(i).Max` property of the controller at run time.

If an output variable does not have an upper bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `OutputVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **ymax** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Upper OV limits** parameter.

umin — Minimum manipulated variable constraints

row vector

Minimum manipulated variable constraints, specified as a row vector that contains N_{mv} finite values, where N_{mv} is the number of manipulated variables. Each element specifies the lower bound for a manipulated variable. The i th element of **umin** replaces the `ManipulatedVariables(i).Min` property of the controller at run time.

If a manipulated variable does not have a lower bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `ManipulatedVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **umin** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Lower MV limits** parameter.

umax — Maximum manipulated variable constraints

row vector

Maximum manipulated variable constraints, specified as a row vector that contains N_{mv} finite values, where N_{mv} is the number of manipulated variables. Each element specifies the upper bound for a manipulated variable. The i th element of **umax** replaces the `ManipulatedVariables(i).Max` property of the controller at run time.

If a manipulated variable does not have an upper bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `ManipulatedVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **umax** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Upper MV limits** parameter.

E — Manipulated variable constraint matrix

matrix

Manipulated variable constraint matrix, specified as an N_c -by- N_{mv} matrix signal, where N_c is the number of mixed input/output constraints and N_{mv} is the number of manipulated variables.

If you define E in the `mpc` object, you must connect a signal to the **E** input port. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **E** input port along with the **F**, **G**, and **S** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the E matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter.

F — Controlled output constraint matrix

matrix

Controlled output constraint matrix, specified as an N_c -by- N_y matrix signal, where N_c is the number of mixed input/output constraints and N_y is the number of plant outputs. If you define F in the `mpc` object, you must connect a signal to the **F** input port with same number of rows. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **F** input port along with the **E**, **G**, and **S** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the F matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter.

G — Custom constraint vector

row vector

Custom constraint vector, specified as a row vector signal of length N_c , where N_c is the number of mixed input/output constraints. If you define G in the `mpc` object, you must connect a signal to the **G** input port with same number of rows. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **G** input port along with the **E**, **F**, and **S** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the G matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter.

S — Measured disturbance constraint matrix

matrix

Measured disturbance constraint matrix, specified as an N_c -by- n_N matrix signal, where N_c is the number of mixed input/output constraints, and N_v is the number of measured disturbances. If you define **S** in the `mpc` object, you must connect a signal to the **S** input port with same number of rows. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **S** input port along with the **E**, **F**, and **G** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the **G** matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter. This port is added only if the `mpc` object has measured disturbances.

Online Tuning Weights**y.wt — Output variable tuning weights**

row vector | matrix

To specify run-time output variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.OutputVariables` property of its controller object. These tuning weights penalize deviations from output references.

If the MPC controller object uses constant output tuning weights over the prediction horizon, you can specify only constant output tuning weights at runtime. Similarly, if the MPC controller object uses output tuning weights that vary over the prediction horizon, you can specify only time-varying output tuning weights at runtime.

To use constant tuning weights over the prediction horizon, connect **y.wt** to a row vector signal with N_y elements, where N_y is the number of outputs. Each element specifies a nonnegative tuning weight for an output variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, connect **y.wt** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **OV weights** parameter.

u.wt — Manipulated variable tuning weights

row vector | matrix

To specify run-time manipulated variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariables` property of its controller object. These tuning weights penalize deviations from MV targets.

If the MPC controller object uses constant manipulated variable tuning weights over the prediction horizon, you can specify only constant manipulated variable tuning weights at runtime. Similarly, if the MPC controller object uses manipulated variable tuning weights that vary over the prediction horizon, you can specify only time-varying manipulated variable tuning weights at runtime.

To use the same tuning weights over the prediction horizon, connect **u.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **u.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MV weights** parameter.

du.wt — Manipulated variable rate tuning weights

row vector | matrix

To specify run-time manipulated variable rate tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariablesRate` property of its controller object. These tuning weights penalize large changes in control moves.

If the MPC controller object uses constant manipulated variable rate tuning weights over the prediction horizon, you can specify only constant manipulated variable tuning rate weights at runtime. Similarly, if the MPC controller object uses manipulated variable rate tuning weights that vary over the prediction horizon, you can specify only time-varying manipulated variable rate tuning weights at runtime.

To use the same tuning weights over the prediction horizon, connect **du.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable rate. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **du.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MVRate weights** parameter.

ecr.wt — Slack variable tuning weight

scalar

To specify a run-time slack variable tuning weight, enable this input port and connect a scalar signal. If this port is disabled, the block uses the tuning weight specified in the `Weights.ECR` property of its controller object.

The slack variable tuning weight has no effect unless your controller object defines soft constraints whose associated ECR values are nonzero. If there are soft constraints, increasing the `ecr.wt` value makes these constraints relatively harder. The controller then places a higher priority on minimizing the magnitude of the predicted worst-case constraint violation.

Dependencies

To enable this port, select the **ECR weight** parameter.

Online Horizons

p — Prediction horizon

positive integer

Prediction horizon, specified as positive integer signal. The prediction horizon signal value must be less than or equal to the **Maximum prediction horizon** parameter.

At run time, the values of `p` overrides the default prediction horizon specified in the controller object. For more information, see “Adjust Horizons at Run Time”.

Dependencies

To enable this port, select the **Adjust prediction horizon and control horizon at run time** parameter.

m — Control horizon

positive integer | vector

Control horizon, specified as one of the following:

- Positive integer signal less than or equal to the prediction horizon.
- Vector signal of positive integers specifying blocking interval lengths. For more information, see “Manipulated Variable Blocking”.

At run time, the values of `m` overrides the default control horizon specified in the controller object. For more information, see “Adjust Horizons at Run Time”.

Dependencies

To enable this port, select the **Adjust prediction horizon and control horizon at run time** parameter.

Output

Required Output

mv — Optimal manipulated variable control action

column vector

Optimal manipulated variable control action, output as a column vector signal of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the solver converges to a local optimum solution (**qp.status** is positive), then **mv** contains the optimal solution.

If the solver fails (**qp.status** is negative), then **mv** remains at its most recent successful solution; that is, the controller output freezes.

If the solver reaches the maximum number of iterations without finding an optimal solution (**qp.status** is zero) and the `Optimization.UseSuboptimalSolution` property of the controller is:

- `true`, then **mv** contains the suboptimal solution
- `false`, then **mv** then **mv** remains at its most recent successful solution

Additional Outputs

cost — Objective function cost

nonnegative scalar

Objective function cost, output as a nonnegative scalar signal. The cost quantifies the degree to which the controller has achieved its objectives. The cost value is calculated using the scaled MPC cost function in which every term is offset-free and dimensionless.

The cost value is only meaningful when the **qp.status** output is nonnegative.

Dependencies

To enable this port, select the **Optimal cost** parameter.

qp.status — Optimization status

integer

Optimization status, output as an integer signal.

If the controller solves the QP problem for a given control interval, the **qp.status** output returns the number of QP solver iterations used in computation. This value is a finite, positive integer and is proportional to the time required for the calculations. Therefore, a large value means a relatively slow block execution for this time interval.

The QP solver can fail to find an optimal solution for the following reasons:

- **qp.status** = 0 — The QP solver cannot find a solution within the maximum number of iterations specified in the `mpc` object. In this case, if the `Optimizer.UseSuboptimalSolution` property of the controller is `false`, the block holds its **mv** output at the most recent successful solution. Otherwise, it uses the suboptimal solution found during the last solver iteration.
- **qp.status** = -1 — The QP solver detects an infeasible QP problem. See “Monitoring Optimization Status to Detect Controller Failures” for an example where a large, sustained disturbance drives the output variable outside its specified bounds. In this case, the block holds its **mv** output at the most recent successful solution.
- **qp.status** = -2 — The QP solver has encountered numerical difficulties in solving a severely ill-conditioned QP problem. In this case, the block holds its **mv** output at the most recent successful solution.

In a real-time application, you can use **qp.status** to set an alarm or take other special action.

Dependencies

To enable this port, select the **Optimization status** parameter.

est.state — Estimated controller states

vector

Estimated controller states at each control instant, output as a vector signal. The estimated states include the plant, disturbance, and noise model states.

Dependencies

To enable this port, select the **Estimated controller states** parameter.

Optimal Sequences**mv.seq — Optimal manipulated variable sequence**

matrix

Optimal manipulated variable sequence, returned as a matrix signal with $p+1$ rows and N_{mv} columns, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

The first p rows of **mv.seq** contain the calculated optimal manipulated variable values from current time k to time $k+p-1$. The first row of **mv.seq** contains the current manipulated variable values (output **mv**). Since the controller does not calculate optimal control moves at time $k+p$, the final two rows of **mv.seq** are identical.

Dependencies

To enable this port, select the **Optimal control sequence** parameter.

x.seq — Optimal prediction model state sequence

matrix

Optimal prediction model state sequence, returned as a matrix signal with $p+1$ rows and N_x columns, where p is the prediction horizon and N_x is the number of states.

The first p rows of **x.seq** contain the calculated optimal state values from current time k to time $k+p-1$. The first row of **x.seq** contains the current estimated state values. Since the controller does not calculate optimal states at time $k+p$, the final two rows of **x.seq** are identical.

Dependencies

To enable this port, select the **Optimal state sequence** parameter.

y.seq — Optimal output variable sequence

matrix

Optimal output variable sequence, returned as a matrix signal with $p+1$ rows and N_y columns, where p is the prediction horizon and N_y is the number of output variables.

The first p rows of **y.seq** contain the calculated optimal output values from current time k to time $k+p-1$. The first row of **y.seq** is computed based on the current estimated states and the current measured disturbances (first row of input **md**). Since the controller does not calculate optimal output values at time $k+p$, the final two rows of **y.seq** are identical.

Dependencies

To enable this port, select the **Optimal output sequence** parameter.

Parameters

MPC Controller — Controller object

`mpc` object name

Specify an `mpc` object that defines an implicit MPC controller by entering the name of an `mpc` object from the MATLAB workspace.

Programmatic Use

Block Parameter: `mpcobj`

Type: string, character vector

Default: ""

Initial Controller State — Initial state

`mpcstate` object name

Specify the initial controller state. If you leave this parameter blank, the block uses the nominal values defined in the `Model.Nominal` property of the `mpc` object. To override the default, create an `mpcstate` object in your workspace, and enter its name in the field.

Use this parameter make the controller states reflect the true plant environment at the start of your simulation to the best of your knowledge. This initial states can differ from the nominal states defined in the `mpc` object.

If custom state estimation is enabled, the block ignores **Initial Controller State** parameter.

Programmatic Use

Block Parameter: `x0`

Type: string, character vector

Default: ""

Design — Interactively design controller

button

To interactively modify the controller specified using the **MPC Controller** parameter, open the **MPC Designer** app by clicking **Design**. For example, you can:

- Import a new prediction model.
- Change horizons, constraints, and weights.
- Evaluate MPC performance with a linear plant.
- Export the updated controller to the MATLAB workspace.

If you have an existing `mpc` object in the MATLAB workspace, specify the name of that object using the **MPC Controller** parameter.

If you do not have an existing `mpc` object in the MATLAB workspace, leave the **MPC Controller** parameter empty. With the MPC Controller block connected to the plant, open **MPC Designer** by clicking **Design**. Using the app, linearize the Simulink model at a specified operating point, and design your controller. To use this design approach, you must have Simulink Control Design software. For more information, see “Design MPC Controller in Simulink” and “Linearize Simulink Models Using MPC Designer”.

Review — Review controller for stability and robustness issues

button

Once you specify a controller using the **MPC Controller** parameter, you can review your design for run-time stability and robustness issues by clicking **Review**. For more information, see “Review Model Predictive Controller for Stability and Robustness Issues”.

General Tab

Measured disturbances — Add measured disturbance input port

on (default) | off

If your controller has measured disturbances, you must select this parameter to add the **md** output port to the block.

Programmatic Use

Block Parameter: md_inport

Type: string, character vector

Values: "off", "on"

Default: "on"

External manipulated variable — Add external manipulated variable input port

off (default) | on

Select this parameter to add the **ext.mv** input port to the block.

Programmatic Use

Block Parameter: mv_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

Targets for manipulated variables — Add manipulated variable target input port

off (default) | on

Select this parameter to add the **mv.target** input port to the block.

Programmatic Use

Block Parameter: uref_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

Optimal cost — Odd optimal cost output port

off (default) | on

Select this parameter to add the **cost** output port to the block.

Programmatic Use

Block Parameter: return_cost

Type: string, character vector

Values: "off", "on"

Default: "off"

Optimization status — Add optimization status output port

off (default) | on

Select this parameter to add the **qp.status** output port to the block.

Programmatic Use**Block Parameter:** return_qpstatus**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Estimated controller states — Add estimated states output port**

off (default) | on

Select this parameter to add the **est.state** output port to the block.

Programmatic Use**Block Parameter:** return_state**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal control sequence — Add optimal control sequence output port**

off (default) | on

Select this parameter to add the **mv.seq** output port to the block.

Programmatic Use**Block Parameter:** return_mvseq**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal state sequence — Add optimal state sequence output port**

off (default) | on

Select this parameter to add the **x.seq** output port to the block.

Programmatic Use**Block Parameter:** return_xseq**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal output sequence — Add optimal output sequence output port**

off (default) | on

Select this parameter to add the **y.seq** output port to the block.

Programmatic Use**Block Parameter:** return_ovseq**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Use custom state estimation instead of using the built-in Kalman filter — Use custom state estimate input port**

off (default) | on

Select this parameter to remove the **mo** input port and add the **x[k|k]** input port.

Programmatic Use**Block Parameter:** state_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Online Features Tab****Lower OV limits — Add minimum OV constraint input port**

off (default) | on

Select this parameter to add the **ymin** input port to the block.**Programmatic Use****Block Parameter:** ymin_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Upper OV limits — Add maximum OV constraint input port**

off (default) | on

Select this parameter to add the **ymin** input port to the block.**Programmatic Use****Block Parameter:** ymax_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Lower MV limits — Add minimum MV constraint input port**

off (default) | on

Select this parameter to add the **umin** input port to the block.**Programmatic Use****Block Parameter:** umin_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Upper MV limits — Add maximum MV constraint input port**

off (default) | on

Select this parameter to add the **umax** input port to the block.**Programmatic Use****Block Parameter:** umax_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Custom constraints — Add custom constraints input ports**

off (default) | on

Select this parameter to add the **E**, **F**, **G**, and **S** input ports to the block.

Programmatic Use**Block Parameter:** cc_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**OV weights — Add OV tuning weights input port**

off (default) | on

Select this parameter to add the **y.wt** input port to the block.

Programmatic Use**Block Parameter:** ywt_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**MV weights — Add MV tuning weights input port**

off (default) | on

Select this parameter to add the **u.wt** input port to the block.

Programmatic Use**Block Parameter:** uwt_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**MVRate weights — Add MV rate tuning weights input port**

off (default) | on

Select this parameter to add the **du.wt** input port to the block.

Programmatic Use**Block Parameter:** duwt_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Slack variable weight — Add ECR tuning weight input port**

off (default) | on

Select this parameter to add the **ecr.wt** input port to the block.

Programmatic Use**Block Parameter:** rhoeps_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Adjust prediction horizon and control horizon at run time — Add horizon input ports**

off (default) | on

Select this parameter to add the **p** and **m** input port to the block.

Programmatic Use**Block Parameter:** pm_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Maximum prediction horizon — Add horizon input ports**

10 (default) | positive integer

Select this parameter to add the **p** and **m** input port to the block.

Dependencies

To enable this parameter, select the **Adjust prediction horizon and control horizon at run time** parameter.

Programmatic Use**Block Parameter:** MaximumP**Type:** string, character vector**Default:** "10"**Default Conditions Tab****Sample time — Default block sample time**

1 (default) | positive scalar

Default block sample time for performing simulation, trimming, or linearization using the **MPC Designer** app. You must specify a sample time that is compatible with your Simulink model design.

Dependencies

This parameter applies only when the **MPC Controller** parameter is empty and you open **MPC Designer** using the **Design** button.

Programmatic Use**Block Parameter:** n_ts**Type:** string, character vector**Default:** "1"**Prediction horizon — Default prediction horizon**

10 (default) | positive integer

Default prediction horizon for performing simulation, trimming, or linearization using the **MPC Designer** app. You must specify a prediction horizon that is compatible with your Simulink model design.

Dependencies

This parameter applies only when the **MPC Controller** parameter is empty and you open **MPC Designer** using the **Design** button.

Programmatic Use**Block Parameter:** n_p**Type:** string, character vector**Default:** "10"**Number of manipulated variables — Default number of manipulated variables**

1 (default) | positive integer

Default number of manipulated variables for performing simulation, trimming, or linearization using the **MPC Designer** app. You must specify a value that is compatible with your Simulink model design.

Dependencies

This parameter applies only when the **MPC Controller** parameter is empty and you open **MPC Designer** using the **Design** button.

Programmatic Use

Block Parameter: n_mv

Type: string, character vector

Default: "1"

Number of measured disturbances — Default number of measured disturbances

1 (default) | nonnegative integer

Default number of measured disturbances for performing simulation, trimming, or linearization using the **MPC Designer** app. You must specify a value that is compatible with your Simulink model design.

Dependencies

- This parameter applies only when the **MPC Controller** parameter is empty and you open **MPC Designer** using the **Design** button.
- To use this parameter, you must select the **Measured disturbance** parameter.

Programmatic Use

Block Parameter: n_md

Type: string, character vector

Default: "1"

Number of unmeasured disturbances — Default number of unmeasured disturbances

0 (default) | nonnegative integer

Default number of unmeasured disturbances for performing simulation, trimming, or linearization using the **MPC Designer** app. You must specify a value that is compatible with your Simulink model design.

Dependencies

This parameter applies only when the **MPC Controller** parameter is empty and you open **MPC Designer** using the **Design** button.

Programmatic Use

Block Parameter: n_ud

Type: string, character vector

Default: "0"

Number of measured outputs — Default number of measured outputs

1 (default) | positive integer

Default number of measured outputs for performing simulation, trimming, or linearization using the **MPC Designer** app. You must specify a value that is compatible with your Simulink model design.

Dependencies

This parameter applies only when the **MPC Controller** parameter is empty and you open **MPC Designer** using the **Design** button.

Programmatic Use

Block Parameter: n_mo

Type: string, character vector

Default: "1"

Number of unmeasured outputs – Default number of unmeasured outputs

0 (default) | nonnegative integer

Default number of unmeasured outputs for performing simulation, trimming, or linearization using the **MPC Designer** app. You must specify a value that is compatible with your Simulink model design.

Dependencies

This parameter applies only when the **MPC Controller** parameter is empty and you open **MPC Designer** using the **Design** button.

Programmatic Use

Block Parameter: n_uo

Type: string, character vector

Default: "0"

Others Tab**Inherit sample time – Inherit the block sample time from the controller object**

off (default) | on

Select this parameter to inherit the sample time of the parent subsystem as the block sample time. Doing so allows you to conditionally execute this block inside Function-Call Subsystem or Triggered Subsystem blocks. For an example, see “Using MPC Controller Block Inside Function-Call and Triggered Subsystems”.

Note You must execute Function-Call Subsystem or Triggered Subsystem blocks at the sample rate of the controller. Otherwise, you can see unexpected results.

To view the sample time of a block, in the Simulink Editor, select **Display > Sample Time**. Select **Colors**, **Annotations**, or **All**. For more information, see “View Sample Time Information” (Simulink).

Programmatic Use

Block Parameter: SampleTimeInherited

Type: string, character vector

Values: "off", "on"

Default: "off"

Use external signal to enable or disable optimization – Add switch input port

off (default) | on

Select this parameter to add the **switch** input port to the block.

Programmatic Use**Block Parameter:** `switch_inport`**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Compatibility Considerations****MPC Simulink block `mv.seq` output port signal dimensions have changed***Behavior changed in R2018b*

The signal dimensions of the `mv.seq` output port of the MPC Controller block have changed. Previously, this signal was a p -by- N_{mv} matrix, where p is the prediction horizon and N_{mv} is the number of manipulated variables. Now, `mv.seq` is a $(p+1)$ -by- N_{mv} matrix, where row $p+1$ duplicates row p .

Extended Capabilities**C/C++ Code Generation**

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also**Blocks**

Adaptive MPC Controller | Multiple MPC Controllers

Functions`mpc` | `mpcstate`**Apps****MPC Designer****Topics**

"MPC Modeling"

"Design MPC Controller in Simulink"

"Simulation and Code Generation Using Simulink Coder"

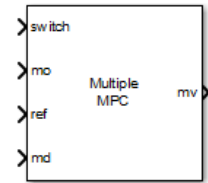
"Simulation and Structured Text Generation Using Simulink PLC Coder"

Introduced before R2006a

Multiple MPC Controllers

Simulate switching between multiple implicit MPC controllers

Library: Model Predictive Control Toolbox



Description

At each control instant the Multiple MPC Controllers block receives the current measured plant output, reference, and measured plant disturbance (if any). In addition, it receives a switching signal that selects the *active controller* from a list of candidate MPC controllers designed at different operating points within the operating range. The active controller then solves a quadratic program to determine the optimal plant manipulated variables for the current input signals.

The Multiple MPC Controllers block enables you to achieve better control when operating conditions change. Using available measurements, you can detect the current operating region at run time and choose the appropriate active controller via the `switch` input port. Switching controllers for different operating regions is a common approach to solving nonlinear control problems using linear control techniques.

To improve efficiency, inactive controllers do not compute optimal control moves. However, to provide bumpless transfer between controllers, the inactive controllers continue to perform state estimation.

The Multiple MPC Controllers block lacks several optional features found in the MPC Controller block, as follows:

- You cannot disable optimization. One controller must always be active.
- You cannot initiate a controller design from within the block dialog box; that is, there is no **Design** button. Design all candidate controllers before configuring the Multiple MPC Controllers block.
- Similarly, there is no **Review** button. Instead, use the `review` command or the **MPC Designer** app.
- You cannot update custom constraints on linear combinations of inputs and outputs at run time.

Both the Multiple MPC Controllers block and the Adaptive MPC Controller block enable your control system to adapt to changing operating conditions at run time. The following table lists the advantages of using each block.

Block	Adaptive MPC Controller	Multiple MPC Controllers
Adaptation approach	Update prediction model for a single controller as operating conditions change	Switch between multiple controllers designed for different operating regions

Block	Adaptive MPC Controller	Multiple MPC Controllers
Advantages	<ul style="list-style-type: none"> • Only need to design a single controller offline • Less run-time computational effort and smaller memory footprint • More robust to real-life changes in plant conditions 	<ul style="list-style-type: none"> • No need for online estimation of plant model • Controllers can have different sample time, horizons, and weights • Prediction models can have different orders or time domains • Finite set of candidate controllers can be tested thoroughly

Ports

Input

ref — Model output reference values

row vector | matrix

Plant output reference values, specified as a row vector signal or matrix signal.

To use the same reference values across the prediction horizon, connect **ref** to a row vector signal with N_y elements, where N_y is the number of output variables. Each element specifies the reference for an output variable.

To vary the references over the prediction horizon (previewing) from time $k+1$ to time $k+p$, connect **ref** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the references for one prediction horizon step. If you specify fewer than p rows, the final references are used for the remaining steps of the prediction horizon.

switch — Controller selection

integer

Use the **switch** input port to select the active controller. The **switch** input signal must be a scalar integer from 1 to N_c , where N_c is the number of specified candidate controllers. At each control instant, this signal designates the active controller. A switch value of 1 corresponds to the first entry in the cell array of candidate controllers, a value of 2 corresponds to the second controller, and so on.

If the **switch** signal is outside of the range 1 to N_c , the block retains the previous controller output.

mo — Measured output

vector

Measured output signals, specified as a vector signal. The candidate controllers use the measured plant outputs to improve their state estimates.

All candidate controllers must use the same state estimation option, either default or custom. If your candidate controllers use default state estimation, you must connect the measured plant outputs to the **mo** input port. If your candidate controllers use custom state estimation, you must connect a signal to the **x[k|k]** input port.

Dependencies

To enable this port, clear the **Use custom state estimation instead of using the built-in Kalman filter** parameter.

x[k|k] — Custom state estimate

vector

Custom state estimate, specified as a vector signal. The candidate controllers use the connected state estimates instead of estimating the states using its built-in estimator. Use custom state estimates when an alternative estimation technique is considered superior to the built-in estimator or when the states are fully measurable.

All candidate controllers must use the same state estimation option, either default or custom. If your candidate controllers use custom state estimation, you must connect current state estimates to the **x[k|k]** input port. If your candidate controllers use default state estimation, you must connect a signal to the **mo** input port.

When you use custom state estimation, all candidate controllers must have the same dimensions. All candidate controllers must use the same state definitions (number and order of states) for their respective plant, disturbance and measurement noise models.

Dependencies

To enable this port, select the **Use custom state estimation instead of using the built-in Kalman filter** parameter.

Online Constraints**ymin — Minimum output variable constraints**

row vector

Minimum output variable constraints, specified as a row vector that contains N_y finite values, where N_y is the number of outputs. Each element specifies the lower bound for an output variable. The i th element of **ymin** replaces the `OutputVariables(i).Min` property of the controller at run time.

If an output variable does not have a lower bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `OutputVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **ymin** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Lower OV limits** parameter.

ymax — Maximum output variable constraints

row vector

Maximum output variable constraints, specified as a row vector that contains N_y finite values, where N_y is the number of outputs. Each element specifies the upper bound for an output variable. The i th element of **ymax** replaces the `OutputVariables(i).Max` property of the controller at run time.

If an output variable does not have an upper bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its mpc object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `OutputVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the *i*th element of **y_{max}** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Upper OV limits** parameter.

umin — Minimum manipulated variable constraints

row vector

Minimum manipulated variable constraints, specified as a row vector that contains N_{mv} finite values, where N_{mv} is the number of manipulated variables. Each element specifies the lower bound for a manipulated variable. The *i*th element of **umin** replaces the `ManipulatedVariables(i).Min` property of the controller at run time.

If a manipulated variable does not have a lower bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its mpc object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `ManipulatedVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the *i*th element of **umin** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Lower MV limits** parameter.

umax — Maximum manipulated variable constraints

row vector

Maximum manipulated variable constraints, specified as a row vector that contains N_{mv} finite values, where N_{mv} is the number of manipulated variables. Each element specifies the upper bound for a manipulated variable. The *i*th element of **umax** replaces the `ManipulatedVariables(i).Max` property of the controller at run time.

If a manipulated variable does not have an upper bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `ManipulatedVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of `umax` replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Upper MV limits** parameter.

Online Tuning Weights

y.wt — Output variable tuning weights

row vector | matrix

To specify run-time output variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.OutputVariables` property of its controller object. These tuning weights penalize deviations from output references.

If the MPC controller object uses constant output tuning weights over the prediction horizon, you can specify only constant output tuning weights at runtime. Similarly, if the MPC controller object uses output tuning weights that vary over the prediction horizon, you can specify only time-varying output tuning weights at runtime.

To use constant tuning weights over the prediction horizon, connect `y.wt` to a row vector signal with N_y elements, where N_y is the number of outputs. Each element specifies a nonnegative tuning weight for an output variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, connect `y.wt` to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **OV weights** parameter.

u.wt — Manipulated variable tuning weights

row vector | matrix

To specify run-time manipulated variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariables` property of its controller object. These tuning weights penalize deviations from MV targets.

If the MPC controller object uses constant manipulated variable tuning weights over the prediction horizon, you can specify only constant manipulated variable tuning weights at runtime. Similarly, if the MPC controller object uses manipulated variable tuning weights that vary over the prediction horizon, you can specify only time-varying manipulated variable tuning weights at runtime.

To use the same tuning weights over the prediction horizon, connect **u.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **u.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MV weights** parameter.

du.wt — Manipulated variable rate tuning weights

row vector | matrix

To specify run-time manipulated variable rate tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariablesRate` property of its controller object. These tuning weights penalize large changes in control moves.

If the MPC controller object uses constant manipulated variable rate tuning weights over the prediction horizon, you can specify only constant manipulated variable tuning rate weights at runtime. Similarly, if the MPC controller object uses manipulated variable rate tuning weights that vary over the prediction horizon, you can specify only time-varying manipulated variable rate tuning weights at runtime.

To use the same tuning weights over the prediction horizon, connect **du.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable rate. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **du.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MVRate weights** parameter.

ecr.wt — Slack variable tuning weight

scalar

To specify a run-time slack variable tuning weight, enable this input port and connect a scalar signal. If this port is disabled, the block uses the tuning weight specified in the `Weights.ECR` property of its controller object.

The slack variable tuning weight has no effect unless your controller object defines soft constraints whose associated ECR values are nonzero. If there are soft constraints, increasing the **ecr.wt** value makes these constraints relatively harder. The controller then places a higher priority on minimizing the magnitude of the predicted worst-case constraint violation.

Dependencies

To enable this port, select the **ECR weight** parameter.

Output**Required Output****mv — Optimal manipulated variable control action**

column vector

Optimal manipulated variable control action, output as a column vector signal of length N_{mv} , where N_{mv} is the number of manipulated variables. The Multiple MPC Controllers block passes the output of the active controller to the **mv** output port.

If the solver of the active controller converges to a local optimum solution (**qp.status** is positive), then **mv** contains the optimal solution.

If the solver fails (**qp.status** is negative), then **mv** remains at its most recent successful solution; that is, the controller output freezes.

If the solver reaches the maximum number of iterations without finding an optimal solution (**qp.status** is zero) and the `Optimization.UseSuboptimalSolution` property of the active controller is:

- `true`, then **mv** contains the suboptimal solution
- `false`, then **mv** then **mv** remains at its most recent successful solution

Additional Outputs**cost — Objective function cost**

nonnegative scalar

Objective function cost, output as a nonnegative scalar signal. The cost quantifies the degree to which the controller has achieved its objectives. The cost value is calculated using the scaled MPC cost function in which every term is offset-free and dimensionless.

The cost value is only meaningful when the **qp.status** output is nonnegative.

Dependencies

To enable this port, select the **Optimal cost** parameter.

qp.status — Optimization status

integer

Optimization status of the active controller, output as an integer signal.

If the active controller solves the QP problem for a given control interval, the **qp.status** output returns the number of QP solver iterations used in computation. This value is a finite, positive integer and is proportional to the time required for the calculations. Therefore, a large value means a relatively slow block execution for this time interval.

The QP solver can fail to find an optimal solution for the following reasons:

- **qp.status** = 0 — The QP solver cannot find a solution within the maximum number of iterations specified in the mpc object. In this case, if the `Optimizer.UseSuboptimalSolution` property of

the active controller is `false`, the block holds its **mv** output at the most recent successful solution. Otherwise, it uses the suboptimal solution found during the last solver iteration.

- **qp.status** = -1 — The QP solver detects an infeasible QP problem. See “Monitoring Optimization Status to Detect Controller Failures” for an example where a large, sustained disturbance drives the output variable outside its specified bounds. In this case, the block holds its **mv** output at the most recent successful solution.
- **qp.status** = -2 — The QP solver has encountered numerical difficulties in solving a severely ill-conditioned QP problem. In this case, the block holds its **mv** output at the most recent successful solution.

In a real-time application, you can use **qp.status** to set an alarm or take other special action.

Dependencies

To enable this port, select the **Optimization status** parameter.

est.state — Estimated controller states

vector

Estimated controller states of the active controller, output as a vector signal. The estimated states include the plant, disturbance, and noise model states.

Dependencies

To enable this port, select the **Estimated controller states** parameter.

Optimal Sequences

mv.seq — Optimal manipulated variable sequence

matrix

Optimal manipulated variable sequence, returned as a matrix signal with $p+1$ rows and N_{mv} columns, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

The first p rows of **mv.seq** contain the calculated optimal manipulated variable values from current time k to time $k+p-1$. The first row of **mv.seq** contains the current manipulated variable values (output **mv**). Since the controller does not calculate optimal control moves at time $k+p$, the final two rows of **mv.seq** are identical.

Dependencies

To enable this port, select the **Optimal control sequence** parameter.

x.seq — Optimal prediction model state sequence

matrix

Optimal prediction model state sequence, returned as a matrix signal with $p+1$ rows and N_x columns, where p is the prediction horizon and N_x is the number of states.

The first p rows of **x.seq** contain the calculated optimal state values from current time k to time $k+p-1$. The first row of **x.seq** contains the current estimated state values. Since the controller does not calculate optimal states at time $k+p$, the final two rows of **x.seq** are identical.

Dependencies

To enable this port, select the **Optimal state sequence** parameter.

y.seq — Optimal output variable sequence

matrix

Optimal output variable sequence, returned as a matrix signal with $p+1$ rows and N_y columns, where p is the prediction horizon and N_y is the number of output variables.

The first p rows of **y.seq** contain the calculated optimal output values from current time k to time $k+p-1$. The first row of **y.seq** is computed based on the current estimated states and the current measured disturbances (first row of input **md**). Since the controller does not calculate optimal output values at time $k+p$, the final two rows of **y.seq** are identical.

Dependencies

To enable this port, select the **Optimal output sequence** parameter.

Parameters**Cell Array of MPC Controllers — Candidate controllers**

cell array of mpc objects | cell array of strings | cell array of character vectors

Candidate controllers, specified as one of the following:

- Cell array of mpc objects.
- Cell array of strings or a cell array of character vectors, where each element is the name of an mpc object in the MATLAB workspace.

The specified array must contain at least two candidate controllers. The first entry in the cell array is the controller that corresponds to a switch input value of 1, the second corresponds to a switch input value of 2, and so on.

Programmatic Use**Block Parameter:** mpcobjs**Type:** string, character vector, cell array of strings, cell array of character vectors**Default:** ""**Cell Array of Initial Controller States — Initial state**

cell array of mpcstate objects | cell array of strings | cell array of character vectors

Initial states for the candidate controllers, specified as one of the following:

- Cell array of mpcstate objects.
- Cell array of strings or a cell array of character vectors, where each element is the name of an mpcstate object in the MATLAB workspace.
- $\{\{[], [], \dots\}, \{ ' [] ', ' [] ', \dots \},$ or $\{ " [] ", " [] ", \dots \}$ — Use the nominal condition defined in `Model.Nominal` property of each candidate controller as its initial state.

Use this parameter make the controller states reflect the true plant environment at the start of your simulation to the best of your knowledge. This initial states can differ from the nominal states defined in the mpc objects.

If custom state estimation is enabled, the block ignores **Cell Array of Initial Controller States** parameter.

Programmatic Use**Block Parameter:** $x\theta s$ **Type:** string, character vector, cell array of strings, cell array of character vectors**Default:** ""**General Tab****Measured disturbances — Add measured disturbance input port**

on (default) | off

If your controller has measured disturbances, you must select this parameter to add the **md** output port to the block.

Programmatic Use**Block Parameter:** md_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "on"**External manipulated variable — Add external manipulated variable input port**

off (default) | on

Select this parameter to add the **ext.mv** input port to the block.

Programmatic Use**Block Parameter:** mv_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Targets for manipulated variables — Add manipulated variable target input port**

off (default) | on

Select this parameter to add the **mv.target** input port to the block.

Programmatic Use**Block Parameter:** uref_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal cost — Odd optimal cost output port**

off (default) | on

Select this parameter to add the **cost** output port to the block.

Programmatic Use**Block Parameter:** return_cost_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimization status — Add optimization status output port**

off (default) | on

Select this parameter to add the **qp.status** output port to the block.

Programmatic Use**Block Parameter:** return_qpstatus_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Estimated controller states — Add estimated states output port**

off (default) | on

Select this parameter to add the **est.state** output port to the block.

Programmatic Use**Block Parameter:** return_state_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal control sequence — Add optimal control sequence output port**

off (default) | on

Select this parameter to add the **mv.seq** output port to the block.

Programmatic Use**Block Parameter:** return_mvseq_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal state sequence — Add optimal state sequence output port**

off (default) | on

Select this parameter to add the **x.seq** output port to the block.

Programmatic Use**Block Parameter:** return_xseq_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal output sequence — Add optimal output sequence output port**

off (default) | on

Select this parameter to add the **y.seq** output port to the block.

Programmatic Use**Block Parameter:** return_ovseq_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Use custom state estimation instead of using the built-in Kalman filter — Use custom state estimate input port**

off (default) | on

Select this parameter to remove the **mo** input port and add the **x[k|k]** input port.

Programmatic Use**Block Parameter:** state_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Online Features Tab****Lower OV limits — Add minimum OV constraint input port**

off (default) | on

Select this parameter to add the **ymin** input port to the block.**Programmatic Use****Block Parameter:** ymin_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Upper OV limits — Add maximum OV constraint input port**

off (default) | on

Select this parameter to add the **ymin** input port to the block.**Programmatic Use****Block Parameter:** ymax_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Lower MV limits — Add minimum MV constraint input port**

off (default) | on

Select this parameter to add the **umin** input port to the block.**Programmatic Use****Block Parameter:** umin_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Upper MV limits — Add maximum MV constraint input port**

off (default) | on

Select this parameter to add the **umax** input port to the block.**Programmatic Use****Block Parameter:** umax_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Custom constraints — Add custom constraints input ports**

off (default) | on

Select this parameter to add the **E**, **F**, **G**, and **S** input ports to the block.

Programmatic Use**Block Parameter:** cc_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**OV weights — Add OV tuning weights input port**

off (default) | on

Select this parameter to add the **y.wt** input port to the block.

Programmatic Use**Block Parameter:** ywt_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**MV weights — Add MV tuning weights input port**

off (default) | on

Select this parameter to add the **u.wt** input port to the block.

Programmatic Use**Block Parameter:** uwt_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**MVRate weights — Add MV rate tuning weights input port**

off (default) | on

Select this parameter to add the **du.wt** input port to the block.

Programmatic Use**Block Parameter:** duwt_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Slack variable weight — Add ECR tuning weight input port**

off (default) | on

Select this parameter to add the **ecr.wt** input port to the block.

Programmatic Use**Block Parameter:** rhoeps_inport_multiple**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Others Tab****Inherit sample time — Inherit block sample time from parent subsystem**

off (default) | on

Select this parameter to inherit the sample time of the parent subsystem as the block sample time. Doing so allows you to conditionally execute this block inside Function-Call Subsystem or Triggered

Subsystem blocks. For an example, see “Using MPC Controller Block Inside Function-Call and Triggered Subsystems”.

Note You must execute Function-Call Subsystem or Triggered Subsystem blocks at the sample rate of the controller. Otherwise, you can see unexpected results.

To view the sample time of a block, in the Simulink Editor, select **Display > Sample Time**. Select **Colors**, **Annotations**, or **All**. For more information, see “View Sample Time Information” (Simulink).

Programmatic Use

Block Parameter: `SampleTimeInherited_multiple`

Type: string, character vector

Values: "off", "on"

Default: "off"

Compatibility Considerations

MPC Simulink block `mv.seq` output port signal dimensions have changed

Behavior changed in R2018b

The signal dimensions of the `mv.seq` output port of the Multiple MPC Controllers block have changed. Previously, this signal was a p -by- N_{mv} matrix, where p is the prediction horizon and N_{mv} is the number of manipulated variables. Now, `mv.seq` is a $(p+1)$ -by- N_{mv} matrix, where row $p+1$ duplicates row p .

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also

Blocks

MPC Controller | Multiple Explicit MPC Controllers

Functions

`mpc` | `mpcmoveMultiple` | `mpcstate`

Topics

“Gain-Scheduled MPC”

“Design Workflow”

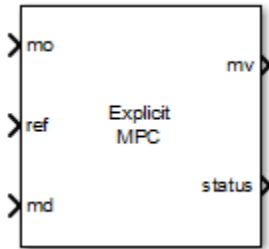
“Simulation and Code Generation Using Simulink Coder”

“Simulation and Structured Text Generation Using Simulink PLC Coder”

Introduced in R2008b

Explicit MPC Controller

Design and simulate explicit model predictive controller



Library

MPC Simulink Library

Description

The Explicit MPC Controller block uses the following input signals:

- Measured plant outputs (*mo*)
- Reference or setpoint (*ref*)
- Measured plant disturbance (*md*), if any

The key difference is that the Explicit MPC Controller block uses a table-lookup control law during each control interval rather than solving a quadratic program. The reduced online computational effort is advantageous in applications requiring a short control interval. The primary trade-off is a heavier offline computational effort to determine the control law and a larger memory footprint to store it. The combinatorial character of this computation restricts its use to applications with relatively few input, output, and state variables, a short prediction horizon, and few output constraints.

The Explicit MPC Controller supports only a subset of optional MPC features, as outlined in the following table.

Supported Features	Unsupported Features
<ul style="list-style-type: none"> • Custom state estimation (default state estimation uses a static Kalman filter) • Output for state estimation results • External manipulated variable feedback signal input • Single-precision block data (default is double precision) • Inherited sample time 	<ul style="list-style-type: none"> • Online tuning (penalty weight adjustments) • Online constraint adjustments • Online manipulated variable target adjustments • Reference and/or measured disturbance previewing

Dialog Box

The Explicit MPC Controller block has the following parameter groupings:

- “Parameters” on page 4-37
- “Required Inports” on page 4-37
- “Required Outports” on page 4-37
- “Additional Inports (General Section)” on page 4-38
- “Additional Outports (General Section)” on page 4-38
- “State Estimation (General Section)” on page 4-38
- “Others Section” on page 4-39

Parameters

Explicit MPC Controller

An `explicitMPC` object containing the control law to be used. It must exist in the workspace. Use the `generateExplicitMPC` command to create this object.

Initial Controller State

An optional `mpcstate` object specifying the initial controller state. By default the block uses the `Model.Nominal` property of the controller object.

Required Inports

Measured output or State estimate

If your controller uses default state estimation, this inport is labeled `mo`. Connect this inport to the measured plant output signals. The MPC controller uses measured plant outputs to improve its state estimates.

To enable custom state estimation, in the **General** section, select the **Use custom state estimation instead of using the built-in Kalman filter**. Selecting this option changes the label on this inport to `x[k|k]`. Connect a signal that provides estimates of the controller state (plant, disturbance, and noise model states). Use custom state estimates when an alternative estimation technique is considered superior to the built-in estimator or when the states are fully measurable.

Reference

At each control instant, the `ref` signal must contain the current reference values (targets or setpoints) for the n_y output variables, where n_y is the total number of outputs, including measured and unmeasured outputs. Since this block does not support reference previewing, `ref` cannot be defined as a matrix.

Required Outports

Manipulated Variables

The `mv` outport provides a signal defining the $n_u \geq 1$ manipulated variables for controlling the plant. The controller updates its `mv` outport at each control instant using the control law contained in the explicit MPC controller object. If the control law evaluation fails, this signal is unchanged; that is, it is held at the previous successful result.

Additional Inports (General Section)

Measured disturbance

Add an inport (`md`) to which you can connect a vector signal containing n_{md} elements, where n_{md} is the number of measured disturbances.

Since this block does not support measured disturbance previewing, `md` cannot be defined as a matrix.

External manipulated variable

Add an inport (`ext.mv`) to which you connect a vector signal that contains the actual manipulated variables (MV) used in the plant. The controller uses this signal to update their controller state estimates at each control interval. Using this inport improves state estimation accuracy when the MVs used in the plant differ from the MVs calculated by the block, for example due to signal saturation or an override condition.

Note Using this option can cause an algebraic loop in the Simulink model, since there is direct feedthrough from the `ext.mv` inport to the `mv` output. To prevent such algebraic loops, insert a Memory block or Unit Delay block.

For additional information, see the corresponding section of the MPC Controller block reference page.

Additional Outports (General Section)

Status of piecewise affine function evaluation

Add an outport (`status`) that indicates whether the latest explicit MPC control-law evaluation succeeded. The outport provides a scalar signal that has one of the following values:

- 1 — Successful explicit control law evaluation
- 0 — Failure: One or more control law parameters out of range.
- -1 — Undefined: Control law parameters were within the valid range but an extrapolation was necessary.

If `status` is either 0 or -1, the `mv` outport remains at the last known good value.

Region number of evaluated piecewise affine function

Add an outport (`region`) providing the index of the polyhedral region used in the latest explicit control law evaluation (a scalar). If the control law evaluation fails, the signal at this outport equals zero.

Estimated plant, disturbance, and noise model states

Add an outport (`est.state`) for the controller state estimates, $x[k|k]$, at each control instant. These estimates include the plant, disturbance, and noise model states.

State Estimation (General Section)

Use custom estimated states instead of measured outputs

Replace `mo` with the $x[k|k]$ inport for custom state estimation as described in “Required Inports” on page 4-37.

Others Section

Block data type

Specify the block data type of the manipulated variables as one of the following:

- `double` — Double-precision floating point (default)
- `single` — Single-precision floating point

If you are implementing the block on a single-precision target, specify the output data type as `single`.

For an example of double-precision and single-precision simulation and code generation for an MPC controller, see “Simulation and Code Generation Using Simulink Coder”.

To view the port data types in a model, in the Simulink Editor, select **Display > Signals & PortsPort Data Types**.

Inherit sample time

Use the sample time of the parent subsystem as the block sample time. Doing so allows you to conditionally execute this block inside Function-Call Subsystem or Triggered Subsystem blocks. For an example, see “Using MPC Controller Block Inside Function-Call and Triggered Subsystems”.

Note You must execute Function-Call Subsystem or Triggered Subsystem blocks at the sample rate of the controller. Otherwise, you can see unexpected results.

To view the sample time of a block, in the Simulink Editor, select **Display > Sample Time**. Select **Colors, Annotations, or All**. For more information, see “View Sample Time Information” (Simulink).

Use external signal to enable controller evaluation

Add an inport (`switch`) whose input specifies whether the controller evaluates its control law. If the input signal is zero, the controller behaves normally. If the input signal is nonzero, the Explicit MPC Controller block turns off controller evaluation. This action reduces computational effort when the controller output is not needed, such as when the system is operating manually or another controller has taken over. However, the controller continues to update its internal state estimates in the usual way. Thus, it is ready to resume optimization calculations whenever the `switch` signal returns to zero. While controller evaluation is off, the MPC Controller block passes the current `ext.mv` signal to the controller output. If the `ext.mv` inport is not enabled, the controller output is held at the value it had when evaluation was disabled.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also

Blocks

MPC Controller | Multiple Explicit MPC Controllers

Functions

generateExplicitMPC | mpc | mpcmoveExplicit | mpcstate

Topics

“Explicit MPC”

“Design Workflow for Explicit MPC”

“Explicit MPC Control of a Single-Input-Single-Output Plant”

“Explicit MPC Control of an Aircraft with Unstable Poles”

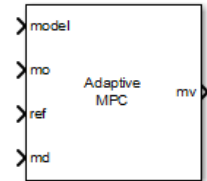
“Explicit MPC Control of DC Servomotor with Constraint on Unmeasured Output”

Introduced in R2014b

Adaptive MPC Controller

Simulate adaptive and time-varying model predictive controllers

Library: Model Predictive Control Toolbox



Description

The Adaptive MPC Controller block uses the following input signals:

- Measured plant outputs (*mo*)
- Reference or setpoint (*ref*)
- Measured plant disturbance (*md*), if any

In addition, the required *model* input signal specifies the prediction model to use when computing the optimal plant manipulated variables *mv*. The linear prediction model can change at each control interval in response to changes in the real plant at run time. The prediction model can represent a single LTI plant used for all prediction steps (adaptive MPC mode) or an array of LTI plants for different prediction steps (time-varying MPC mode). Two common ways to modify this model are as follows:

- Given a nonlinear plant model, linearize it at the current operating point.
- Use plant data to estimate parameters in an empirical linear-time-varying (LTV) model.

By default, the block estimates its prediction model states. Since the prediction model parameters change at run time, the static Kalman filter used in the MPC Controller block is inappropriate. Instead, the Adaptive MPC Controller block uses a linear-time-varying Kalman filter (LTVKF). For more information, see “Adaptive MPC”.

In all other ways, the Adaptive MPC Controller block mimics the MPC Controller block. Since the adaptive version involves additional overhead, use the MPC Controller block unless you need to control a nonlinear plant across a wide range of operating conditions where plant dynamics vary significantly.

Both the Adaptive MPC Controller block and the Multiple MPC Controllers block enable your control system to adapt to changing operating conditions at run time. The following table lists the advantages of using each block.

Block	Adaptive MPC Controller	Multiple MPC Controllers
Adaptation approach	Update prediction model for a single controller as operating conditions change	Switch between multiple controllers designed for different operating regions

Block	Adaptive MPC Controller	Multiple MPC Controllers
Advantages	<ul style="list-style-type: none"> • Only need to design a single controller offline • Less run-time computational effort and smaller memory footprint • More robust to real-life changes in plant conditions 	<ul style="list-style-type: none"> • No need for online estimation of plant model • Controllers can have different sample time, horizons, and weights • Prediction models can have different orders or time domains • Finite set of candidate controllers can be tested thoroughly

Ports

Input

Required Inputs

model — Updated plant model and nominal operating point

bus signal

Updated plant model and nominal operating point, specified as a bus signal. a bus signal to the `model` input. At the beginning of each control interval, this signal modifies the controller object `Model.Plant` and `Model.Nominal` properties.

The Adaptive MPC Controller requires the plant model to be an LTI discrete-time state-space object with no delays. The following command extracts the state-space matrices comprising such a model.

```
[A,B,C,D] = ssdata(MPCobj.Model.Plant)
```

The purpose of the `model` input is to replace these matrices with new ones having the same dimensions and representing the same control interval. You must also retain the sequence in which the input, output, and state variables appear in the `Model.Plant` property of the controller.

When operating in:

- Adaptive MPC mode, the bus you connect to the `model` input must contain the following signals, each identified by the specified name:
 - **A** — n_x -by- n_x matrix signal, where n_x is the number of plant model states.
 - **B** — n_x -by- n_u matrix signal, where n_u is the total number of plant model inputs (i.e., manipulated variables, measured disturbances, and unmeasured disturbances).
 - **C** — n_y -by- n_x matrix signal, where n_y is the number of plant model outputs.
 - **D** — n_y -by- n_u matrix signal.
 - **X** — Vector signal of length n_x , replacing the controller `Model.Nominal.X` property.
 - **Y** — Vector signal of length n_y , replacing the controller `Model.Nominal.Y` property.
 - **U** — Vector signal of length n_u , replacing the controller `Model.Nominal.U` property.
 - **DX** — Vector signal of length n_x , replacing the controller `Model.Nominal.DX` property. It must be appropriate for use with a discrete-time model of the assumed control interval. For more information, see “Adaptive MPC”.

To compute DX values, use the discrete-time state update function (f) for your model. Here, u_k and x_k are the respective input and state values for the current time step.

$$DX = f(u_k, x_k) - x_k$$

- Time-varying MPC mode, the bus you connect to the `model` inport must contain the following 3-dimensional bus signals:
 - A — n_x -by- n_x -by- $(p+1)$ matrix signal
 - B — n_x -by- n_u -by- $(p+1)$ matrix signal
 - C — n_y -by- n_x -by- $(p+1)$
 - D — n_y -by- n_u -by- $(p+1)$ matrix signal
 - X — n_x -by- $(p+1)$ matrix signal
 - Y — n_y -by- $(p+1)$ matrix signal
 - U — n_u -by- $(p+1)$ matrix signal
 - DX — n_x -by- $(p+1)$ matrix signal

Here, p is the controller prediction horizon. For each signal, specify $p+1$ values representing the model and nominal conditions at each step of the prediction horizon. For more information, see “Time-Varying MPC”.

One way to form the bus is to use a Bus Creator block.

Dependencies

The dimensions of the bus elements in `model` depend on the operating mode of the controller. To place the controller in:

- Adaptive MPC mode, clear the **Linear Time-Varying (LTV) plants** parameter
- Time-varying MPC mode, select the **Linear Time-Varying (LTV) plants** parameter

ref — Model output reference values

row vector | matrix

Plant output reference values, specified as a row vector signal or matrix signal.

To use the same reference values across the prediction horizon, connect `ref` to a row vector signal with N_y elements, where N_y is the number of output variables. Each element specifies the reference for an output variable.

To vary the references over the prediction horizon (previewing) from time $k+1$ to time $k+p$, connect `ref` to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the references for one prediction horizon step. If you specify fewer than p rows, the final references are used for the remaining steps of the prediction horizon.

mo — Measured output

vector

Measured output signals, specified as a vector signal. The MPC controller uses the measured plant outputs to improve its state estimates. If your controller uses default state estimation, you must connect the measured plant outputs to the `mo` input port. If your controller uses custom state estimation, you must connect a signal to the `x[k|k]` input port.

Dependencies

To enable this port, clear the **Use custom state estimation instead of using the built-in Kalman filter** parameter.

$\mathbf{x}[k|k]$ — Custom state estimate

vector

Custom state estimate, specified as a vector signal. The MPC controller uses the connected state estimates instead of estimating the states using its build-in estimator. If your controller uses custom state estimation, you must connect current state estimates to the $\mathbf{x}[k|k]$ input port. If your controller uses default state estimation, you must connect a signal to the **mo** input port.

Even though measurement noise states (if any) are not used in MPC optimization, the custom state vector must contain all the states defined in the `mpcstate` object of the controller, including the plant, disturbance, and noise model states.

Use custom state estimates when an alternative estimation technique is considered superior to the built-in estimator or when the states are fully measurable.

Dependencies

To enable this port, select the **Use custom state estimation instead of using the built-in Kalman filter** parameter.

Additional Inputs

md — input

row vector | matrix

If your controller model has measured disturbances, enable this input port, and connect a row vector or matrix signal. If your controller has measured disturbances, you must enable this port.

To use the same measured disturbance values across the prediction horizon, connect **md** to a row vector signal with N_{md} elements, where N_{md} is the number of manipulated variables. Each element specifies the value for a measured disturbance.

To vary the disturbances over the prediction horizon (previewing) from time k to time $k+p$, connect **md** to a matrix signal with N_{md} columns and up to $p+1$ rows. Here, k is the current time and p is the prediction horizon. Each row contains the disturbances for one prediction horizon step. If you specify fewer than $p+1$ rows, the final disturbances are used for the remaining steps of the prediction horizon.

ext.mv — Control signals used in plant at previous control interval

vector

Control signals used in plant at previous control interval, specified as a vector signal of length N_{mv} , where N_{mv} is the number of manipulated variables. Use this input port when:

- You know your controller is not always in control of the plant
- When the actual MV signals applied to the plant can potentially differ from the values generated by the controller, such as control signal saturation

Controller state estimation assumes that the MV is piecewise constant. Therefore, at time t_k , the **ext.mv** value must be the effective MV between times t_{k-1} and t_k . For example, if the MV is actually varying over this interval, you might supply the time-averaged value evaluated at time t_k .

Note

- Connect **ext.mv** to the MV signals actually applied to the plant in the previous control interval. Typically, these MV signals are the values generated by the controller, though this is not always the case. For example, if your controller is offline and running in tracking mode; that is, the controller output is not driving the plant, then feeding the actual control signal to **ext.mv** can help achieve bumpless transfer when the controller is switched back online.
 - Using this option can cause an algebraic loop in the Simulink model, since there is direct feedthrough from the **ext.mv** input to the **mv** output. To prevent such algebraic loops, insert a Memory block or Unit Delay block.
-

For an example that uses the external manipulated variable input port for bumpless transfer, see “Switch Controller Online and Offline with Bumpless Transfer”.

Dependencies

To enable this port, select the **External manipulated variable** parameter.

switch — Enable or disable optimization

scalar

To turn off the controller optimization calculations, connect **switch** to a nonzero signal.

Disabling optimization calculations reduces computational effort when the controller output is not needed, such as when the system is operating manually or another controller has taken over. However, the controller continues to update its internal state estimates in the usual way. Therefore, it is ready to resume optimization calculations whenever the **switch** signal returns to zero. While controller optimization is off, the block passes the current **ext.mv** signal to the controller output. If the **ext.mv** inport is not enabled, the controller output is held at the value it had when optimization was disabled.

For an example that uses the external manipulated variable input port for bumpless transfer, see “Switch Controller Online and Offline with Bumpless Transfer”.

Dependencies

To enable this port, select the **Use external signal to enable or disable optimization** parameter.

mv.target — Manipulated variable targets

row vector | array

To specify manipulated variable targets, enable this input port, and connect a row vector or matrix signal. To make a given manipulated variable track its specified target value, you must also specify a nonzero tuning weight for that manipulated variable.

To use the same manipulated variable targets across the prediction horizon, connect **mv.target** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies the target for a manipulated variable.

To vary the targets over the prediction horizon (previewing) from time k to time $k+p-1$, connect **mv.target** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the targets for one prediction horizon step. If you specify fewer than p rows, the final targets are used for the remaining steps of the prediction horizon.

Dependencies

To enable this port, select the **Targets for manipulated variables** parameter.

Online Constraints

ymin — Minimum output variable constraints

row vector

Minimum output variable constraints, specified as a row vector that contains N_y finite values, where N_y is the number of outputs. Each element specifies the lower bound for an output variable. The i th element of **ymin** replaces the `OutputVariables(i).Min` property of the controller at run time.

If an output variable does not have a lower bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its mpc object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `OutputVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **ymin** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Lower OV limits** parameter.

ymax — Maximum output variable constraints

row vector

Maximum output variable constraints, specified as a row vector that contains N_y finite values, where N_y is the number of outputs. Each element specifies the upper bound for an output variable. The i th element of **ymax** replaces the `OutputVariables(i).Max` property of the controller at run time.

If an output variable does not have an upper bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its mpc object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `OutputVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **ymax** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Upper OV limits** parameter.

umin — Minimum manipulated variable constraints

row vector

Minimum manipulated variable constraints, specified as a row vector that contains N_{mv} finite values, where N_{mv} is the number of manipulated variables. Each element specifies the lower bound for a manipulated variable. The i th element of **umin** replaces the `ManipulatedVariables(i).Min` property of the controller at run time.

If a manipulated variable does not have a lower bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `ManipulatedVariables(i).Min` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **umin** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Lower MV limits** parameter.

umax — Maximum manipulated variable constraints

row vector

Maximum manipulated variable constraints, specified as a row vector that contains N_{mv} finite values, where N_{mv} is the number of manipulated variables. Each element specifies the upper bound for a manipulated variable. The i th element of **umax** replaces the `ManipulatedVariables(i).Max` property of the controller at run time.

If a manipulated variable does not have an upper bound specified in the controller object, then the corresponding connected signal value is ignored.

If this parameter is not selected, the block uses the constant constraint values stored within its `mpc` object.

Note You cannot specify time-varying constraints at run time using a matrix signal.

If the `ManipulatedVariables(i).Max` property of the controller is specified as a vector (that is, the constraint varies over the prediction horizon), the i th element of **umax** replaces the first finite entry in this vector, and the remaining values shift to retain the same constraint profile.

Dependencies

To enable this port, select the **Upper MV limits** parameter.

E — Manipulated variable constraint matrix

matrix

Manipulated variable constraint matrix, specified as an N_c -by- N_{mv} matrix signal, where N_c is the number of mixed input/output constraints and N_{mv} is the number of manipulated variables.

If you define **E** in the `mpc` object, you must connect a signal to the **E** input port. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **E** input port along with the **F**, **G**, and **S** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the **E** matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter.

F — Controlled output constraint matrix

matrix

Controlled output constraint matrix, specified as an N_c -by- N_y matrix signal, where N_c is the number of mixed input/output constraints and N_y is the number of plant outputs. If you define **F** in the `mpc` object, you must connect a signal to the **F** input port with same number of rows. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **F** input port along with the **E**, **G**, and **S** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the **F** matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter.

G — Custom constraint vector

row vector

Custom constraint vector, specified as a row vector signal of length N_c , where N_c is the number of mixed input/output constraints. If you define **G** in the `mpc` object, you must connect a signal to the **G** input port with same number of rows. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **G** input port along with the **E**, **F**, and **S** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the **G** matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter.

S — Measured disturbance constraint matrix

matrix

Measured disturbance constraint matrix, specified as an N_c -by- n_N matrix signal, where N_c is the number of mixed input/output constraints, and N_v is the number of measured disturbances. If you define **S** in the **mpc** object, you must connect a signal to the **S** input port with same number of rows. Otherwise, connect a zero matrix with the correct size.

To specify run-time mixed input/output constraints, use the **S** input port along with the **E**, **F**, and **G** ports. These constraints replace the mixed input/output constraints previously set using `setconstraint`. For more information on mixed input/output constraints, see “Constraints on Linear Combinations of Inputs and Outputs”.

The number of mixed input/output constraints cannot change at run time. Therefore, N_c must match the number of rows in the **G** matrix you specified using `setconstraint`.

Dependencies

To enable this port, select the **Custom constraints** parameter. This port is added only if the **mpc** object has measured disturbances.

Online Tuning Weights**y.wt — Output variable tuning weights**

row vector | matrix

To specify run-time output variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.OutputVariables` property of its controller object. These tuning weights penalize deviations from output references.

If the MPC controller object uses constant output tuning weights over the prediction horizon, you can specify only constant output tuning weights at runtime. Similarly, if the MPC controller object uses output tuning weights that vary over the prediction horizon, you can specify only time-varying output tuning weights at runtime.

To use constant tuning weights over the prediction horizon, connect **y.wt** to a row vector signal with N_y elements, where N_y is the number of outputs. Each element specifies a nonnegative tuning weight for an output variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, connect **y.wt** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **OV weights** parameter.

u.wt — Manipulated variable tuning weights

row vector | matrix

To specify run-time manipulated variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariables` property of its controller object. These tuning weights penalize deviations from MV targets.

If the MPC controller object uses constant manipulated variable tuning weights over the prediction horizon, you can specify only constant manipulated variable tuning weights at runtime. Similarly, if the MPC controller object uses manipulated variable tuning weights that vary over the prediction horizon, you can specify only time-varying manipulated variable tuning weights at runtime.

To use the same tuning weights over the prediction horizon, connect **u.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **u.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MV weights** parameter.

du.wt — Manipulated variable rate tuning weights

row vector | matrix

To specify run-time manipulated variable rate tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariablesRate` property of its controller object. These tuning weights penalize large changes in control moves.

If the MPC controller object uses constant manipulated variable rate tuning weights over the prediction horizon, you can specify only constant manipulated variable tuning rate weights at runtime. Similarly, if the MPC controller object uses manipulated variable rate tuning weights that vary over the prediction horizon, you can specify only time-varying manipulated variable rate tuning weights at runtime.

To use the same tuning weights over the prediction horizon, connect **du.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable rate. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **du.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MVRate weights** parameter.

ecr.wt — Slack variable tuning weight

scalar

To specify a run-time slack variable tuning weight, enable this input port and connect a scalar signal. If this port is disabled, the block uses the tuning weight specified in the `Weights.ECR` property of its controller object.

The slack variable tuning weight has no effect unless your controller object defines soft constraints whose associated ECR values are nonzero. If there are soft constraints, increasing the **ecr.wt** value makes these constraints relatively harder. The controller then places a higher priority on minimizing the magnitude of the predicted worst-case constraint violation.

Dependencies

To enable this port, select the **ECR weight** parameter.

Online Horizons

p — Prediction horizon

positive integer

Prediction horizon, specified as positive integer signal. The prediction horizon signal value must be less than or equal to the **Maximum prediction horizon** parameter.

At run time, the values of p overrides the default prediction horizon specified in the controller object. For more information, see “Adjust Horizons at Run Time”.

Dependencies

To enable this port, select the **Adjust prediction horizon and control horizon at run time** parameter.

m — Control horizon

positive integer | vector

Control horizon, specified as one of the following:

- Positive integer signal less than or equal to the prediction horizon.
- Vector signal of positive integers specifying blocking interval lengths. For more information, see “Manipulated Variable Blocking”.

At run time, the values of m overrides the default control horizon specified in the controller object. For more information, see “Adjust Horizons at Run Time”.

Dependencies

To enable this port, select the **Adjust prediction horizon and control horizon at run time** parameter.

Output

Required Output

mv — Optimal manipulated variable control action

column vector

Optimal manipulated variable control action, output as a column vector signal of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the solver converges to a local optimum solution (**qp.status** is positive), then **mv** contains the optimal solution.

If the solver fails (**qp.status** is negative), then **mv** remains at its most recent successful solution; that is, the controller output freezes.

If the solver reaches the maximum number of iterations without finding an optimal solution (**qp.status** is zero) and the `Optimizer.UseSuboptimalSolution` property of the controller is:

- `true`, then **mv** contains the suboptimal solution
- `false`, then **mv** then **mv** remains at its most recent successful solution

Additional Outputs

cost — Objective function cost

nonnegative scalar

Objective function cost, output as a nonnegative scalar signal. The cost quantifies the degree to which the controller has achieved its objectives. The cost value is calculated using the scaled MPC cost function in which every term is offset-free and dimensionless.

The cost value is only meaningful when the **qp.status** output is nonnegative.

Dependencies

To enable this port, select the **Optimal cost** parameter.

qp.status — Optimization status

integer

Optimization status, output as an integer signal.

If the controller solves the QP problem for a given control interval, the **qp.status** output returns the number of QP solver iterations used in computation. This value is a finite, positive integer and is proportional to the time required for the calculations. Therefore, a large value means a relatively slow block execution for this time interval.

The QP solver can fail to find an optimal solution for the following reasons:

- **qp.status** = 0 — The QP solver cannot find a solution within the maximum number of iterations specified in the `mpc` object. In this case, if the `Optimizer.UseSuboptimalSolution` property of the controller is `false`, the block holds its **mv** output at the most recent successful solution. Otherwise, it uses the suboptimal solution found during the last solver iteration.
- **qp.status** = -1 — The QP solver detects an infeasible QP problem. See “Monitoring Optimization Status to Detect Controller Failures” for an example where a large, sustained disturbance drives the output variable outside its specified bounds. In this case, the block holds its **mv** output at the most recent successful solution.
- **qp.status** = -2 — The QP solver has encountered numerical difficulties in solving a severely ill-conditioned QP problem. In this case, the block holds its **mv** output at the most recent successful solution.

In a real-time application, you can use **qp.status** to set an alarm or take other special action.

Dependencies

To enable this port, select the **Optimization status** parameter.

est.state — Estimated controller states

vector

Estimated controller states at each control instant, output as a vector signal. The estimated states include the plant, disturbance, and noise model states.

Dependencies

To enable this port, select the **Estimated controller states** parameter.

Optimal Sequences**mv.seq — Optimal manipulated variable sequence**

matrix

Optimal manipulated variable sequence, returned as a matrix signal with $p+1$ rows and N_{mv} columns, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

The first p rows of **mv.seq** contain the calculated optimal manipulated variable values from current time k to time $k+p-1$. The first row of **mv.seq** contains the current manipulated variable values (output **mv**). Since the controller does not calculate optimal control moves at time $k+p$, the final two rows of **mv.seq** are identical.

Dependencies

To enable this port, select the **Optimal control sequence** parameter.

x.seq — Optimal prediction model state sequence

matrix

Optimal prediction model state sequence, returned as a matrix signal with $p+1$ rows and N_x columns, where p is the prediction horizon and N_x is the number of states.

The first p rows of **x.seq** contain the calculated optimal state values from current time k to time $k+p-1$. The first row of **x.seq** contains the current estimated state values. Since the controller does not calculate optimal states at time $k+p$, the final two rows of **x.seq** are identical.

Dependencies

To enable this port, select the **Optimal state sequence** parameter.

y.seq — Optimal output variable sequence

matrix

Optimal output variable sequence, returned as a matrix signal with $p+1$ rows and N_y columns, where p is the prediction horizon and N_y is the number of output variables.

The first p rows of **y.seq** contain the calculated optimal output values from current time k to time $k+p-1$. The first row of **y.seq** is computed based on the current estimated states and the current measured disturbances (first row of input **md**). Since the controller does not calculate optimal output values at time $k+p$, the final two rows of **y.seq** are identical.

Dependencies

To enable this port, select the **Optimal output sequence** parameter.

Parameters**Adaptive MPC Controller — Controller object**

mpc object name

Specify an mpc object that defines an MPC controller by entering the name of an mpc object designed at the nominal operating point of the block. At run time, the controller replaces the original

prediction model (A, B, C, and D) and nominal values (U, Y, X, and DX) with the data specified in the **model** input port at each control instant.

By default, the block assumes all other controller object properties (for example tuning weights, constraints) are constant. You can override this assumption using the options in the **Online Features** section.

The following restrictions apply to the mpc controller object:

- It must exist in the MATLAB workspace.
- Its prediction model must be an LTI discrete-time, state-space object with no delays. Use the `absorbDelay` command to convert delays to discrete states. The dimensions of the A, B, C, and D matrices in the prediction determine the dimensions required by the `model` input signal.

Programmatic Use

Block Parameter: `mpcobj`

Type: string, character vector

Default: ""

Initial Controller State — Initial state

`mpcstate` object name

Specify the initial controller state. If you leave this parameter blank, the block uses the nominal values defined in the `Model.Nominal` property of the mpc object. To override the default, create an `mpcstate` object in your workspace, and enter its name in the field.

Use this parameter make the controller states reflect the true plant environment at the start of your simulation to the best of your knowledge. This initial states can differ from the nominal states defined in the mpc object.

If custom state estimation is enabled, the block ignores **Initial Controller State** parameter.

Programmatic Use

Block Parameter: `x0`

Type: string, character vector

Default: ""

General Tab

Measured disturbances — Add measured disturbance input port

on (default) | off

If your controller has measured disturbances, you must select this parameter to add the **md** output port to the block.

Programmatic Use

Block Parameter: `md_inport`

Type: string, character vector

Values: "off", "on"

Default: "on"

External manipulated variable — Add external manipulated variable input port

off (default) | on

Select this parameter to add the **ext.mv** input port to the block.

Programmatic Use**Block Parameter:** mv_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Targets for manipulated variables — Add manipulated variable target input port**

off (default) | on

Select this parameter to add the **mv.target** input port to the block.

Programmatic Use**Block Parameter:** uref_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal cost — Odd optimal cost output port**

off (default) | on

Select this parameter to add the **cost** output port to the block.

Programmatic Use**Block Parameter:** return_cost**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimization status — Add optimization status output port**

off (default) | on

Select this parameter to add the **qp.status** output port to the block.

Programmatic Use**Block Parameter:** return_qpstatus**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Estimated controller states — Add estimated states output port**

off (default) | on

Select this parameter to add the **est.state** output port to the block.

Programmatic Use**Block Parameter:** return_state**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal control sequence — Add optimal control sequence output port**

off (default) | on

Select this parameter to add the **mv.seq** output port to the block.

Programmatic Use**Block Parameter:** return_mvseq**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal state sequence — Add optimal state sequence output port**

off (default) | on

Select this parameter to add the **x.seq** output port to the block.

Programmatic Use**Block Parameter:** return_xseq**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Optimal output sequence — Add optimal output sequence output port**

off (default) | on

Select this parameter to add the **y.seq** output port to the block.

Programmatic Use**Block Parameter:** return_ovseq**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Use custom state estimation instead of using the built-in Kalman filter — Use custom state estimate input port**

off (default) | on

Select this parameter to remove the **mo** input port and add the **x[k|k]** input port.

Programmatic Use**Block Parameter:** state_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Online Features Tab****Linear Time-Varying (LTV) plants — Use custom state estimate input port**

off (default) | on

To operate your controller in time-varying MPC mode, select this option. When operating in this mode, connect a 3-dimensional bus signal to the **model** input port

For an example, see “Time-Varying MPC Control of a Time-Varying Plant”.

Programmatic Use**Block Parameter:** isltv_plant**Type:** string, character vector**Values:** "off", "on"**Default:** "off"

Lower OV limits – Add minimum OV constraint input port

off (default) | on

Select this parameter to add the **ymin** input port to the block.

Programmatic Use**Block Parameter:** ymin_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Upper OV limits – Add maximum OV constraint input port**

off (default) | on

Select this parameter to add the **ymax** input port to the block.

Programmatic Use**Block Parameter:** ymax_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Lower MV limits – Add minimum MV constraint input port**

off (default) | on

Select this parameter to add the **umin** input port to the block.

Programmatic Use**Block Parameter:** umin_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Upper MV limits – Add maximum MV constraint input port**

off (default) | on

Select this parameter to add the **umax** input port to the block.

Programmatic Use**Block Parameter:** umax_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Custom constraints – Add custom constraints input ports**

off (default) | on

Select this parameter to add the **E**, **F**, **G**, and **S** input ports to the block.

Programmatic Use**Block Parameter:** cc_inport**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**OV weights – Add OV tuning weights input port**

off (default) | on

Select this parameter to add the **y.wt** input port to the block.

Programmatic Use

Block Parameter: ywt_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

MV weights — Add MV tuning weights input port

off (default) | on

Select this parameter to add the **u.wt** input port to the block.

Programmatic Use

Block Parameter: uwt_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

MVRate weights — Add MV rate tuning weights input port

off (default) | on

Select this parameter to add the **du.wt** input port to the block.

Programmatic Use

Block Parameter: duwt_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

Slack variable weight — Add ECR tuning weight input port

off (default) | on

Select this parameter to add the **ecr.wt** input port to the block.

Programmatic Use

Block Parameter: rhoeps_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

Adjust prediction horizon and control horizon at run time — Add horizon input ports

off (default) | on

Select this parameter to add the **p** and **m** input port to the block.

Programmatic Use

Block Parameter: pm_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

Maximum prediction horizon — Add horizon input ports

10 (default) | positive integer

Select this parameter to add the **p** and **m** input port to the block.

Dependencies

To enable this parameter, select the **Adjust prediction horizon and control horizon at run time** parameter.

Programmatic Use

Block Parameter: MaximumP

Type: string, character vector

Default: "10"

Others Tab**Inherit sample time — Inherit the block sample time from the controller object**

off (default) | on

Select this parameter to inherit the sample time of the parent subsystem as the block sample time. Doing so allows you to conditionally execute this block inside Function-Call Subsystem or Triggered Subsystem blocks. For an example, see “Using MPC Controller Block Inside Function-Call and Triggered Subsystems”.

Note You must execute Function-Call Subsystem or Triggered Subsystem blocks at the sample rate of the controller. Otherwise, you can see unexpected results.

To view the sample time of a block, in the Simulink Editor, select **Display > Sample Time**. Select **Colors**, **Annotations**, or **All**. For more information, see “View Sample Time Information” (Simulink).

Programmatic Use

Block Parameter: SampleTimeInherited

Type: string, character vector

Values: "off", "on"

Default: "off"

Use external signal to enable or disable optimization — Add switch input port

off (default) | on

Select this parameter to add the **switch** input port to the block.

Programmatic Use

Block Parameter: switch_inport

Type: string, character vector

Values: "off", "on"

Default: "off"

Compatibility Considerations**MPC Simulink block mv . seq output port signal dimensions have changed**

Behavior changed in R2018b

The signal dimensions of the mv . seq output port of the Adaptive MPC Controller block have changed. Previously, this signal was a p -by- N_{mv} matrix, where p is the prediction horizon and N_{mv} is the number of manipulated variables. Now, mv . seq is a $(p+1)$ -by- N_{mv} matrix, where row $p+1$ duplicates row p .

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also

Blocks

MPC Controller | Multiple MPC Controllers

Functions

mpc | mpcmoveAdaptive | mpcstate

Topics

“Adaptive MPC”

“Time-Varying MPC”

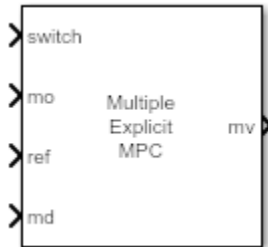
“Simulation and Code Generation Using Simulink Coder”

“Simulation and Structured Text Generation Using Simulink PLC Coder”

Introduced in R2014b

Multiple Explicit MPC Controllers

Simulate switching between multiple explicit MPC controllers



Library

MPC Simulink Library

Description

The Multiple Explicit MPC Controllers block uses the following input signals:

- Measured plant outputs (*mo*)
- Reference or setpoint (*ref*)
- Measured plant disturbance (*md*), if any
- Switching signal (*switch*)

The switching signal selects the *active controller* from among a list of two or more candidate controllers. However, for the Multiple Explicit MPC Controllers block, the candidates are explicit MPC controllers. These controllers reduce online computational effort by using a table-lookup control law during each control interval rather than solving a quadratic program. For more information, see Explicit MPC Controller.

The Multiple Explicit MPC Controllers block enables you to transition between multiple explicit MPC controllers in real time based on the current operating conditions. Typically, you design each controller for a particular region of the operating space. Using available measurements, you detect the current operating region and select the appropriate active controller via the *switch* input.

To improve efficiency, inactive controllers do not evaluate their control law. However, to provide bumpless transfer between controllers, the inactive controllers continue to perform state estimation.

Like for the Multiple MPC Controllers block, you cannot disable evaluation for the Multiple Explicit MPC Controllers. One controller must always be active.

Like the Explicit MPC Controller block, the Multiple Explicit MPC Controllers supports only a subset of optional MPC features, as outlined in the following table.

Supported Features	Unsupported Features
<ul style="list-style-type: none"> • Custom state estimation (default state estimation uses a static Kalman filter) • Outport for state estimation results • External manipulated variable feedback signal inport • Single-precision block data (default is double precision) • Inherited sample time 	<ul style="list-style-type: none"> • Online tuning (penalty weight adjustments) • Online constraint adjustments • Online manipulated variable target adjustments • Reference and/or measured disturbance previewing

Dialog Box

The Multiple Explicit MPC Controller block has the following parameter groupings:

- “Parameters” on page 4-62
- “Required Inports” on page 4-62
- “Required Outports” on page 4-63
- “Additional Inports (General Section)” on page 4-63
- “Additional Outports (General Section)” on page 4-64
- “State Estimation (General Section)” on page 4-64
- “Others Section” on page 4-64

Parameters

Cell Array of Explicit MPC Controllers

Candidate controllers, specified as:

- A cell array of `explicitMPC` objects. Use the `generateExplicitMPC` command to create these objects.
- A cell array of character vectors, where each element is the name of an explicit MPC controller object in the MATLAB workspace.

The specified array must contain at least two candidate controllers. The first entry in the cell array is the controller that corresponds to a switch input value of 1, the second corresponds to a switch input value of 2, and so on.

Cell Array of Initial Controller States

Optional initial states for each candidate controller, specified as:

- A cell array of `mpcstate` objects.
- A cell array of character vectors, where each element is the name of an `mpcstate` object in the MATLAB workspace.
- `{[], [], ...}` or `{'[]', '[]', ...}` — Use the nominal condition defined in `Model.Nominal` as the initial state for each controller.

Required Inports

Controller Selection

The switch input signal must be a scalar integer between 1 and n_c , where n_c is the number of specified candidate controllers. At each control instant, this signal designates the active

controller. A switch value of 1 corresponds to the first entry in the cell array of candidate controllers, a value of 2 corresponds to the second controller, and so on.

If the `switch` signal is outside of the range 1 and n_c , the previous controller output is retained.

Measured output or State estimate

If candidate controllers use default state estimation, this inport is labeled `mo`. Connect this inport to the measured plant output signals.

If your candidate controllers use custom state estimation, select the **Use custom state estimation instead of using the built-in Kalman filter** parameter. Selecting this option changes the label on this inport to `x[k|k]`. Connect a signal providing the controller state estimates. (The controller state includes the plant, disturbance, and noise model states.) The estimates supplied at time t_k must be based on the measurements and other data available at time t_k .

All candidate controllers must use the same state estimation option, either default or custom. When you use custom state estimation, all candidate controllers must have the same dimension.

Reference

At each control instant, the `ref` signal must contain the current reference values (targets or setpoints) for the n_y output variables, where n_y is the total number of outputs, including measured and unmeasured outputs. Since this block does not support reference previewing, `ref` cannot be defined as a matrix.

Required Outputs

Manipulated Variables

The `mv` outport provides a signal defining the $n_u \geq 1$ manipulated variables for controlling the plant. The active controller updates its manipulated variable output at each control instant using the control law contained in its explicit MPC controller object. If the control law evaluation fails, this signal is unchanged; that is, it is held at the previous successful result. The Multiple Explicit MPC Controller block passes the output of the active controller to the `mv` outport.

Additional Inports (General Section)

Measured disturbance

Add an inport (`md`) to which you can connect a vector signal containing n_{md} elements, where n_{md} is the number of measured disturbances.

Since this block does not support measured disturbance previewing, `md` cannot be defined as a matrix.

External manipulated variable

Add an inport (`ext_mv`) to which you connect a vector signal that contains the actual manipulated variables (MV) used in the plant. All candidate controllers use this signal to update their controller state estimates at each control interval. Using this inport improves state estimation accuracy when the MVs used in the plant differ from the MVs calculated by the block, for example due to signal saturation or an override condition.

For additional information, see the corresponding section of the MPC Controller block reference page.

Additional Outputs (General Section)

Status of piecewise affine function evaluation

Add an output (`status`) that indicates whether the latest explicit MPC control-law evaluation succeeded. The output provides a scalar signal that has one of the following values:

- 1 — Successful explicit control law evaluation
- 0 — Failure: One or more control law parameters out of range.
- -1 — Undefined: Control law parameters were within the valid range but an extrapolation was necessary.

If `status` is either 0 or -1, the `mv` output remains at the last known good value.

Region number of evaluated piecewise affine function

Add an output (`region`) providing the index of the polyhedral region used in the latest explicit control law evaluation (a scalar). If the control law evaluation fails, the signal at this output equals zero.

Estimated plant, disturbance, and noise model states

Add an output (`est.state`) for the controller state estimates, $x[k|k]$, at each control instant. These estimates include the plant, disturbance, and noise model states.

State Estimation (General Section)

Use custom estimated states instead of measured outputs

Replace `mo` with the $x[k|k]$ inport for custom state estimation as described in “Required Inports” on page 4-62. All candidate controllers must use the same state estimation option, either default or custom. When you use custom state estimation, all candidate controllers must have the same dimension.

Others Section

Block data type

Specify the block data type of the manipulated variables as one of the following:

- `double` — Double-precision floating point (default)
- `single` — Single-precision floating point

If you are implementing the block on a single-precision target, specify the output data type as `single`.

For an example of double-precision and single-precision simulation and code generation for an MPC controller, see “Simulation and Code Generation Using Simulink Coder”.

To view the port data types in a model, in the Simulink Editor, select **Display > Signals & PortsPort Data Types**.

Inherit sample time

Use the sample time of the parent subsystem as the block sample time. Doing so allows you to conditionally execute this block inside Function-Call Subsystem or Triggered Subsystem blocks. For an example, see “Using MPC Controller Block Inside Function-Call and Triggered Subsystems”.

Note You must execute Function-Call Subsystem or Triggered Subsystem blocks at the sample rate of the controller. Otherwise, you can see unexpected results.

To view the sample time of a block, in the Simulink Editor, select **Display > Sample Time**. Select **Colors**, **Annotations**, or **All**. For more information, see “View Sample Time Information” (Simulink).

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also

Blocks

Explicit MPC Controller | Multiple MPC Controllers

Functions

mpc | mpcmove | mpcstate

Topics

“Simulation and Code Generation Using Simulink Coder”

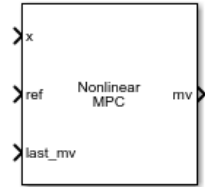
“Simulation and Structured Text Generation Using Simulink PLC Coder”

Introduced in R2016b

Nonlinear MPC Controller

Simulate nonlinear model predictive controllers

Library: Model Predictive Control Toolbox



Description

The Nonlinear MPC Controller block simulates a nonlinear model predictive controller. At each control interval, the block computes optimal control moves by solving a nonlinear programming problem. For more information on nonlinear MPC, see “Nonlinear MPC”.

To use this block, you must first create an `nmpc` object in the MATLAB workspace.

Limitations

- None of the Nonlinear MPC Controller block parameters are tunable.

Ports

Input

Required Inputs

x — input

vector

Current prediction model states, specified as a vector signal of length N_x , where N_x is the number of prediction model states. Since the nonlinear MPC controller does not perform state estimation, you must either measure or estimate the current prediction model states at each control interval.

ref — Model output reference values

row vector | matrix

Plant output reference values, specified as a row vector signal or matrix signal.

To use the same reference values across the prediction horizon, connect **ref** to a row vector signal with N_y elements, where N_y is the number of output variables. Each element specifies the reference for an output variable.

To vary the references over the prediction horizon (previewing) from time $k+1$ to time $k+p$, connect **ref** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the references for one prediction horizon step. If you specify fewer than p rows, the final references are used for the remaining steps of the prediction horizon.

last_mv — Control signals used in plant at previous control interval

vector

Control signals used in plant at previous control interval, specified as a vector signal of length N_{mv} , where N_{mv} is the number of manipulated variables.

Note Connect **last_mv** to the MV signals actually applied to the plant in the previous control interval. Typically, these MV signals are the values generated by the controller, though this is not always the case. For example, if your controller is offline and running in tracking mode; that is, the controller output is not driving the plant, then feeding the actual control signal to **last_mv** can help achieve bumpless transfer when the controller is switched back online.

Additional Inputs

md — input

row vector | matrix

If your controller model has measured disturbances, enable this input port, and connect a row vector or matrix signal. If your controller has measured disturbances, you must enable this port.

To use the same measured disturbance values across the prediction horizon, connect **md** to a row vector signal with N_{md} elements, where N_{md} is the number of manipulated variables. Each element specifies the value for a measured disturbance.

To vary the disturbances over the prediction horizon (previewing) from time k to time $k+p$, connect **md** to a matrix signal with N_{md} columns and up to $p+1$ rows. Here, k is the current time and p is the prediction horizon. Each row contains the disturbances for one prediction horizon step. If you specify fewer than $p+1$ rows, the final disturbances are used for the remaining steps of the prediction horizon.

params — Optional parameters

bus

If your controller uses optional parameters in its prediction model, custom cost function, or custom constraint functions, enable this input port, and connect a parameter bus signal with N_p elements, where N_p is the number of parameters. For more information on creating a parameter bus signal, see `createParameterBus`. The controller, passes these parameters to its model functions, cost function, constraint functions, and Jacobian functions.

If your controller does not use optional parameters, you must disable **params**.

Dependencies

To enable this port, select the **Model parameters** parameter.

mv.target — Manipulated variable targets

row vector | array

To specify manipulated variable targets, enable this input port, and connect a row vector or matrix signal. To make a given manipulated variable track its specified target value, you must also specify a nonzero tuning weight for that manipulated variable.

To use the same manipulated variable targets across the prediction horizon, connect **mv.target** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies the target for a manipulated variable.

To vary the targets over the prediction horizon (previewing) from time k to time $k+p-1$, connect **mv.target** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the targets for one prediction horizon step. If you specify fewer than p rows, the final targets are used for the remaining steps of the prediction horizon.

Dependencies

To enable this port, select the **Targets for manipulated variables** parameter.

Online Constraints

y.min — Minimum output variable constraints

row vector | matrix

To specify run-time minimum output variable constraints, enable this input port. If this port is disabled, the block uses the lower bounds specified in the `OutputVariables.Min` property of its controller object.

To use the same bounds over the prediction horizon, connect **y.min** to a row vector signal with N_y elements, where N_y is the number of outputs. Each element specifies the lower bound for an output variable.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **y.min** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Lower OV limits** parameter.

y.max — Maximum output variable constraints

row vector | matrix

To specify run-time maximum output variable constraints, enable this input port. If this port is disabled, the block uses the upper bounds specified in the `OutputVariables.Min` property of its controller object.

To use the same bounds over the prediction horizon, connect **y.max** to a row vector signal with N_y elements, where N_y is the number of outputs. Each element specifies the upper bound for an output variable.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **y.max** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Upper OV limits** parameter.

mv.min — Minimum manipulated variable constraints

row vector | matrix

To specify run-time minimum manipulated variable constraints, enable this input port. If this port is disabled, the block uses the lower bounds specified in the `ManipulatedVariables.Min` property of its controller object.

To use the same bounds over the prediction horizon, connect **mv.min** to a row vector signal with N_{mv} elements, where N_{mv} is the number of outputs. Each element specifies the lower bound for a manipulated variable.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **mv.min** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Lower MV limits** parameter.

mv.max — Maximum manipulated variable constraints

row vector | matrix

To specify run-time maximum manipulated variable constraints, enable this input port. If this port is disabled, the block uses the upper bounds specified in the `ManipulatedVariables.Max` property of its controller object.

To use the same bounds over the prediction horizon, connect **mv.max** to a row vector signal with N_{mv} elements, where N_{mv} is the number of outputs. Each element specifies the upper bound for a manipulated variable.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **mv.max** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Upper MV limits** parameter.

dmv.min — Minimum manipulated variable rate constraints

row vector | matrix

To specify run-time minimum manipulated variable rate constraints, enable this input port. If this port is disabled, the block uses the lower bounds specified in the `ManipulatedVariable.RateMin` property of its controller object. **dmv.min** bounds must be nonpositive.

To use the same bounds over the prediction horizon, connect **dmv.min** to a row vector signal with N_{mv} elements, where N_{mv} is the number of outputs. Each element specifies the lower bound for a manipulated variable rate of change.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **dmv.min** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Lower MVRate limits** parameter.

dmv.max — Maximum manipulated variable rate constraints

row vector | matrix

To specify run-time maximum manipulated variable rate constraints, enable this input port. If this port is disabled, the block uses the upper bounds specified in the `ManipulatedVariables.RateMax` property of its controller object. **dmv.max** bounds must be nonnegative.

To use the same bounds over the prediction horizon, connect **dmv.max** to a row vector signal with N_{mv} elements, where N_{mv} is the number of outputs. Each element specifies the upper bound for a manipulated variable rate of change.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **dmv.max** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Upper MVRate limits** parameter.

x.min — Minimum state constraints

row vector | matrix

To specify run-time minimum state constraints, enable this input port. If this port is disabled, the block uses the lower bounds specified in the `States.Min` property of its controller object.

To use the same bounds over the prediction horizon, connect **x.min** to a row vector signal with N_x elements, where N_x is the number of outputs. Each element specifies the lower bound for a state.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **x.min** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Lower state limits** parameter.

x.max — Maximum state constraints

row vector | matrix

To specify run-time maximum state constraints, enable this input port. If this port is disabled, the block uses the upper bounds specified in the `States.Max` property of its controller object.

To use the same bounds over the prediction horizon, connect **x.max** to a row vector signal with N_x elements, where N_x is the number of outputs. Each element specifies the upper bound for a state.

To vary the bounds over the prediction horizon from time k to time $k+p-1$, connect **x.max** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the bounds for one prediction horizon step. If you specify fewer than p rows, the bounds in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Upper state limits** parameter.

Online Tuning Weights

y.wt — Output variable tuning weights

row vector | matrix

To specify run-time output variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.OutputVariables` property of its controller object. These tuning weights penalize deviations from output references.

If the MPC controller object uses constant output tuning weights over the prediction horizon, you can specify only constant output tuning weights at runtime. Similarly, if the MPC controller object uses output tuning weights that vary over the prediction horizon, you can specify only time-varying output tuning weights at runtime

To use constant tuning weights over the prediction horizon, connect **y.wt** to a row vector signal with N_y elements, where N_y is the number of outputs. Each element specifies a nonnegative tuning weight for an output variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time $k+1$ to time $k+p$, connect **y.wt** to a matrix signal with N_y columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **OV weights** parameter.

mv.wt — Manipulated variable tuning weights

row vector | matrix

To specify run-time manipulated variable tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariables` property of its controller object. These tuning weights penalize deviations from MV targets.

To use the same tuning weights over the prediction horizon, connect **mv.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **mv.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MV weights** parameter.

dmv.wt — Manipulated variable rate tuning weights

row vector | matrix

To specify run-time manipulated variable rate tuning weights, enable this input port. If this port is disabled, the block uses the tuning weights specified in the `Weights.ManipulatedVariablesRate` property of its controller object. These tuning weights penalize large changes in control moves.

To use the same tuning weights over the prediction horizon, connect **dmv.wt** to a row vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies a nonnegative tuning weight for a manipulated variable rate. For more information on specifying tuning weights, see “Tune Weights”.

To vary the tuning weights over the prediction horizon from time k to time $k+p-1$, connect **dmv.wt** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the tuning weights for one prediction horizon step. If you specify fewer than p rows, the tuning weights in the final row apply for the remainder of the prediction horizon. For more information on varying weights over the prediction horizon, see “Time-Varying Weights and Constraints”.

Dependencies

To enable this port, select the **MVRate weights** parameter.

ecr.wt — Slack variable tuning weight

scalar

To specify a run-time slack variable tuning weight, enable this input port and connect a scalar signal. If this port is disabled, the block uses the tuning weight specified in the `Weights.ECR` property of its controller object.

The slack variable tuning weight has no effect unless your controller object defines soft constraints whose associated ECR values are nonzero. If there are soft constraints, increasing the **ecr.wt** value makes these constraints relatively harder. The controller then places a higher priority on minimizing the magnitude of the predicted worst-case constraint violation.

Dependencies

To enable this port, select the **ECR weight** parameter.

Initial Guesses

mv.init — Initial guesses for the optimal manipulated variable solutions

vector | matrix

To specify initial guesses for the optimal manipulated variable solutions, enable this input port. If this port is disabled, the block uses the optimal control sequences calculated in the previous control interval as initial guesses.

To use the same initial guesses over the prediction horizon, connect **mv.init** to a vector signal with N_{mv} elements, where N_{mv} is the number of manipulated variables. Each element specifies the initial guess for a manipulated variable.

To vary the initial guesses over the prediction horizon from time k to time $k+p-1$, connect **mv.init** to a matrix signal with N_{mv} columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the initial guesses for one prediction horizon step. If you specify fewer than p rows, the guesses in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Initial guess** parameter.

x.init — Initial guesses for the optimal state variable solutions

vector | matrix

To specify initial guesses for the optimal state solutions, enable this input port. If this port is disabled, the block uses the optimal state sequences calculated in the previous control interval as initial guesses.

To use the same initial guesses over the prediction horizon, connect **x.init** to a vector signal with N_x elements, where N_x is the number of states. Each element specifies the initial guess for a state.

To vary the initial guesses over the prediction horizon from time k to time $k+p-1$, connect **x.init** to a matrix signal with N_x columns and up to p rows. Here, k is the current time and p is the prediction horizon. Each row contains the initial guesses for one prediction horizon step. If you specify fewer than p rows, the guesses in the final row apply for the remainder of the prediction horizon.

Dependencies

To enable this port, select the **Initial guess** parameter.

e.init — Initial guess for the slack variable at the solution

nonnegative scalar

To specify an initial guess for the slack variable at the solution, enable this input port and connect a nonnegative scalar signal. If this port is disabled, the block uses an initial guess of 0.

Dependencies

To enable this port, select the **Initial guess** parameter.

Output**Required Output****mv — Optimal manipulated variable control action**

column vector

Optimal manipulated variable control action, output as a column vector signal of length N_{mv} , where N_{mv} is the number of manipulated variables.

If the solver converges to a local optimum solution (**nlp.status** is positive), then **mv** contains the optimal solution.

If the solver reaches the maximum number of iterations without finding an optimal solution (**nlp.status** is zero) and the `Optimization.UseSuboptimalSolution` property of the controller is:

- `true`, then **mv** contains the suboptimal solution
- `false`, then **mv** is the same as **last_mv**

If the solver fails (**nlp.status** is negative), then **mv** is the same as **last_mv**.

Additional Outputs**cost — Objective function cost**

nonnegative scalar

Objective function cost, output as a nonnegative scalar signal. The cost quantifies the degree to which the controller has achieved its objectives.

The cost value is only meaningful when the **nlp.status** output is nonnegative.

Dependencies

To enable this port, select the **Optimal cost** parameter.

slack — Slack variable

0 | nonnegative scalar

Slack variable, ε , used in constraint softening, output as 0 or a positive scalar value.

- $\varepsilon = 0$ — All soft constraints are satisfied over the entire prediction horizon.
- $\varepsilon > 0$ — At least one soft constraint is violated. When more than one constraint is violated, ε represents the worst-case soft constraint violation (scaled by the ECR values for each constraint).

Dependencies

To enable this port, select the **Slack variable** parameter.

nlp.status — Optimization status

scalar

Optimization status, output as one of the following:

- Positive Integer — Solver converged to an optimal solution
- 0 — Maximum number of iterations reached without converging to an optimal solution
- Negative integer — Solver failed

Dependencies

To enable this port, select the **Optimization status** parameter.

Optimal Sequences

mv.seq — Optimal manipulated variable sequence

matrix

Optimal manipulated variable sequence, returned as a matrix signal with $p+1$ rows and N_{mv} columns, where p is the prediction horizon and N_{mv} is the number of manipulated variables.

The first p rows of **mv.seq** contain the calculated optimal manipulated variable values from current time k to time $k+p-1$. The first row of **mv.seq** contains the current manipulated variable values (output **mv**). Since the controller does not calculate optimal control moves at time $k+p$, the final two rows of **mv.seq** are identical.

Dependencies

To enable this port, select the **Optimal control sequence** parameter.

x.seq — Optimal prediction model state sequence

matrix

Optimal prediction model state sequence, returned as a matrix signal with $p+1$ rows and N_x columns, where p is the prediction horizon and N_x is the number of states.

The first p rows of **x.seq** contain the calculated optimal state values from current time k to time $k + p - 1$. The first row of **x.seq** contains the current estimated state values. Since the controller does not calculate optimal states at time $k + p$, the final two rows of **x.seq** are identical.

Dependencies

To enable this port, select the **Optimal state sequence** parameter.

y.seq — Optimal output variable sequence

matrix

Optimal output variable sequence, returned as a matrix signal with $p + 1$ rows and N_y columns, where p is the prediction horizon and N_y is the number of output variables.

The first p rows of **y.seq** contain the calculated optimal output values from current time k to time $k + p - 1$. The first row of **y.seq** is computed based on the current estimated states and the current measured disturbances (first row of input **md**). Since the controller does not calculate optimal output values at time $k + p$, the final two rows of **y.seq** are identical.

Dependencies

To enable this port, select the **Optimal output sequence** parameter.

Parameters

Nonlinear MPC Controller — Controller object

nmpc object name

You must provide an `nmpc` object that defines a nonlinear MPC controller. To do so, enter the name of an `nmpc` object in the MATLAB workspace.

Programmatic Use

Block Parameter: `nmpcobj`

Type: string, character vector

Default: ""

Use prediction model sample time — Flag for using the prediction model sample time

on (default) | off

Select this parameter to run the controller using the same sample time as its prediction model. To use a different controller sample time, clear this parameter, and specify the sample time using the **Make block run at a different sample time** parameter.

To limit the number of decision variables and improve computational efficiency, you can run the controller with a sample time that is different from the prediction horizon. For example, consider the case of a nonlinear MPC controller running at 10 Hz. If the plant and controller sample times match, predicting plant behavior for ten seconds requires a prediction horizon of length 100, which produces a large number of decision variables. To reduce the number of decision variables, you can use a plant sample time of 1 second and a prediction horizon of length 10.

Programmatic Use

Block Parameter: `UseObjectTs`

Type: string, character vector

Values: "off", "on"

Default: "on"

Make block run at a different sample time – Controller sample time

positive finite scalar

Specify this parameter to run the controller using a different sample time from its prediction model.

Dependencies

To enable this parameter, clear the **Use prediction model sample time** parameter.

Programmatic Use**Block Parameter:** TsControl**Type:** string, character vector**Default:** ""**Use MEX to speed up simulation – Flag for simulating controller use MEX function**

off (default) | on

Select this parameter to simulate the controller using a MEX function generated using buildMEX. Doing so reduces the simulation time of the controller. To specify the name of the MEX function, use the **Specify MEX function name** parameter.

Programmatic Use**Block Parameter:** UseMEX**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Specify MEX function name – Controller MEX function name**

string

Use this parameter to specify the name of the MEX function to use during simulation. To create the MEX function, use the buildMEX function.

Dependencies

To enable this parameter, select the **Use MEX to speed up simulation** parameter.

Programmatic Use**Block Parameter:** mexname**Type:** string, character vector**Default:** ""**General Tab****Measured disturbances – Add measured disturbance input port**

off (default) | on

If your controller has measured disturbances, you must select this parameter to add the **md** output port to the block.

Programmatic Use**Block Parameter:** md_enabled**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Targets for manipulated variables – Add manipulated variable target input port**

off (default) | on

Select this parameter to add the **mv.target** input port to the block.

Programmatic Use

Block Parameter: mvtarget_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Model parameters — Add model parameters input port

off (default) | on

If your controller uses optional parameters, you must select this parameter to add the **params** output port to the block.

For more information on creating a parameter bus signal, see `createParameterBus`.

Programmatic Use

Block Parameter: param_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Optimal cost — Odd optimal cost output port

off (default) | on

Select this parameter to add the **cost** output port to the block.

Programmatic Use

Block Parameter: cost_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Optimal control sequence — Add optimal control sequence output port

off (default) | on

Select this parameter to add the **mv.seq** output port to the block.

Programmatic Use

Block Parameter: mvseq_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Optimal state sequence — Add optimal state sequence output port

off (default) | on

Select this parameter to add the **x.seq** output port to the block.

Programmatic Use

Block Parameter: stateseq_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Optimal output sequence — Add optimal output sequence output port

off (default) | on

Select this parameter to add the **y.seq** output port to the block.

Programmatic Use

Block Parameter: ovseq_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Slack variable — Add slack variable output port

off (default) | on

Select this parameter to add the **slack** output port to the block.

Programmatic Use

Block Parameter: slack_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Optimization status — Add optimization status output port

off (default) | on

Select this parameter to add the **nlp.status** output port to the block.

Programmatic Use

Block Parameter: status_enabled

Type: string, character vector

Values: "off", "on"

Default: "off"

Online Features Tab

Lower OV limits — Add minimum OV constraint input port

off (default) | on

Select this parameter to add the **ov.min** input port to the block.

Programmatic Use

Block Parameter: ov_min

Type: string, character vector

Values: "off", "on"

Default: "off"

Upper OV limits — Add maximum OV constraint input port

off (default) | on

Select this parameter to add the **ov.max** input port to the block.

Programmatic Use

Block Parameter: ov_max

Type: string, character vector

Values: "off", "on"

Default: "off"

Lower MV limits — Add minimum MV constraint input port

off (default) | on

Select this parameter to add the **mv.min** input port to the block.

Programmatic Use

Block Parameter: mv_min

Type: string, character vector

Values: "off", "on"

Default: "off"

Upper MV limits — Add maximum MV constraint input port

off (default) | on

Select this parameter to add the **mv.max** input port to the block.

Programmatic Use

Block Parameter: mv_max

Type: string, character vector

Values: "off", "on"

Default: "off"

Lower MVRate limits — Add minimum MV rate constraint input port

off (default) | on

Select this parameter to add the **dmv.min** input port to the block.

Programmatic Use

Block Parameter: mvrate_min

Type: string, character vector

Values: "off", "on"

Default: "off"

Upper MVRate limits — Add maximum MV rate constraint input port

off (default) | on

Select this parameter to add the **dmv.max** input port to the block.

Programmatic Use

Block Parameter: mvrate_max

Type: string, character vector

Values: "off", "on"

Default: "off"

Lower state limits — Add minimum state constraint input port

off (default) | on

Select this parameter to add the **x.min** input port to the block.

Programmatic Use

Block Parameter: state_min

Type: string, character vector

Values: "off", "on"

Default: "off"

Upper state limits — Add maximum state constraint input port

off (default) | on

Select this parameter to add the **x.max** input port to the block.

Programmatic Use**Block Parameter:** `state_max`**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**OV weights — Add OV tuning weights input port**

off (default) | on

Select this parameter to add the **y.wt** input port to the block.**Programmatic Use****Block Parameter:** `ov_weight`**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**MV weights — Add MV tuning weights input port**

off (default) | on

Select this parameter to add the **mv.wt** input port to the block.**Programmatic Use****Block Parameter:** `mv_weight`**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**MVRate weights — Add MV rate tuning weights input port**

off (default) | on

Select this parameter to add the **dmv.wt** input port to the block.**Programmatic Use****Block Parameter:** `mvrate_weight`**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**ECR weight — Add ECR tuning weight input port**

off (default) | on

Select this parameter to add the **ecr.wt** input port to the block.**Programmatic Use****Block Parameter:** `ecr_weight`**Type:** string, character vector**Values:** "off", "on"**Default:** "off"**Initial guess — Add initial guess input ports**

off (default) | on

Select this parameter to add the **mv.init**, **x.init**, and **e.init** input ports to the block.

Note By default, the Nonlinear MPC Controller block uses the calculated optimal manipulated variable and state trajectories from one control interval as the initial guesses for the next control interval.

Enable the initial guess ports only if it is necessary for your application.

Programmatic Use

Block Parameter: `nlp_initialize`

Type: string, character vector

Values: "off", "on"

Default: "off"

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

Usage notes and limitations:

- The Nonlinear MPC Controller block supports generating code only for nonlinear MPC controllers that use the default `fmincon` solver with the SQP algorithm.
- When used for code generation, nonlinear MPC controllers do not support anonymous functions for the prediction model, custom cost function, or custom constraint functions.
- If your controller uses optional parameters, you must also generate code for the Bus Creator block connected to the **params** input port. To do so, place the Nonlinear MPC Controller and Bus Creator blocks within a subsystem, and generate code for that subsystem.

See Also

`createParameterBus` | `nmpc` | `nmpcmove`

Topics

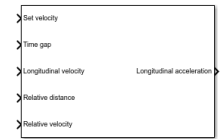
"Nonlinear MPC"

Introduced in R2018b

Adaptive Cruise Control System

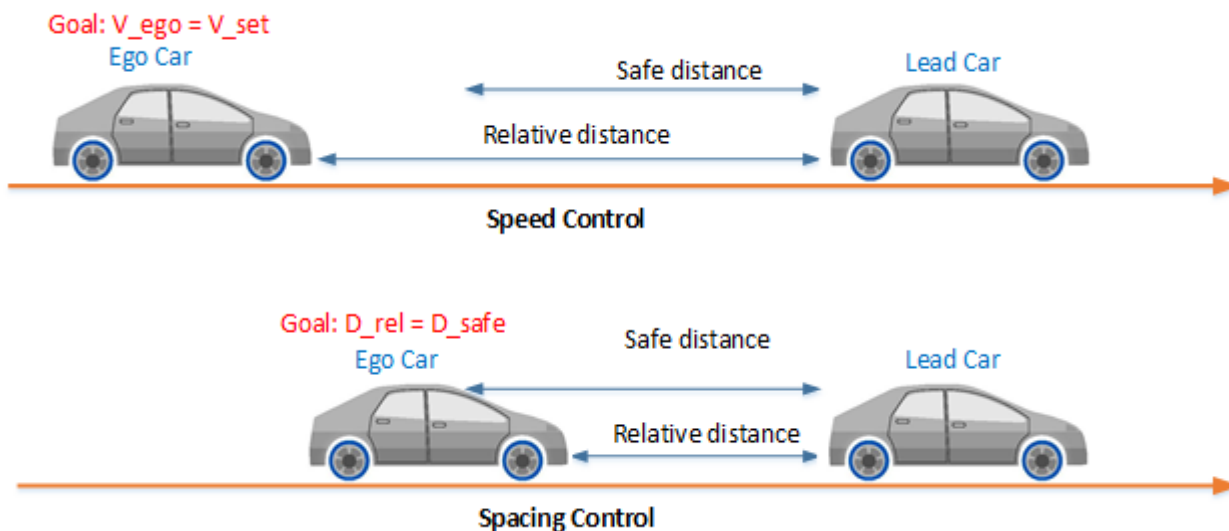
Simulate adaptive cruise control using model predictive controller

Library: Model Predictive Control Toolbox / Automated Driving



Description

The Adaptive Cruise Control System block simulates an adaptive cruise control (ACC) system that tracks a set velocity and maintains a safe distance from a lead vehicle by adjusting the longitudinal acceleration of an ego vehicle. The block computes optimal control actions while satisfying safe distance, velocity, and acceleration constraints using model predictive control (MPC).



To customize your controller, for example to use advanced MPC features or modify controller initial conditions, click **Create ACC subsystem**.

Ports

Input

Set velocity — Ego vehicle velocity setpoint

nonnegative scalar

Ego vehicle velocity setpoint in m/s. When there is no lead vehicle, the controller tracks this velocity.

Time gap — Safe time gap

nonnegative scalar

Safe time gap in seconds between the lead vehicle and the ego vehicle. This time gap is used to calculate the minimum safe following distance constraint. For more information, see “Safe Following Distance” on page 4-86.

Longitudinal velocity – Ego vehicle velocity

nonnegative scalar

Ego vehicle velocity in m/s.

Relative distance – Distance between lead vehicle and ego vehicle

positive scalar

Distance in meters between lead vehicle and ego vehicle. To calculate this signal, subtract the ego vehicle position from the lead vehicle position.

Relative velocity – Velocity difference between lead vehicle and ego vehicle

scalar

Velocity difference in meters per second between lead vehicle and ego vehicle. To calculate this signal, subtract the ego vehicle velocity from the lead vehicle velocity.

Minimum longitudinal acceleration – Minimum ego vehicle acceleration

negative scalar

Minimum ego vehicle longitudinal acceleration constraint in m/s^2 . Use this input port when the minimum acceleration varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Minimum longitudinal acceleration** parameter.

Maximum longitudinal acceleration – Maximum ego vehicle acceleration

positive scalar

Maximum ego vehicle longitudinal acceleration constraint in m/s^2 . Use this input port when the maximum acceleration varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Maximum longitudinal acceleration** parameter.

Enable optimization – Controller optimization enable signal

scalar

Controller optimization enable signal. When this signal is:

- Nonzero, the controller performs optimization calculations and generates a **Longitudinal acceleration** control signal.
- Zero, the controller does not perform optimization calculations. In this case, the **Longitudinal acceleration** output signal remains at the value it had when the optimization was disabled. The controller continues to update its internal state estimates.

Dependencies

To enable this port, select the **Use external signal to enable or disable optimization** parameter.

External control signal – Longitudinal acceleration applied to ego vehicle

scalar

Actual longitudinal acceleration in m/s^2 applied to the ego vehicle. The controller uses this signal to estimate the ego vehicle model states. Use this input port when the control signal applied to the ego vehicle does not match the optimal control signal computed by the model predictive controller. This mismatch can occur when, for example:

- The Adaptive Cruise Control System is not the active controller. Maintaining an accurate state estimate when the controller is not active prevents bumps in the control signal when the controller becomes active.
- The acceleration actuator fails and does not provide the correct control signal to the ego vehicle.

Dependencies

To enable this port, select the **Use external control signal for bumpless transfer between ACC and other controllers** parameter.

Output**Longitudinal acceleration – Acceleration control signal**

scalar

Acceleration control signal in m/s^2 generated by the controller.

Parameters**Parameters Tab****Ego Vehicle Model****Linear model from longitudinal acceleration to longitudinal velocity – Ego vehicle model**

`tf(1, [0.5, 1, 0])` (default) | LTI model | linear System Identification Toolbox model

The linear model from the ego vehicle longitudinal acceleration to its longitudinal velocity, specified as an LTI model or a linear System Identification Toolbox model. The controller creates its internal predictive model by augmenting the ego vehicle dynamic model.

Initial condition for longitudinal velocity – Initial velocity of the ego vehicle model

20 (default) | nonnegative scalar

Initial velocity in m/s of the ego vehicle model, which can differ from the actual ego vehicle initial velocity.

This value is used to configure the initial conditions of the model predictive controller. For more information, see “Initial Conditions” on page 4-87.

Default spacing – Minimum spacing to lead vehicle

10 (default) | nonnegative scalar

Minimum spacing in meters between the lead vehicle and the ego vehicle. This value corresponds to the target relative distance between the ego and lead vehicles when the ego vehicle velocity is zero.

This value is used to calculate the:

- Minimum safe following distance. For more information, see “Safe Following Distance” on page 4-86.
- Controller initial conditions. For more information, see “Initial Conditions” on page 4-87.

Maximum velocity – Maximum longitudinal velocity

50 (default) | positive scalar

Maximum ego vehicle longitudinal velocity in m/s.

Adaptive Cruise Controller Constraints

Minimum longitudinal acceleration – Minimum ego vehicle acceleration

-3 (default) | negative scalar

Minimum ego vehicle longitudinal acceleration constraint in m/s^2 .

If the minimum acceleration varies over time, add the **Minimum longitudinal acceleration** input port to the block by selecting **Use external source**.

Maximum longitudinal acceleration – Maximum ego vehicle acceleration

2 (default) | nonnegative scalar

Maximum ego vehicle longitudinal acceleration constraint in m/s^2 .

If the maximum acceleration varies over time, add the **Maximum longitudinal acceleration** input port to the block by selecting **Use external source**.

Model Predictive Controller Settings

Sample time – Controller sample time

0.1 (default) | positive scalar

Controller sample time in seconds.

Prediction horizon – Controller prediction horizon

10 (default) | positive integer

Controller prediction horizon steps. The controller prediction time is the product of the sample time and the prediction horizon.

Controller behavior – Closed-loop controller performance

0.5 (default) | scalar between 0 and 1

Closed-loop controller performance. The default parameter value provides a balanced controller design. Specifying a:

- Smaller value produces a more robust controller with smoother control actions.
- Larger value produces a more aggressive controller with a faster response time.

When you modify this parameter, the change is applied to the controller immediately.

Block Tab

Use suboptimal solution — Apply suboptimal solution after specified number of iterations

off (default) | on

Configure the controller to apply a suboptimal solution after a specified maximum number of iterations, which guarantees the worst-case execution time for your controller.

For more information, see “Suboptimal QP Solution”.

Dependencies

After selecting this parameter, specify the **Maximum iteration number** parameter.

Maximum iteration number — Maximum optimization iterations

10 (default) | positive integer

Maximum number of controller optimization iterations.

Dependencies

To enable this parameter, select the **Use suboptimal solution** parameter.

Use external signal to enable or disable optimization — Add port for enabling optimization

off (default) | on

To add the **Enable optimization** input port to the block, select this parameter.

Use external signal for bumpless transfer between ACC and other controllers — Add external control signal input port

off (default) | on

Select this parameter to add the **External control signal** input port to the block.

Create ACC subsystem — Create custom controller

button

Generate a custom ACC subsystem, which you can modify for your application. The configuration data for the custom controller is exported to the MATLAB workspace as a structure.

You can modify the custom controller subsystem to:

- Modify default MPC settings or use advanced MPC features.
- Modify the default controller initial conditions.
- Use different application settings, such as a custom safe following distance definition.

Algorithms

Safe Following Distance

By default, the model predictive controller computes the safe following distance constraint; that is, the minimum relative distance between the lead and ego vehicle, as:

$$D_R = D_S + G_T * V_E$$

Here:

- D_S is the **Default spacing** parameter.
- G_T is the **Time gap** input signal.
- V_E is the **Longitudinal velocity** input signal.

To define a different safe following distance constraint, create a custom cruise control system by, on the **Block** tab, clicking **Create ACC subsystem**.

Initial Conditions

By default, the model predictive controller assumes the following initial conditions:

- Longitudinal velocity of both the ego vehicle and the lead vehicle equal the **Initial condition for longitudinal velocity** parameter value.
- Ego vehicle longitudinal acceleration is zero.
- Relative distance between the lead vehicle and ego vehicle is:

$$D_R = D_S + G_T * V_E$$

Here:

- D_S is the **Default spacing** parameter.
- G_T is the time gap and is assumed to be 1.4.
- V_E is the **Initial longitudinal velocity** parameter.

If the initial conditions in your model do not match these conditions, the **Longitudinal acceleration** output can exhibit an initial bump at the start of the simulation.

To modify the controller initial conditions to match your simulation, create a custom cruise control system by, on the **Block** tab, clicking **Create ACC subsystem**.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also

Blocks

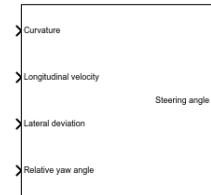
MPC Controller

Introduced in R2018a

Lane Keeping Assist System

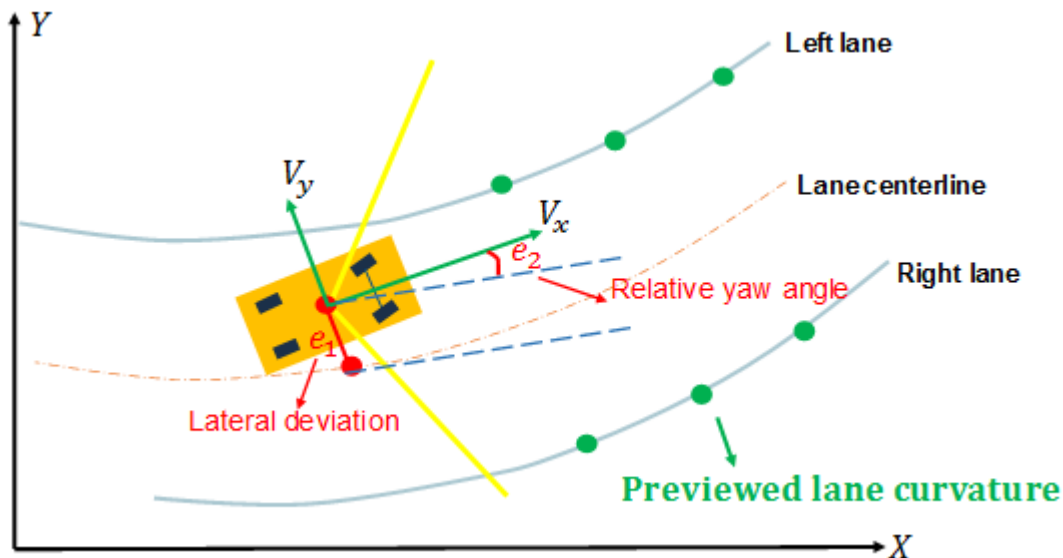
Simulate lane-keeping assistance using adaptive model predictive controller

Library: Model Predictive Control Toolbox / Automated Driving



Description

The Lane Keeping Assist System block simulates a lane keeping assist (LKA) system that keeps an ego vehicle traveling along the center of a straight or curved road by adjusting the front steering angle. The controller reduces the lateral deviation and relative yaw angle of the ego vehicle with respect to the lane centerline. The block computes optimal control actions while satisfying steering angle constraints using adaptive model predictive control (MPC).



To customize your controller, for example to use advanced MPC features or modify controller initial conditions, click **Create LKA subsystem**.

Ports

Input

Curvature — Road curvature

scalar

Road curvature, specified as $1/R$, where R is the radius of the curve in meters.

The road curvature is:

- Positive when the road curves toward the positive Y axis of the global coordinate system.
- Negative when the road curves toward the negative Y axis of the global coordinate system.
- Zero for a straight road.

The controller models the road curvature as a measured disturbance with previewing. You can specify the curvature as a:

- Scalar signal — Specify the curvature for the current control interval. The controller uses this curvature value across the prediction horizon.
- Vector signal with length less than or equal to the **Prediction Horizon** — Specify the current and predicted curvature values across the prediction horizon. If the length of the vector is less than the prediction horizon, then the controller uses the final curvature value in the vector for the remainder of the prediction horizon.

Longitudinal velocity — Ego vehicle velocity

nonnegative scalar

Ego vehicle velocity in m/s.

Lateral deviation — Ego vehicle lateral deviation

scalar

Ego vehicle lateral deviation in meters from the centerline of the lane.

Relative yaw angle — Angle from lane centerline

scalar

Ego vehicle longitudinal axis angle in radians from the centerline of the lane.

Minimum steering angle — Minimum front steering angle

scalar

Minimum front steering angle constraint in radians. Use this input port when the minimum steering angle varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Minimum steering angle** parameter.

Maximum steering angle — Maximum front steering angle

scalar

Maximum front steering angle constraint in radians. Use this input port when the maximum steering angle varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Maximum steering angle** parameter.

Enable optimization — Controller optimization enable signal

scalar

Controller optimization enable signal. When this signal is:

- Nonzero, the controller performs optimization calculations and generates a **Steering angle** control signal.

- Zero, the controller does not perform optimization calculations. In this case, the **Steering angle** output signal remains at the value it had when the optimization was disabled. The controller continues to update its internal state estimates.

Dependencies

To enable this port, select the **Use external signal to enable or disable optimization** parameter.

External control signal — Steering angle applied to ego vehicle

scalar

Actual steering angle in radians applied to the ego vehicle. The controller uses this signal to estimate the ego vehicle model states. Use this input port when the control signal applied to the ego vehicle does not match the optimal control signal computed by the model predictive controller. This mismatch can occur when, for example:

- The Lane Keeping Assist System is not the active controller. Maintaining an accurate state estimate when the controller is not active prevents bumps in the control signal when the controller becomes active.
- The steering actuator fails and does not provide the correct control signal to the ego vehicle.

Dependencies

To enable this port, select the **Use external control signal for bumpless transfer between PFC and other controllers** parameter.

Vehicle dynamics matrix A — State matrix of ego vehicle predictive model

square matrix

State matrix of ego vehicle predictive model. The number of rows in the state matrix corresponds to the number of states in the predictive model. This matrix must be square.

The ego vehicle predictive model defined by **Vehicle dynamics matrix A**, **Vehicle dynamics matrix B**, and **Vehicle dynamics matrix C** must be minimal.

Dependencies

To enable this port, select the **Use vehicle model** parameter.

Vehicle dynamics matrix B — Input-to-state matrix of ego vehicle predictive model

column vector

Input-to-state matrix of ego vehicle predictive model. The number of rows in this signal must match the number of rows in **Vehicle dynamics matrix A**.

The ego vehicle predictive model defined by **Vehicle dynamics matrix A**, **Vehicle dynamics matrix B**, and **Vehicle dynamics matrix C** must be minimal.

Dependencies

To enable this port, select the **Use vehicle model** parameter.

Vehicle dynamics matrix C — State-to-output matrix of ego vehicle predictive model

matrix with two rows

State-to-output matrix of ego vehicle predictive model. The number of columns in this signal must match the number of rows in **Vehicle dynamics matrix A**.

The ego vehicle predictive model defined by **Vehicle dynamics matrix A**, **Vehicle dynamics matrix B**, and **Vehicle dynamics matrix C** must be minimal.

Dependencies

To enable this port, select the **Use vehicle model** parameter.

Output

Steering angle – Front steering angle control signal

scalar

Front steering angle control signal in radians generated by the controller. The front steering angle is the angle of the front tires from the longitudinal axis of the vehicle. The steering angle is positive towards the positive lateral axis of the ego vehicle.

Parameters

Parameters Tab

Ego Vehicle

Use vehicle parameters – Define ego vehicle model using vehicle properties

on (default) | off

Select this parameter to define the ego vehicle model used by the MPC controller by specifying properties of the ego vehicle. The ego vehicle model is the linear model from the front steering angle to the lateral velocity and yaw angle rate. For more information, see “Ego Vehicle Predictive Model” on page 4-96.

To define the vehicle model, specify the following block parameters:

- **Total mass**
- **Yaw moment of inertia**
- **Longitudinal distance from center of gravity to front tires**
- **Longitudinal distance from center of gravity to rear tires**
- **Cornering stiffness of front tires**
- **Cornering stiffness of rear tires**

For more information on the ego vehicle model, see “Ego Vehicle Predictive Model” on page 4-96.

Selecting this parameter clears the **Use vehicle model** parameter.

Use vehicle model – Define ego vehicle model using state-space matrices

off (default) | on

Select this parameter to define the state-space matrices of the ego vehicle model used by the MPC controller. This model is the linear model from the front steering angle in radians to the lateral velocity in meters per second and yaw angle rate in radians per second. For more information on the ego vehicle model, see “Ego Vehicle Predictive Model” on page 4-96.

To define the initial internal model, specify the **A**, **B**, and **C** state-space matrices. The internal model must be a minimal realization with no direct feedthrough, and the dimensions of **A**, **B**, and **C** must be consistent.

Typically, the ego vehicle steering model is velocity-dependent, and therefore, it varies over time. To update the internal model at run time, use the **Vehicle dynamics A**, **Vehicle dynamics B**, and **Vehicle dynamics C** input ports.

Selecting this parameter clears the **Use vehicle parameters** parameter.

Total mass — Ego vehicle mass

1575 (default) | positive scalar

Ego vehicle mass in kg.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Yaw moment of inertia — Moment of inertia about the ego vehicle vertical axis

2875 (default) | positive scalar

Moment of inertia about the ego vehicle vertical axis in mNs^2 .

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Longitudinal distance from center of gravity to front tires — Distance from the ego vehicle center of mass to its front tires

1.2 (default) | positive scalar

Distance from the ego vehicle center of mass to its front tires in meters, measured along the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Longitudinal distance from center of gravity to rear tires — Distance from the ego vehicle center of mass to its rear tires

1.6 (default) | positive scalar

Distance from the ego vehicle center of mass to its rear tires in meters, measured along the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Cornering stiffness of front tires — Front tire stiffness

19000 (default) | positive scalar

Front tire stiffness in N/rad , defined as the relationship between the side force on the front tires and the angle of the tires to the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Cornering stiffness of rear tires — Rear tire stiffness

33000 (default) | positive scalar

Rear tire stiffness in N/rad, defined as the relationship between the side force on the rear tires and the angle of the tires to the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

A – Initial state matrix of ego vehicle predictive model

square matrix

Initial state matrix of ego vehicle predictive model. The number of rows in the state matrix corresponds to the number of states in the predictive model. This matrix must be square.

The initial ego vehicle predictive model defined by **A**, **B**, and **C** must be minimal.

Typically, the ego vehicle model varies over time. To update the state matrix at run time, use the **Vehicle dynamics A** input port.

Dependencies

To enable this parameter, select the **Use vehicle model** parameter.

B – Initial input-to-state matrix of ego vehicle predictive model

column vector

Initial input-to-state matrix of ego vehicle predictive model. The number of rows in this parameter must match the number of rows in **A**.

The initial ego vehicle predictive model defined by **A**, **B**, and **C** must be minimal.

Typically, the ego vehicle model varies over time. To update the input-to-state matrix at run time, use the **Vehicle dynamics B** input port.

Dependencies

To enable this parameter, select the **Use vehicle model** parameter.

C – Initial state-to-output matrix of ego vehicle predictive model

matrix with two rows

Initial state-to-output matrix of ego vehicle predictive model. The number of columns in this parameter must match the number of rows in **A**.

The initial ego vehicle predictive model defined by **A**, **B**, and **C** must be minimal.

Typically, the ego vehicle model varies over time. To update the state-to-output matrix at run time, use the **Vehicle dynamics C** input port.

Dependencies

To enable this parameter, select the **Use vehicle model** parameter.

Initial longitudinal velocity – Initial velocity of the ego vehicle

15 (default) | positive scalar

Initial velocity of the ego vehicle model when the lane-keeping assist is enabled in m/s. This velocity can differ from the actual ego vehicle initial velocity.

Note A very small initial velocity, for example `eps`, can produce a nonminimal realization for the controller plant model, causing an error. To prevent this error, set the initial velocity to a larger value, for example `1e-3`.

Transport lag between model inputs and outputs – Total transport lag in ego vehicle model

0 (default) | nonnegative scalar

Total transport lag, τ , in the ego vehicle model in seconds. This lag includes actuator, sensor, and communication lags. For each input-output channel, the transport lag is approximated by:

$$\frac{1}{\tau s + 1}$$

Lane Keeping Controller Constraints

Minimum steering angle – Minimum front steering angle

-0.26 (default) | scalar between $-\pi/2$ and $\pi/2$

Minimum front steering angle constraint in radians.

If the minimum steering angle varies over time, add the **Minimum steering angle** input port to the block by selecting **Use external source**.

Dependencies

This parameter must be less than the **Maximum steering angle** parameter.

Maximum steering angle – Maximum front steering angle

0.26 (default) | scalar between $-\pi/2$ and $\pi/2$

Maximum front steering angle constraint in radians.

If the maximum steering angle varies over time, add the **Maximum steering angle** input port to the block by selecting **Use external source**.

Dependencies

This parameter must be greater than the **Minimum steering angle** parameter.

Model Predictive Controller Settings

Sample time – Controller sample time

0.1 (default) | positive scalar

Controller sample time in seconds.

Prediction horizon – Controller prediction horizon

10 (default) | positive integer

Controller prediction horizon steps. The controller prediction time is the product of the sample time and the prediction horizon.

Controller behavior – Closed-loop controller performance

0.5 (default) | scalar between 0 and 1

Closed-loop controller performance. The default parameter value provides a balanced controller design. Specifying a:

- Smaller value produces a more robust controller with smoother control actions.
- Larger value produces a more aggressive controller with a faster response time.

When you modify this parameter, the change is applied to the controller immediately.

Block Tab

Use suboptimal solution — Apply suboptimal solution after specified number of iterations

off (default) | on

Configure the controller to apply a suboptimal solution after a specified maximum number of iterations, which guarantees the worst-case execution time for your controller.

For more information, see “Suboptimal QP Solution”.

Dependencies

After selecting this parameter, specify the **Maximum iteration number** parameter.

Maximum iteration number — Maximum optimization iterations

10 (default) | positive integer

Maximum number of controller optimization iterations.

Dependencies

To enable this parameter, select the **Use suboptimal solution** parameter.

Use external signal to enable or disable optimization — Add port for enabling optimization

off (default) | on

To add the **Enable optimization** input port to the block, select this parameter.

Use external signal for bumpless transfer between LKA and other controllers — Add external control signal input port

off (default) | on

To add the **External control signal** input port to the block, select this parameter.

Create LKA subsystem — Create custom controller

button

Generate a custom LKA subsystem, which you can modify for your application. The controller configuration data for the custom controller is exported to the MATLAB workspace as a structure.

You can modify the custom controller subsystem to:

- Modify default MPC settings or use advanced MPC features.
- Modify the default controller initial conditions.

Algorithms

Ego Vehicle Predictive Model

The default ego vehicle predictive model is the following state-space model:

$$A = \begin{bmatrix} -2(C_F + C_R)/m/V_X & -V_X - 2(C_FL_F - C_RL_R)/m/V_X \\ -2(C_FL_F - C_RL_R)/I_Z/V_X & -2(C_FL_F^2 + C_RL_R^2)/I_Z/V_X \end{bmatrix}$$

$$B = 2C_F \begin{bmatrix} 1/m \\ L_F/I_Z \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Here:

- V_X is the longitudinal velocity of the car. At the start of the simulation, this velocity is equal to the **Initial condition for longitudinal velocity** parameter. At run time, this velocity is equal to the **Longitudinal velocity** input signal.
- m is the **Total mass** parameter.
- I_Z is the **Yaw moment of inertia** parameter.
- L_F is the **Longitudinal distance from center of gravity to front tires** parameter.
- L_R is the **Longitudinal distance from center of gravity to rear tires** parameter.
- C_F is the **Cornering stiffness of front tires** parameter.
- C_R is the **Cornering stiffness of rear tires** parameter.

The input to this model is the steering angle in radians, and the outputs are the lateral velocity in meters per second and yaw angle rate in radians per second.

To define a different ego vehicle predictive model, select the **Use vehicle model** parameter, and specify the initial state-space model. Then, specify the run-time values of the state-space matrices using the **Vehicle dynamics A**, **Vehicle dynamics B**, and **Vehicle dynamics C** input signals.

The controller creates its internal predictive model by augmenting the ego vehicle dynamic model. The augmented model includes the road curvature as a measured disturbance input signal.

Initial Conditions

By default, the model predictive controller assumes the following initial conditions for the ego vehicle:

- Longitudinal velocity is equal to the **Initial longitudinal velocity** parameter.
- Lateral velocity is zero.
- Steering angle is zero.
- Yaw angle rate is zero.

If the initial conditions in your model do not match these conditions, the **Steering angle** output can exhibit an initial bump at the start of the simulation.

To modify the controller initial conditions to match your simulation, create a custom lane-keeping control system by, on the **Block** tab, clicking **Create LKA subsystem**.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also

Blocks

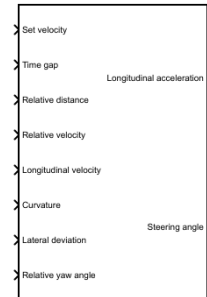
Adaptive MPC Controller

Introduced in R2018a

Path Following Control System

Simulate path-following control using adaptive model predictive controller

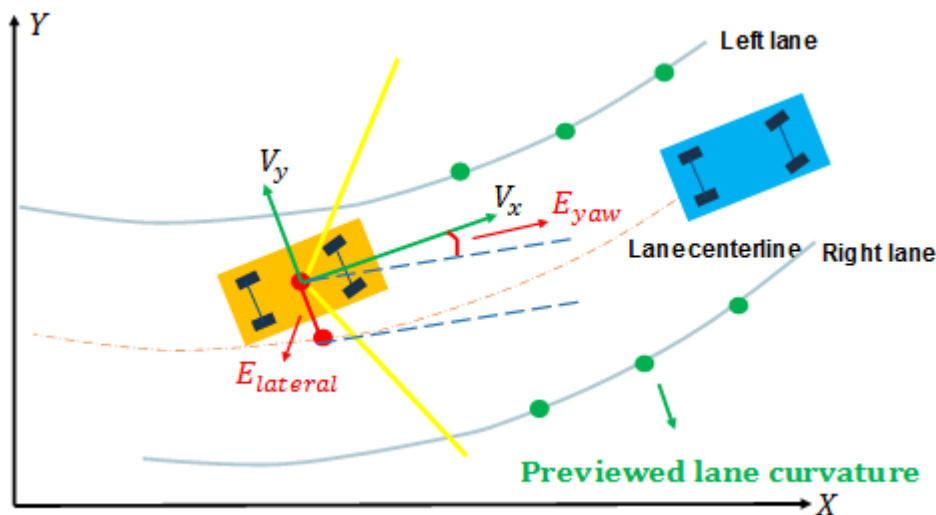
Library: Model Predictive Control Toolbox / Automated Driving



Description

The Path Following Control System block simulates a path-following control (PFC) system that keeps an ego vehicle traveling along the center of a straight or curved road while tracking a set velocity and maintaining a safe distance from a lead vehicle. To do so, the controller adjusts both the longitudinal acceleration and front steering angle of the ego vehicle. The block computes optimal control actions while satisfying safe distance, velocity, acceleration, and steering angle constraints using adaptive model predictive control (MPC).

This block combines the capabilities of the Lane Keeping Assist System and Adaptive Cruise Control System blocks into a single controller.



To customize your controller, for example to use advanced MPC features or modify controller initial conditions, click **Create PFC subsystem**.

Ports

Input

Set velocity — Ego vehicle velocity setpoint

nonnegative scalar

Ego vehicle velocity setpoint in m/s. When there is no lead vehicle, the controller tracks this velocity.

Time gap — Safe time gap

nonnegative scalar

Safe time gap in seconds between the lead vehicle and the ego vehicle. This time gap is used to calculate the minimum safe following distance constraint. For more information, see “Safe Following Distance” on page 4-110.

Relative distance — Distance between lead vehicle and ego vehicle

positive scalar

Distance in meters between lead vehicle and ego vehicle. To calculate this signal, subtract the ego vehicle position from the lead vehicle position.

Relative velocity — Velocity difference between lead vehicle and ego vehicle

scalar

Velocity difference in meters per second between lead vehicle and ego vehicle. To calculate this signal, subtract the ego vehicle velocity from the lead vehicle velocity.

Longitudinal velocity — Ego vehicle velocity

nonnegative scalar

Ego vehicle velocity in m/s.

Curvature — Road curvature

scalar

Road curvature, specified as $1/R$, where R is the radius of the curve in meters.

The road curvature is:

- Positive when the road curves toward the positive Y axis of the global coordinate system.
- Negative when the road curves toward the negative Y axis of the global coordinate system.
- Zero for a straight road.

The controller models the road curvature as a measured disturbance with previewing. You can specify the curvature as a:

- Scalar signal — Specify the curvature for the current control interval. The controller uses this curvature value across the prediction horizon.
- Vector signal with length less than or equal to the **Prediction Horizon** — Specify the current and predicted curvature values across the prediction horizon. If the length of the vector is less than the prediction horizon, then the controller uses the final curvature value in the vector for the remainder of the prediction horizon.

Lateral deviation — Ego vehicle lateral deviation

scalar

Ego vehicle lateral deviation in meters from the centerline of the lane.

Relative yaw angle — Angle from lane centerline

scalar

Ego vehicle longitudinal axis angle in radians from the centerline of the lane.

Minimum longitudinal acceleration — Minimum ego vehicle acceleration

scalar

Minimum ego vehicle longitudinal acceleration constraint in m/s^2 . Use this input port when the minimum acceleration varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Minimum longitudinal acceleration** parameter.

Maximum longitudinal acceleration — Maximum ego vehicle acceleration

scalar

Maximum ego vehicle longitudinal acceleration constraint in m/s^2 . Use this input port when the maximum acceleration varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Maximum longitudinal acceleration** parameter.

Minimum steering angle — Minimum front steering angle

scalar

Minimum front steering angle constraint in radians. Use this input port when the minimum steering angle varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Minimum steering angle** parameter.

Maximum steering angle — Maximum front steering angle

scalar

Maximum front steering angle constraint in radians. Use this input port when the maximum steering angle varies at run time.

Dependencies

To enable this port, select **Use external source** for the **Maximum steering angle** parameter.

Enable optimization — Controller optimization enable signal

scalar

Controller optimization enable signal. When this signal is:

- Nonzero, the controller performs optimization calculations and generates the **Longitudinal acceleration** and **Steering angle** control signals.
- Zero, the controller does not perform optimization calculations. In this case, the **Longitudinal acceleration** and **Steering angle** output signals remain at the values they had when the optimization was disabled. The controller continues to update its internal state estimates.

Dependencies

To enable this port, select the **Use external signal to enable or disable optimization** parameter.

External control signal — Control signals applied to ego vehicle

vector of length two

Actual control signals applied to the ego vehicle. The first element of this signal is the longitudinal acceleration in m/s^2 , and the second element is the steering angle in radians. The controller uses these signals to estimate the ego vehicle model states. Use this input port when the control signals applied to the ego vehicle do not match the optimal control signals computed by the model predictive controller. This mismatch can occur when, for example:

- The Path Following Control System is not the active controller. Maintaining an accurate state estimate when the controller is not active prevents bumps in the control signals when the controller becomes active.
- The steering or acceleration actuator fails and does not provide the correct control signal to the ego vehicle.

Dependencies

To enable this port, select the **Use external control signal for bumpless transfer between PFC and other controllers** parameter.

Vehicle dynamics matrix A — State matrix of ego vehicle predictive model

square matrix

State matrix of ego vehicle predictive model. The number of rows in the state matrix corresponds to the number of states in the predictive model. This matrix must be square.

The ego vehicle predictive model defined by **Vehicle dynamics matrix A**, **Vehicle dynamics matrix B**, and **Vehicle dynamics matrix C** must be minimal.

Dependencies

To enable this port, select the **Use vehicle model** parameter.

Vehicle dynamics matrix B — Input-to-state matrix of ego vehicle predictive model

matrix with two columns

Input-to-state matrix of ego vehicle predictive model. The number of rows in this signal must match the number of rows in **Vehicle dynamics matrix A**.

The ego vehicle predictive model defined by **Vehicle dynamics matrix A**, **Vehicle dynamics matrix B**, and **Vehicle dynamics matrix C** must be minimal.

Dependencies

To enable this port, select the **Use vehicle model** parameter.

Vehicle dynamics matrix C — State-to-output matrix of ego vehicle predictive model

matrix with three rows

State-to-output matrix of ego vehicle predictive model. The number of columns in this signal must match the number of rows in **Vehicle dynamics matrix A**.

The ego vehicle predictive model defined by **Vehicle dynamics matrix A**, **Vehicle dynamics matrix B**, and **Vehicle dynamics matrix C** must be minimal.

Dependencies

To enable this port, select the **Use vehicle model** parameter.

Output

Longitudinal acceleration — Acceleration control signal

scalar

Acceleration control signal in m/s^2 generated by the controller.

Steering angle — Front steering angle control signal

scalar

Front steering angle control signal in radians generated by the controller. The front steering angle is the angle of the front tires from the longitudinal axis of the vehicle. The steering angle is positive towards the positive lateral axis of the ego vehicle.

Parameters

Parameters Tab

Ego Vehicle

Use vehicle parameters — Define ego vehicle model using vehicle properties

on (default) | off

Select this parameter to define the ego vehicle model used by the MPC controller by specifying properties of the ego vehicle. The ego vehicle model is the linear model from the longitudinal acceleration and front steering angle to the longitudinal velocity, lateral velocity, and yaw angle rate.

To define the vehicle model, specify the following block parameters:

- **Total mass**
- **Yaw moment of inertia**
- **Longitudinal distance from center of gravity to front tires**
- **Longitudinal distance from center of gravity to rear tires**
- **Cornering stiffness of front tires**
- **Cornering stiffness of rear tires**
- **Longitudinal acceleration tracking time constant**

For more information on the ego vehicle model, see “Ego Vehicle Predictive Model” on page 4-108

Selecting this parameter clears the **Use vehicle model** parameter.

Use vehicle model — Define ego vehicle model using state-space matrices

off (default) | on

Select this parameter to define the state-space matrices of the ego vehicle model used by the MPC controller. The ego vehicle model is the linear model from the longitudinal acceleration and front steering angle to the longitudinal velocity, lateral velocity, and yaw angle rate.

To define the initial internal model, specify the **A**, **B**, and **C** state-space matrices. The internal model must be a minimal realization with no direct feedthrough, and the dimensions of **A**, **B**, and **C** must be consistent.

Typically, the ego vehicle model is velocity-dependent, and therefore, it varies over time. To update the internal model at run time, use the **Vehicle dynamics A**, **Vehicle dynamics B**, and **Vehicle dynamics C** input ports.

For more information on the ego vehicle model, see “Ego Vehicle Predictive Model” on page 4-108

Selecting this parameter clears the **Use vehicle parameters** parameter.

Total mass — Ego vehicle mass

1575 (default) | positive scalar

Ego vehicle mass in kg.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Yaw moment of inertia — Moment of inertia about the ego vehicle vertical axis

2875 (default) | positive scalar

Moment of inertia about the ego vehicle vertical axis in mNs^2 .

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Longitudinal distance from center of gravity to front tires — Distance from the ego vehicle center of mass to its front tires

1.2 (default) | positive scalar

Distance from the ego vehicle center of mass to its front tires in meters, measured along the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Longitudinal distance from center of gravity to rear tires — Distance from the ego vehicle center of mass to its rear tires

1.6 (default) | positive scalar

Distance from the ego vehicle center of mass to its rear tires in meters, measured along the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Cornering stiffness of front tires – Front tire stiffness

19000 (default) | positive scalar

Front tire stiffness in N/rad, defined as the relationship between the side force on the front tires and the angle of the tires to the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Cornering stiffness of rear tires – Rear tire stiffness

33000 (default) | positive scalar

Rear tire stiffness in N/rad, defined as the relationship between the side force on the rear tires and the angle of the tires to the longitudinal axis of the vehicle.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

Longitudinal acceleration tracking time constant – Time constant for acceleration tracking

0.5 (default) | positive scalar

Time constant for tracking longitudinal acceleration, specified in seconds.

Dependencies

To enable this parameter, select the **Use vehicle parameters** parameter.

A – Initial state matrix of ego vehicle predictive model

square matrix

Initial state matrix of ego vehicle predictive model. The number of rows in the state matrix corresponds to the number of states in the predictive model. This matrix must be square.

The initial ego vehicle predictive model defined by **A**, **B**, and **C** must be minimal.

Typically, the ego vehicle model varies over time. To update the state matrix at run time, use the **Vehicle dynamics A** input port.

Dependencies

To enable this parameter, select the **Use vehicle model** parameter.

B – Initial input-to-state matrix of ego vehicle predictive model

matrix with two columns

Initial input-to-state matrix of ego vehicle predictive model. The number of rows in this parameter must match the number of rows in **A**.

The initial ego vehicle predictive model defined by **A**, **B**, and **C** must be minimal.

Typically, the ego vehicle model varies over time. To update the input-to-state matrix at run time, use the **Vehicle dynamics B** input port.

Dependencies

To enable this parameter, select the **Use vehicle model** parameter.

C — Initial state-to-output matrix of ego vehicle predictive model

matrix with three rows

Initial state-to-output matrix of ego vehicle predictive model. The number of columns in this parameter must match the number of rows in **A**.

The initial ego vehicle predictive model defined by **A**, **B**, and **C** must be minimal.

Typically, the ego vehicle model varies over time. To update the state-to-output matrix at run time, use the **Vehicle dynamics C** input port.

Dependencies

To enable this parameter, select the **Use vehicle model** parameter.

Initial longitudinal velocity — Initial velocity of the ego vehicle model

15 (default) | nonnegative scalar

Initial velocity of the ego vehicle model in m/s, which can differ from the actual ego vehicle initial velocity.

This value is used to configure the initial conditions of the model predictive controller. For more information, see “Initial Conditions” on page 4-110.

Note A very small initial velocity, for example ϵ s, can produce a nonminimal realization for the controller plant model, causing an error. To prevent this error, set the initial velocity to a larger value, for example $1e-3$.

Transport lag between model inputs and outputs — Total transport lag in ego vehicle model

0 (default) | nonnegative scalar

Total transport lag, τ , in the ego vehicle model in seconds. This lag includes actuator, sensor, and communication lags. For each input-output channel, the transport lag model is:

$$\frac{1}{\tau s + 1}$$

Spacing Control**Maintain safe distance between lead vehicle and ego vehicle — Enable spacing control**

on (default) | off

To configure the safe following distance, set the **Default spacing** parameter. For more information on the safe following distance used by the controller, see “Safe Following Distance” on page 4-110.

Default spacing — Minimum spacing to lead vehicle

10 (default) | nonnegative scalar

Minimum spacing in meters between the lead vehicle and the ego vehicle. This value corresponds to the target relative distance between the ego and lead vehicles when the ego vehicle velocity is zero.

This value is used to calculate the:

- Minimum safe following distance. For more information, see “Safe Following Distance” on page 4-110.
- Controller initial conditions. For more information, see “Initial Conditions” on page 4-110.

Dependencies

To enable this parameter, select the **Maintain safe distance between lead vehicle and ego vehicle** parameter.

Controller Tab

Path Following Controller Constraints

Minimum steering angle — Minimum front steering angle

-0.26 (default) | scalar between $-\pi/2$ and $\pi/2$

Minimum front steering angle constraint in radians.

If the minimum steering angle varies over time, add the **Minimum steering angle** input port to the block by selecting **Use external source**.

Dependencies

This parameter must be less than the **Maximum steering angle** parameter.

Maximum steering angle — Maximum front steering angle

0.26 (default) | scalar between $-\pi/2$ and $\pi/2$

Maximum front steering angle constraint in radians.

If the maximum steering angle varies over time, add the **Maximum steering angle** input port to the block by selecting **Use external source**.

Dependencies

This parameter must be greater than the **Minimum steering angle** parameter.

Minimum longitudinal acceleration — Minimum ego vehicle acceleration

-3 (default) | scalar

Minimum ego vehicle longitudinal acceleration constraint in m/s^2 .

If the minimum acceleration varies over time, add the **Minimum longitudinal acceleration** input port to the block by selecting **Use external source**.

Maximum longitudinal acceleration — Maximum ego vehicle acceleration

2 (default) | scalar

Maximum ego vehicle longitudinal acceleration constraint in m/s^2 .

If the maximum acceleration varies over time, add the **Maximum longitudinal acceleration** input port to the block by selecting **Use external source**.

Model Predictive Controller Settings

Sample time — Controller sample time

0.1 (default) | positive scalar

Controller sample time in seconds.

Prediction horizon — Controller prediction horizon

10 (default) | positive integer

Controller prediction horizon steps. The controller prediction time is the product of the sample time and the prediction horizon.

Control horizon — Controller control horizon

3 (default) | positive integer | vector of positive integers

Controller control horizon, specified as one of the following:

- Positive integer less than or equal to the **Prediction horizon** parameter. In this case, the controller computes m free control moves occurring at times k through $k+m-1$, and holds the controller output constant for the remaining prediction horizon steps from $k+m$ through $k+p-1$. Here, k is the current control interval.
- Vector of positive integers, $[m_1, m_2, \dots]$, where the sum of the integers equals the **Prediction horizon** parameter. In this case, the controller computes M blocks of free moves, where M is the length of the control horizon vector. The first free move applies to times k through $k+m_1-1$, the second free move applies from time $k+m_1$ through $k+m_1+m_2-1$, and so on. Using block moves can improve the robustness of your controller.

Controller Behavior

Weight on velocity tracking — Tuning weight for longitudinal velocity tracking

0.1 (default) | positive scalar

Tuning weight for longitudinal velocity tracking. To produce smaller velocity-tracking errors, increase this weight.

Weight on lateral error — Tuning weight for lateral error

1 (default) | positive scalar

Tuning weight for lateral error. To produce smaller lateral errors, increase this weight.

Weight on change of longitudinal acceleration — Tuning weight for change in longitudinal acceleration

0.1 (default) | positive scalar

Tuning weight for changes in longitudinal acceleration. To produce less-aggressive vehicle acceleration, increase this weight.

Weight on change of steering angle — Tuning weight for change in steering angle

0.1 (default) | positive scalar

Tuning weight for changes in steering angle. To produce less-aggressive steering angle changes, increase this weight.

Block Tab

Use suboptimal solution — Apply suboptimal solution after specified number of iterations

off (default) | on

Configure the controller to apply a suboptimal solution after a specified maximum number of iterations, which guarantees the worst-case execution time for your controller.

For more information, see “Suboptimal QP Solution”.

Dependencies

After selecting this parameter, specify the **Maximum iteration number** parameter.

Maximum iteration number — Maximum optimization iterations

10 (default) | positive integer

Maximum number of controller optimization iterations.

Dependencies

To enable this parameter, select the **Use suboptimal solution** parameter.

Use external signal to enable or disable optimization — Add port for enabling optimization

off (default) | on

To add the **Enable optimization** input port to the block, select this parameter.

Use external signal for bumpless transfer between PFC and other controllers — Add external control signal input port

off (default) | on

To add the **External control signal** input port to the block, select this parameter.

Create PFC subsystem — Create custom controller

button

Generate a custom PFC subsystem, which you can modify for your application. The configuration data for the custom controller is exported to the MATLAB workspace as a structure.

You can modify the custom controller subsystem to:

- Modify default MPC settings or use advanced MPC features.
- Modify the default controller initial conditions.
- Use different application settings, such as a custom safe following distance definition.

Algorithms

Ego Vehicle Predictive Model

The default ego vehicle predictive model for path-following control is the combination of two state-space models, one for adaptive cruise control and one for lane keeping.

Adaptive Cruise Control Predictive Model

The predictive state-space model for adaptive cruise control is:

$$\begin{aligned} A_1 &= \begin{bmatrix} -1/\tau & 0 \\ 1 & 0 \end{bmatrix} \\ B_1 &= \begin{bmatrix} 1/\tau \\ 0 \end{bmatrix} \\ C_1 &= [0 \ 1] \\ D_1 &= 0 \end{aligned}$$

Here, τ is the **Longitudinal acceleration tracking time constant** parameter.

The input to this model is the longitudinal acceleration in m/s^2 , and the output is the longitudinal velocity in meters per second.

Lane-Keeping Predictive Model

The predictive state-space model for lane keeping is:

$$\begin{aligned} A_2 &= \begin{bmatrix} -2(C_F + C_R)/m/V_X & -V_X - 2(C_F L_F - C_R L_R)/m/V_X \\ -2(C_F L_F - C_R L_R)/I_Z/V_X & -2(C_F L_F^2 + C_R L_R^2)/I_Z/V_X \end{bmatrix} \\ B_2 &= 2C_F \begin{bmatrix} 1/m \\ L_F/I_Z \end{bmatrix} \\ C_2 &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \\ D_2 &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} \end{aligned}$$

Here:

- V_X is the longitudinal velocity of the car. At the start of the simulation, this velocity is equal to the **Initial condition for longitudinal velocity** parameter. At run time, this velocity is equal to the **Longitudinal velocity** input signal.
- m is the **Total mass** parameter.
- I_Z is the **Yaw moment of inertia** parameter.
- L_F is the **Longitudinal distance from center of gravity to front tires** parameter.
- L_R is the **Longitudinal distance from center of gravity to rear tires** parameter.
- C_F is the **Cornering stiffness of front tires** parameter.
- C_R is the **Cornering stiffness of rear tires** parameter.

The input to this model is the steering angle in radians. The outputs are the lateral velocity in meters per second and yaw angle rate in radians per second.

Combined Path-Following Predictive Model

The Path Following Control System block combines these models as follows:

$$A = \begin{bmatrix} A_1 & 0 \\ 0 & A_2 \end{bmatrix}$$

$$B = \begin{bmatrix} B_1 & 0 \\ 0 & B_2 \end{bmatrix}$$

$$C = \begin{bmatrix} C_1 & 0 \\ 0 & C_2 \end{bmatrix}$$

$$D = \begin{bmatrix} D_1 & 0 \\ 0 & D_2 \end{bmatrix}$$

The inputs to this combined model are the longitudinal acceleration in m/s² and steering angle in radians. The outputs are the longitudinal velocity in meters per second, lateral velocity in meters per second, and yaw angle rate in radians per second.

The controller creates its internal predictive model by augmenting the ego vehicle dynamic model. The augmented model includes the road curvature as a measured disturbance input signal.

Define a Custom Model

To define a different ego vehicle predictive model, select the **Use vehicle model** parameter, and specify the initial state-space model. Then, specify the run-time values of the state-space matrices using the **Vehicle dynamics A**, **Vehicle dynamics B**, and **Vehicle dynamics C** input signals.

Safe Following Distance

When the **Maintain safe distance between lead vehicle and ego vehicle** parameter is selected, the model predictive controller computes the safe following distance constraint; that is, the minimum relative distance between the lead and ego vehicle, as:

$$D_R = D_S + G_T * V_E$$

Here:

- D_S is the **Default spacing** parameter.
- G_T is the **Time gap** input signal.
- V_E is the **Longitudinal velocity** input signal.

To define a different safe following distance constraint, create a custom path-following control system by, on the **Block** tab, clicking **Create PFC subsystem**.

Initial Conditions

By default, the model predictive controller assumes the following initial conditions for the ego vehicle:

- Longitudinal velocity is equal to the **Initial longitudinal velocity** parameter.
- Longitudinal acceleration is zero.
- Lateral velocity is zero.
- Steering angle is zero.
- Yaw angle rate is zero.

When the **Maintain safe distance between lead vehicle and ego vehicle** parameter is selected, the controller assumes the following additional initial conditions:

- The lead vehicle longitudinal velocity is equal to the **Initial longitudinal velocity** parameter.
- Relative distance between the lead vehicle and ego vehicle is:

$$D_R = D_S + G_T * V_E$$

Here:

- D_S is the **Default spacing** parameter.
- G_T is the time gap and is assumed to be 1.4.
- V_E is the **Initial longitudinal velocity** parameter.

If the initial conditions in your model do not match these conditions, the **Steering angle** and **Longitudinal acceleration** outputs can exhibit initial bumps at the start of the simulation.

To modify the controller initial conditions to match your simulation, create a custom path-following control system by, on the **Block** tab, clicking **Create PFC subsystem**.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

PLC Code Generation

Generate Structured Text code using Simulink® PLC Coder™.

See Also

Blocks

Adaptive Cruise Control System | Lane Keeping Assist System

Introduced in R2019a

