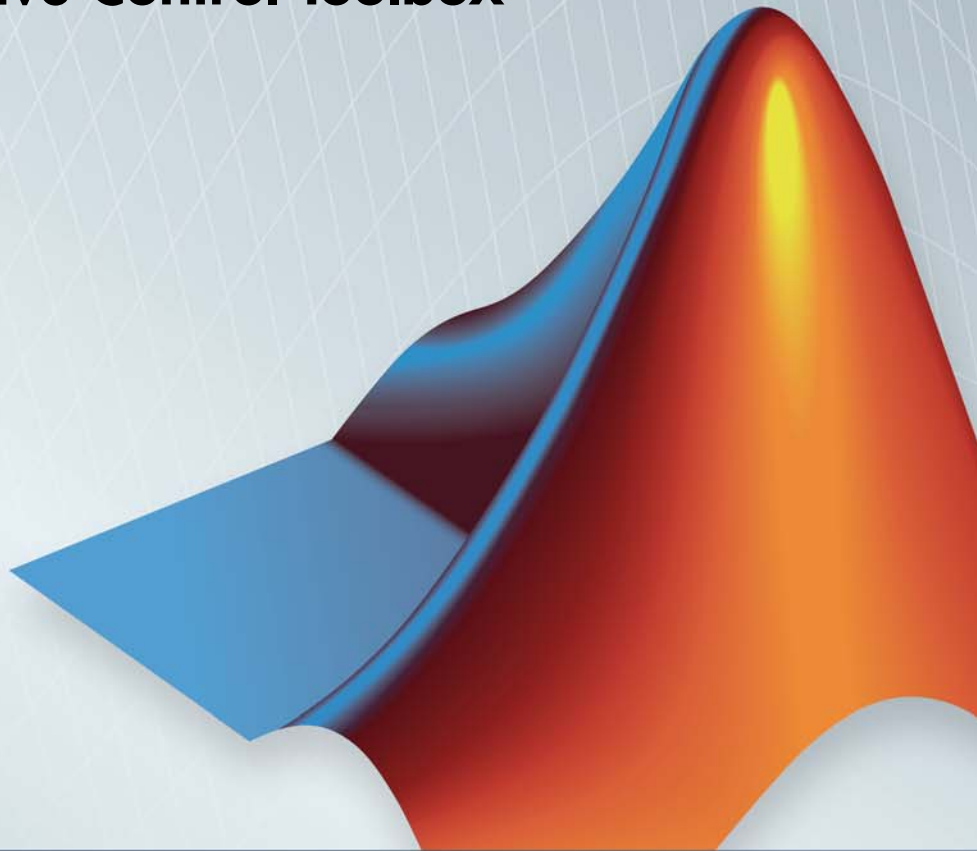# Model Predictive Control Toolbox™

Reference

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MATLAB®

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Functions – Alphabetical List

cloffset

Purpose   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.
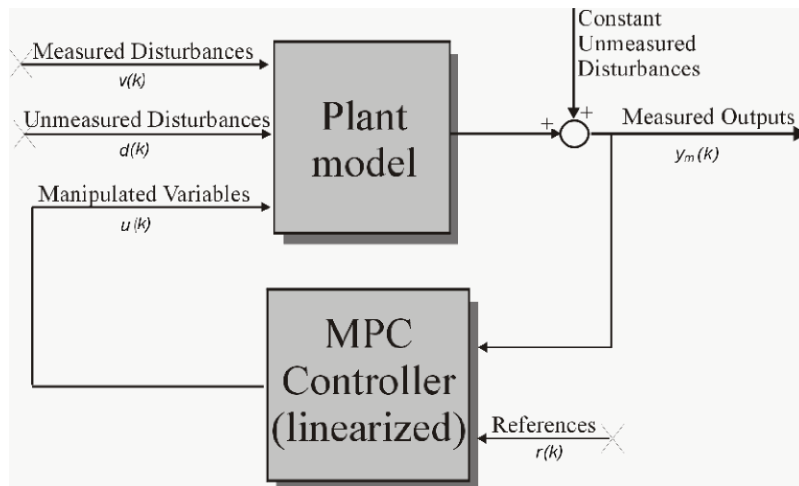
Computing the Effect of Output Disturbances

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.

Examples   See `misocloffset.m` in `mpcdemos`.

See Also   `mpc` | `ss`

Purpose	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 | pack

Purpose   Change MPC controller's sampling time

Syntax   `MPCobj=d2d(MPCobj,ts)`

Description   The d2d function changes the sampling time of the MPC controller
                   `MPCobj` to `ts`. All models are sampled or resampled as soon as the QP
                   matrices must be computed, e.g., when `sim` or `mpcmove` are used.

See Also   `mpc` | `set`

get

Purpose	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`. The string `'PropertyName'` can be 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

Purpose	Model Predictive Control custom constraint definitions
Syntax	`[E,F,G,V,S] = getconstraint(mpcobj)`

Description `[E,F,G,V,S] = getconstraint(mpcobj)` returns the custom constraints previously defined for the mpc object, `mpcobj`. The constraints are in the general form

$$Eu(k+j) + Fy(k+j) + Sv(k+j) \le G + \varepsilon V \qquad \text{(1-1)}$$

where:

- p — MPC prediction horizon.
- k — current time index.
- u — column vector of manipulated variables.
- y — column vector of all plant output variables.
- v — column vector of measured disturbance variables.
- ε — scalar slack variable used for constraint softening.
- E, F, G, V and S — constant matrices.

`getconstraint` calculates the last constraint at time $k+p$ assuming that `u(k+p|k) = u(k+p-1|k)`. This is because `u(k+p|k)` is not optimized by the model predictive controller.

Input Arguments

mpcobj

MPC controller, specified as an mpc object.

Output Arguments

E

Constant used in custom constraints as defined in Equation 1-1.

`[]` if `mpcobj` contains no custom constraints.

E is an n_c-by-n_u matrix, where n_c is the number of custom constraints and n_u is the number of manipulated variables.

getconstraint

F

Constant used in custom constraints as defined in Equation 1-1.

[ ] if mpcobj contains no custom constraints.

F is an n_c-by-n_y matrix, where n_c is the number of custom constraints and n_y is the number of output variables (measured and unmeasured).

G

Constant used in custom constraints as defined in Equation 1-1.

[ ] if mpcobj contains no custom constraints.

G is an n_c-by-1 vector, where n_c is the number of custom constraints.

V

Constant used in custom constraints as defined in Equation 1-1.

[ ] if mpcobj contains no custom constraints.

V is an n_c-by-1 vector, where n_c is the number of custom constraints.

If

- V(i) = 0 — the ith constraint is hard

- V(i) > 0 — the ith constraint is soft

  Where i = 1,...,n_c.

  In general, as V(i) decreases, the controller decreases the allowed constraint violation, i.e. the constraint becomes harder.

S

Constant used in custom constraints as defined in Equation 1-1.

[ ] if mpcobj contains no custom constraints or there are no measured disturbances in the custom constraints.

S is an n_c-by-n_{md} matrix, where n_c is the number of custom constraints and n_{md} is the number of measured disturbance inputs.

Examples   Obtain the constraints associated with an MPC controller.

Create an `mpc` object with 2 manipulated variables and 2 measured outputs.

```
p = rss(3,2,3);
p.D = 0;
p = setmpcsignals(p,'mv',[1 2],'md',3);
c = mpc(p,0.1);
```

Assume that you have two soft constraints.

$$u_1 + u_2 \le 5$$
$$y_2 + v \le 10$$

Set the constraints for the `mpc` object.

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

Obtain the constraints for `c`.

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

     1     1
     0     0


F =

     0     0
     0     1
```

```
G =

     5
    10


V =

     1
     1


S =

     0
     1
```

See Also   setconstraint

Purpose   Model and gain for observer design

Syntax   M=getestim(MPCobj)
                [M,A,Cm]=getestim(MPCobj)
                [M,A,Cm,Bu,Bv,Dvm]=getestim(MPCobj)
                [M,model,Index]=getestim(MPCobj,'sys')

Description M=getestim(MPCobj) extracts the estimator gain M used by
                the MPC controller MPCobj for observer design. The observer
                is based on the models specified in MPCobj.Model.Plant, in
                MPCobj.Model.Disturbance, by the output disturbance model
                (default is integrated white noise, see "Output Disturbance Model"
                in the Model Predictive Control Toolbox™ User's Guide), and by
                MPCobj.Model.Noise.

The state estimator is based on the linear model (see "State Estimation" in the Model Predictive Control Toolbox User's Guide)

$$x(k + 1) = Ax(k) + B_u u(k) + B_v v(k)$$

$$y_m(k) = C_m x(k) + D_{vm} v(k)$$

where $v(k)$ are the measured disturbances, $u(k)$ are the manipulated plant inputs, $y_m(k)$ are the measured plant outputs, and $x(k)$ is the overall state vector collecting states of plant, unmeasured disturbance, and measurement noise models.

The estimator used in the Model Predictive Control Toolbox software is described in "State Estimation". The estimator's equations are

Predicted Output Computation:

$$\hat{y}_m\left(k|k-1\right) = C_m \hat{x}(k|k-1) + D_{vm} v(k)$$

Measurement Update:

$$\hat{x}(k|k) = \hat{x}(k|k-1) + M\left(y_m(k) - \hat{y}_m\left(k|k-1\right)\right)$$

Time Update:

$$\hat{x}(k+1|k) = A\hat{x}(k|k) + B_u u(k) + B_v v(k)$$

By combining these three equations, the overall state observer is

$$\hat{x}(k+1|k) = (A - LC_m)\hat{x}(k|k-1) + Ly_m(k) + B_u u(k) + (B_v - LD_{vm})v(k)$$

where *L=AM*.

`[M,A,Cm]=getestim(MPCobj)` also returns matrices A, C_m used for observer design. This includes plant model, disturbance model, noise model, offsets. The extended state is

x=plant states; disturbance models states; noise model states]

`[M,A,Cm,Bu,Bv,Dvm]=getestim(MPCobj)` retrieves the whole linear system used for observer design.

`[M,model,Index]=getestim(MPCobj,'sys')` retrieves the overall model used for observer design (specified in the `Model` field of the MPC object) as an LTI state-space object, and optionally a structure `Index` summarizing I/O signal types.

The extended input vector of model `model` is

u=[manipulated vars;measured disturbances; 1; noise exciting disturbance model;noise exciting noise model]

Model `model` has an extra measured disturbance input v=1 used for handling possible nonequilibrium nominal values (see "Offsets" in the Model Predictive Control Toolbox User's Guide)

Input, output, and state names and input/output groups are defined for model `model`.

The structure `Index` has the fields detailed in the following table.

Field Name	Description
ManipulatedVariables	Indices of manipulated variables within input vector
MeasuredDisturbances	Indices of measured disturbances within input vector (not including offset=1)
Offset	Index of offset=1
WhiteNoise	Indices of white noise signals within input vector
MeasuredOutputs	Indices of measured outputs within output vector
UnmeasuredOutputs	Indices of unmeasured outputs within output vector

The model returned by getestim does not include the additional white noise added on manipulated variables and measured disturbances to ease the solvability of the Kalman filter design, as described in Equation (2–6) the Model Predictive Control Toolbox User's Guide.

See Also   setestim | mpc | mpcstate

getindist

Purpose	Unmeasured input disturbance model
Syntax	`model=getindist(MPCobj)`
Description	`model=getindist(MPCobj)` retrieves the linear discrete-time transfer function used to model unmeasured input disturbances in the MPC setup described by the MPC object `MPCobj`. Model `model` is an LTI object with as many outputs as the number of unmeasured input disturbances, and as many inputs as the number of white noise signals driving the input disturbance model. See "Model Used for State Estimation" in the Model Predictive Control Toolbox User's Guide for details about the overall model used in the MPC algorithm for state estimation purposes.
See Also	mpc | setindist | setestim | getestim | getoutdist

getmpcdata

Purpose
Private MPC data structure

> **Note** getmpcdata will be removed in a future version. Use get, getconstraint, getestim, getindist andgetoutdist instead.

Syntax
mpcdata=getmpcdata(MPCobj)

Description
mpcdata=getmpcdata(MPCobj) returns the private field MPCData of the MPC object MPCobj. Here, all internal QP matrices, models, estimator gains are stored at initalization of the object. You can manually change the private data structure using the setmpcdata command, although you may only need this for very advanced use of Model Predictive Control Toolbox software.

> **Note** Changes to the data structure may easily lead to unpredictable results.

See Also
setmpcdata | set | get

getname

Purpose	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 I-th 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 I-th 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	setname | mpc | set

Purpose   Unmeasured output disturbance model

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

Description `outdist=getoutdist(MPCobj)` retrieves the linear discrete-time transfer function used to model output disturbances in the MPC setup described by the MPC object `MPCobj`. Model `outdist` is an LTI object with as many outputs as the number of measured + unmeasured outputs, and as many inputs as the number of white noise signals driving the output disturbance model.

See "Model Used for State Estimation" in the Model Predictive Control Toolbox User's Guide for details about the overall model used in the MPC algorithm for state estimation purposes.

`[outdist,channels]=getoutdist(MPCobj)` also returns the output channels where integrated white noise was added as an output disturbance model. This is only meaninful when the default output disturbance model is used, namely when `MPCobj.OutputVariables(i).Integrators` is empty for all channels `i`. The array `channels` is empty for output disturbance models.

See Also   `mpc` | `setoutdist` | `setestim` | `getestim` | `getindist`

gpc2mpc

Purpose	Generate MPC controller using generalized predictive controller (GPC) settings
Syntax	*mpc* = gpc2mpc(*plant*) *gpcOptions* = gpc2mpc *mpc* = gpc2mpc(*plant*,*gpcOptions*)
Description	*mpc* = gpc2mpc(*plant*) generates a single-input single-output MPC controller with default GPC settings and sampling time of the plant, *plant*. The GPC is a nonminimal state-space representation described in [1]. *plant* is a discrete-time LTI model with sampling time greater than 0.
	gpcOptions = gpc2mpc creates a structure *gpcOptions* containing default values of GPC settings.
	mpc = gpc2mpc(*plant*,*gpcOptions*) generates an MPC controller using the GPC settings in *gpcOptions*.
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.
Input Arguments	**plant** Discrete-time LTI model with sampling time greater than 0.
	gpcOptions GPC settings, specified as a structure with the following fields.

N1	Starting interval in prediction horizon, specified as a positive integer. **Default:** 1.
N2	Last interval in prediction horizon, specified as a positive integer greater than N1. **Default:** 10.
NU	Control horizon, specified as a positive integer less than the prediction horizon. **Default:** 1.
Lam	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.

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);
```

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

See Also   "MPC Controller Object" on page 3-2

- "Design Controller Using the Design Tool"

- "Design Controller at the Command Line"

—

Purpose   Create MPC controller

Syntax
```
MPCobj=mpc(plant)
MPCobj=mpc(plant,ts)
MPCobj=mpc(plant,ts,p,m)
MPCobj=mpc(plant,ts,p,m,weights)
MPCobj=mpc(plant,ts,p,m,weights,MV,OV,DV)
MPCobj=mpc(models,ts,p,m,weights,MV,OV,DV)
MPCobj=mpc
```

Description   `MPCobj=mpc(plant)` creates an MPC controller based on the
discrete-time model `plant`. The model can be specified either as an LTI
object, or as an object in System Identification Toolbox™ format. See
"Identify Plant from Data".

`MPCobj=mpc(plant,ts)` also specifies the sampling time `ts` for the MPC
controller. A continuous-time `plant` is discretized with sampling time
`ts`. A discrete-time `plant` is resampled if its sampling time is different
than the controller's sampling time `ts`. If `plant` is a discrete-time model
with unspecified sampling time, namely `plant.ts=-1`, then Model
Predictive Control Toolbox software assumes that the plant is sampled
with the controller's sampling time `ts`. `ts` has the same unit as the
internal predictive plant model, i.e., `plant.TimeUnit`.

`MPCobj=mpc(plant,ts,p,m)` also specifies prediction horizon `p` and
control horizon `m`.

`MPCobj=mpc(plant,ts,p,m,weights)`also specifies the structure
`weights` of input, input increments, and output weights (see "Weights"
on page 3-7).

`MPCobj=mpc(plant,ts,p,m,weights,MV,OV,DV)` also specifies
limits on manipulated variables (MV) and output variables (OV), as
well as equal concern relaxation values, units, etc. Names and
units of input disturbances can be also specified in the optional
input DV. The fields of structures MV, OV, and DV are described in
"ManipulatedVariables" on page 3-3, in "OutputVariables" on page 3-4,
and in "DisturbanceVariables" on page 3-6, respectively).

MPCobj=mpc(models,ts,p,m,weights,MV,OV,DV) where model is
a structure containing models for plant, unmeasured disturbances,
measured disturbances, and nominal linearization values, as described
in "Model" on page 3-9.

MPCobj=mpc returns an empty MPC object.

Note Other MPC properties are specified by using
set(MPCobj,Property1, Value1,Property2,Value2,...)
or MPCobj.Property=Value.

Construction and Initialization

An MPC controller is built in two steps. The first step happens *at construction* when the object constructor mpc is invoked, or properties are changed by a set command. At this first stage, only basic consistency checks are performed, such as dimensions of signals, weights, constraints, etc. The second step happens *at initialization*, namely when the object is used for the first time by methods such as mpcmove and sim, that require the full computation of the QP matrices and the estimator gain. At this second stage, further checks are performed, such as a test of observability of the overall extended model.

Informative messages are displayed in the command window in both phases, you can turn them on or off using the mpcverbosity command.

Properties

All the parameters defining the MPC control law (prediction horizon, weights, constraints, etc.) are stored in an MPC object, whose properties are listed in the following table (MPC Controller Object on page 3-2).

MPC Controller Object

Property	Description
`ManipulatedVariables` (or `MV` or `Manipulated` or `Input`)	Input and input-rate upper and lower bounds, ECR values, names, units, and input target
`OutputVariables` (or `OV` or `Controlled` or `Output`)	Output upper and lower bounds, ECR values, names, units
`DisturbanceVariables` (or `DV` or `Disturbance`)	Disturbance names and units
`Weights`	Weights defining the performance function
`Model`	Plant, input disturbance, and output noise models, and nominal conditions.
`Ts`	Controller's sampling time
`Optimizer`	Parameters for the QP solver
`PredictionHorizon`	Prediction horizon
`ControlHorizon`	Number of free control moves or vector of blocking moves
`History`	Creation time
`Notes`	Text or comments about the MPC controller object
`UserData`	Any additional data
`MPCData` (private)	Matrices for the QP problem and other accessorial data
`Version` (private)	Model Predictive Control Toolbox version number

ManipulatedVariables

ManipulatedVariables (or MV or Manipulated or Input) is an
n_u-dimensional array of structures (n_u = number of manipulated
variables), one per manipulated variable. Each structure has the fields
described in the following table (Structure ManipulatedVariables on
page 3-3), where p denotes the prediction horizon.

Structure ManipulatedVariables

Field Name	Content	Default
Min	1 to p dimensional vector of lower constraints on a manipulated variable u	-Inf
Max	1 to p dimensional vector of upper constraints on a manipulated variable u	Inf
MinECR	1 to p dimensional vector describing the equal concern for the relaxation of the lower constraints on u	0
MaxECR	1 to p dimensional vector describing the equal concern for the relaxation of the upper constraints on u	0
Target	1 to p dimensional vector of target values for the input variable u	'nominal'
RateMin	1 to p dimensional vector of lower constraints on the rate of a manipulated variable u	-Inf if problem is unconstrained, otherwise -10
RateMax	1 to p dimensional vector of upper constraints on the rate of a manipulated variable u	Inf

Structure ManipulatedVariables (Continued)

Field Name	Content	Default
RateMinECR	1 to *p* dimensional vector describing the equal concern for the relaxation of the lower constraints on the rate of *u*	0
RateMaxECR	1 to *p* dimensional vector describing the equal concern for the relaxation of the upper constraints on the rate of *u*	0
Name	Name of input signal. This is inherited from `InputName` of the LTI plant model.	`InputName` of LTI plant model
Units	String specifying the measurement units for the manipulated variable	' '

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 $du/dt \cong \Delta u(k)/T_s$.

OutputVariables

`OutputVariables` (or `OV` or `Controlled` or `Output`) is an n_y-dimensional array of structures (n_y = number of outputs), one per output signal. Each structure has the fields described in the following table (Structure OutputVariables on page 3-5), where *p* denotes the prediction horizon.

Structure OutputVariables

Field Name	Content	Default
Min	1 to *p* dimensional vector of lower constraints on an output *y*	-Inf
Max	1 to *p* dimensional vector of upper constraints on an output *y*	Inf
MinECR	1 to *p* dimensional vector describing the equal concern for the relaxation of the lower constraints on an output *y*	1
MaxECR	1 to *p* dimensional vector describing the equal concern for the relaxation of the upper constraints on an output *y*	1
Name	Name of output signal. This is inherited from OutputName of the LTI plant model.	OutputName of LTI plant model
Units	String specifying the measurement units for the measured output	''
Integrator	Magnitude of integrated white noise on the output channel (0=no integrator)	[]

In order to reject constant disturbances due for instance to gain nonlinearities, the default output disturbance model used in Model Predictive Control Toolbox software is a collection of integrators driven by white noise on measured outputs (see "Output Disturbance Model"in the Model Predictive Control Toolbox User's Guide). Output integrators are added according to the following rule:

1 Measured outputs are ordered by decreasing output weight (in case of time-varying weights, the sum of the absolute values over time

is considered for each output channel, and in case of equal output weight, the order within the output vector is followed).

2 By following such order, an output integrator is added per measured outputs, unless there is a violation of observability, or you force it by zeroing the corresponding value in OutputVariables.Integrators).

By default, OutputVariables.Integrators is empty on all outputs. This enforces the default action of Model Predictive Control Toolbox software, namely add integrators on measured outputs, do not add integrators on unmeasured outputs. By setting the entry of OutputVariables(i).Integrators to zero, no attempt will be made to add integrated white noise on the i-th output . On the contrary, by setting the entry of OutputVariables(i).Integrators to one, an attempt will be made to add integrated white noise on the i-th output (see getoutdist).

DisturbanceVariables

DisturbanceVariables (or DV or Disturbance) is an $(n_v + n_d)$-dimensional array of structures (n_v = number of measured input disturbances, n_d = number of unmeasured input disturbances), one per input disturbance. Each structure has the fields described in the following table (Structure DisturbanceVariables on page 3-6).

Structure DisturbanceVariables

Field Name	Content	Default
Name	Name of input signal. This is inherited from InputName of the LTI plant model.	InputName of LTI plant model
Units	String specifying the measurement units for the manipulated variable	''

The order of the disturbance signals within the array DisturbanceVariables is the following: the first n_v entries relate to

measured input disturbances, the last n_d entries relate to unmeasured input disturbances.

Note The `Name` properties of `ManipulatedVariables`, `OutputVariables`, and `DisturbanceVariables` are read only. You can set signal names in the `Model.Plant.InputName` and `Model.Plant.OutputName`properties of the MPC object, for instance by using the method `setname`.

Weights

`Weights` is the structure defining the QP weighting matrices. Unlike the `InputSpecs` and `OutputSpecs`, which are arrays of structures, `weights` is a single structure containing four fields. The values of these fields depend on whether you are using the standard quadratic cost function (Equation (2–3)) or the alternative cost function (Equation (2–5)).

Standard Cost Function

The table below, Weights for the Standard Cost Function (MATLAB® Structure) on page 3-7, lists the content of the four fields where *p* denotes the prediction horizon, n_u the number of manipulated variables, n_y the number of output variables.

The fields `ManipulatedVariables`, `ManipulatedVariablesRate`, and `OutputVariables` are arrays with n_u, n_u, and n_y columns, respectively. If weights are time invariant, then `ManipulatedVariables`, `ManipulatedVariablesRate`, and `OutputVariables` are row vectors. However, for time-varying weights, each field is a matrix with up to *p* rows. If the number of rows is less than the prediction horizon, *p*, the object constructor duplicates the last row to create a matrix with *p* rows.

Weights for the Standard Cost Function (MATLAB Structure)

Field Name	Content	Default
ManipulatedVariables (or MV or Manipulated or Input)	(1 to p)-by-n_u dimensional array of input weights	zeros(1,nu)
ManipulatedVariablesRate (or MVRate or ManipulatedRate or InputRate)	(1 to p)-by-n_u dimensional array of input-rate weights	0.1*ones(1,nu)
OutputVariables (or OV or Controlled or Output)	(1 to p)-by-n_y dimensional array of output weights	1 (The default for output weights is the following: if $n_u \geq n_y$, all outputs are weighted with unit weight; if $n_u < n_y$, n_u outputs are weighted with unit weight (with preference given to measured outputs), while the remaining outputs receive zero weight.)
ECR	Weight on the slack variable ε used for softening the constraints	1e5*(max weight)

The default ECR weight is 10^5 times the largest weight specified in ManipulatedVariables, ManipulatedVariablesRate, and OutputVariables.

> **Note** All weights must be greater than or equal to zero. If all weights
> on manipulated variable increments are strictly positive, the resulting
> QP problem is always strictly convex. If some of those weights are
> zero, the Hessian matrix of the QP problem may become only positive
> semidefinite. In order to keep the QP problem always strictly convex,
> if the condition number of the Hessian matrix $K_{\Delta U}$ is larger than 10^{12},
> the quantity `10*sqrt(eps)` is added on each diagonal term. This may
> only occur when all input rates are not weighted ($W^{\Delta u}$=0) (see "Cost
> Function" in the *Model Predictive Control Toolbox User's Guide*).

Alternative Cost Function

You can specify off-diagonal Q and R weight matrices in the cost function.
To accomplish this, you must define the fields `ManipulatedVariables`,
`ManipulatedVariablesRate`, and `OutputVariables` as cell arrays, each
containing a single positive-semi-definite matrix of the appropriate
size. Specifically, `OutputVariables` must be a cell array containing
the n_y-by-n_y Q matrix, `ManipulatedVariables` must be a cell array
containing the n_u-by-n_u R_u matrix, and `ManipulatedVariablesRate`
must be a cell array containing the n_u-by-n_u $R_{\Delta u}$ matrix (see Equation
(2–5)) and the `mpcweightsdemo` example). You can abbreviate the field
names as shown in Weights for the Standard Cost Function (MATLAB®
Structure) on page 3-7. You can also use diagonal weights (as defined
in Weights for the Standard Cost Function (MATLAB® Structure) on
page 3-7) for one or more of these fields. If you omit a field, the object
constructor uses the defaults shown in Weights for the Standard Cost
Function (MATLAB® Structure) on page 3-7.

For example, you can specify off-diagonal weights, as follows

```
MPCobj.Weights.OutputVariables={Q};
MPCobj.ManipulatedVariables={Ru};
MPCobj.ManipulatedVariablesRate={Rdu};
```

where `Q`=Q. `Ru`=R_u, and $Rdu = R_{\Delta u}$ are positive semidefinite matrices.

Note You cannot specify off-diagonal time-varying weights.

Model

The property Model specifies plant, input disturbance, and output noise models, and nominal conditions, according to the model setup described in "Model Used for State Estimation" in the Model Predictive Control Toolbox User's Guide. It is specified through a structure containing the fields reported in Structure Model Describing the Models Used by MPC on page 3-9.

Structure Model Describing the Models Used by MPC

Field Name	Content	Default
Plant	LTI model or identified linear model of the plant	No default
Disturbance	LTI model describing color of input disturbances	An integrator on each Unmeasured input channel
Noise	LTI model describing color of plant output measurement noise	Unit white noise on each measured output = identity static gain
Nominal	Structure containing the state, input, and output values where Model.Plant is linearized	See Nominal Values at Operating Point on page 3-11.

Note Direct feedthrough from manipulated variables to any output in Model.Plant is not allowed. See "Prediction Model" in the Model Predictive Control Toolbox User's Guide.

The type of input and output signals is assigned either through the `InputGroup` and `OutputGroup` properties of `Model.Plant`, or, more conveniently, through function `setmpcsignals`, according to the nomenclature described in Input Groups in Plant Model on page 3-10 and Output Groups in Plant Model on page 3-11.

Input Groups in Plant Model

Name	Value
`ManipulatedVariables` (or `MV` or `Manipulated` or `Input`)	Indices of manipulated variables
`MeasuredDisturbances` (or `MD` or `Measured`)	Indices of measured disturbances
`UnmeasuredDisturbances` (or `UD` or `Unmeasured`)	Indices of unmeasured disturbances

Output Groups in Plant Model

Name	Value
`MeasuredOutputs` (or `MO` or `Measured`)	Indices of measured outputs
`UnmeasuredOutputs` (or `UO` or `Unmeasured`)	Indices of unmeasured outputs

By default, all inputs are manipulated variables, and all outputs are measured.

> **Note** With this current release, the `InputGroup` and `OutputGroup` properties of LTI objects are defined as structures, rather than cell arrays (see the Control System Toolbox™ documentation for more details).

The structure `Nominal` contains the nominal values for states, inputs, outputs and state derivatives/differences at the operating point where `Model.Plant` was linearized. The fields are reported in Nominal Values at Operating Point on page 3-11 (see "Offsets" in the Model Predictive Control Toolbox User's Guide).

Nominal Values at Operating Point

Field	Description	Default
X	Plant state at operating point	0
U	Plant input at operating point, including manipulated variables, measured and unmeasured disturbances	0
Y	Plant output at operating point	0
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.	0

Ts

Sampling time of the MPC controller. By default, if `Model.Plant` is a discrete-time model, `Ts=Model.Plant.ts`. For continuous-time plant models, you must specify a sampling time for the MPC controller.

Optimizer

Parameters for the QP optimization. Optimizer is a structure with the fields reported in the following table (Optimizer Properties on page 3-12).

Optimizer Properties

Field	Description	Default
MaxIter	Maximum number of iterations allowed in the QP solver	200
Trace	On/off	'off'
Solver	QP solver used (only 'ActiveSet')	'ActiveSet'
MinOutputECR	Minimum positive value allowed for OutputMinECR and OutputMaxECR	1e-10

MinOutputECR is a positive scalar used to specify the minimum allowed ECR for output constraints. If values smaller than MinOutputECR are provided in the OutputVariables property of the MPC objects a warning message is issued and the value is raised to MinOutputECR.

PredictionHorizon

PredictionHorizon is an integer value expressing the number p of sampling steps of prediction.

ControlHorizon

ControlHorizon is either a number of free control moves, or a vector of blocking moves (see "Optimization Variables" in the Model Predictive Control Toolbox User's Guide).

History

History stores the time the MPC controller was created.

Notes

Notes stores text or comments as a cell array of strings.

UserData

Any additional data stored within the MPC controller object.

MPCData

MPCData is a private property of the MPC object used for storing intermediate operations, QP matrices, internal flags, etc.

Version

Version is a private property indicating the Model Predictive Control Toolbox version number.

Examples Define an MPC controller based on the transfer function model s+1/(s^2+2s), with sampling time T_s=0.1 s, and satisfying the input constraint -1≤ u ≤1:

```
Ts=.1;    %Sampling time
MV=struct('Min',-1,'Max',1);
p=20;
m=3;

mpc1=mpc(tf([1 1],[1 2 0]),Ts,p,m,[],MV);
```

See Also set | get

mpchelp

Purpose	MPC property and function help
| **Syntax** | ```
mpchelp
mpchelp name
out=mpchelp(`name')
mpchelp(obj)
mpchelp(obj,'name')
out=mpchelp(obj,'name')
``` |
Description	`mpchelp` provides a complete listing of Model Predictive Control Toolbox help.
	`mpchelp name` provides online help for the function or property `name`.
	`out=mpchelp(`name')` returns the help text in string, `out`.
	`mpchelp(obj)` displays a complete listing of functions and properties for the MPC object, `obj`, along with the online help for the object's constructor.
	`mpchelp(obj,'name')` displays the help for function or property, `name`, for the MPC object, `obj`.
	`out=mpchelp(obj,'name')` returns the help text in string, `out`.
Examples	To get help on the MPC method `getoutdist`, you can type:

```
mpchelp getoutdist
``` |
| **See Also** | `mpcprops` |

Purpose	Optimal control action
Syntax	u = mpcmove(MPCobj,x,ym,r,v) [u,Info] = mpcmove(MPCobj,x,ym,r,v) [u,Info] = mpcmove(MPCobj,x,ym,r,v,Options)

Description   u = mpcmove(MPCobj,x,ym,r,v) computes the optimal manipulated variable moves, *u(k)*. *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 time *k*. Call mpcmove repeatedly to simulate closed-loop model predictive control.

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

[u,Info] = mpcmove(MPCobj,x,ym,r,v,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 in constraints and weights during the closed-loop simulation.

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.

Input Arguments

MPCobj

mpc object that defines the model predictive controller.

x

mpcstate object that contains the following:

- Estimated plant model states, *x(k|k-1)*

- Estimated input and output disturbance model states, x_d*(k|k-1)*

- Estimated measurement noise model states, x_m*(k|k-1)*

- Last controller moves, *u(k-1)*

To initialize `x`, use `x = mpcstate(MPCobj)` and modify default properties as needed.

You may need to change the value of `x` before using it at the next time step under certain circumstances. Suppose that the optimal value for *u* calculated in the previous call to `mpcmove` was not used in the plant for some reason (e.g., saturation). You must replace `LastMove` with the values actually used.

`mpcmove` updates all four properties of `x` to prepare for an `mpcmove` call at the next time step. For example, it copies the recommended *u* values into the `LastMove` field.

To retain the original contents of `x`, create a copy of it before calling `mpcmove`.

ym

1-by-n_{ym} vector of current measured output values at time *k*.

n_{ym} is the number of measured outputs.

r

p-by-n_y array of future reference values for the outputs, where *p* is the prediction horizon and n_y is the number of outputs. The ith row of `r` defines the reference values at time *k*+i, for `i = 1,...,p`.

The first row must contain the reference signal at time *k*+1. Additional rows represent known future references and are optional (future values are unknown in most applications). If you supply fewer than *p* rows of data, `mpcmove` duplicates the last row to fill the array.

You cannot preview the reference signal (also referred to as look-ahead and anticipation) if r contains a single row. To support reference previewing, supply at least two rows of data for r.

v

p-by-n_{md} array of current and future measured disturbance, where p is the prediction horizon and n_{md} is the number of measured disturbances used in feed-forward control. The ith row of v defines the measured disturbance values at time k+i-1, for i = 1,...,p.

The first row must contain the current measured disturbance values. Additional rows represent known future values and are optional (future values are unknown in most applications). If you supply fewer than p rows of data, mpcmove duplicates the last row to fill the array.

You cannot preview the measured disturbance signal (also referred to as look-ahead and anticipation) if v contains a single row. To support disturbance previewing, supply at least two rows of data for v.

Options

mpcmoveopt object that overrides constraints and weights in MPCobj. This approach is computationally efficient to simulate run-time changes in controller tuning and limit values. The same behavior can be found in a Simulink® MPC Controller block when supplied with controller tuning and limit input signals.

Output Arguments

u

1-by-n_u array of optimal manipulated variable moves, where n_u is the number of manipulated variables.

mpcmove holds u at its most recent successful solution if the QP solver fails to find a solution for the current time k.

Info

Information regarding the model predictive controller.

Info is a structure with the following fields:

- Uopt — p+1-by-n_u array containing the optimal manipulated variable adjustments (moves),where p is the prediction horizon and n_u is the number of manipulated variables.

  The first row is the same as u, which is to be applied at the current time k. $Uopt$(i,:) contains the predicted optimal values at time $k+i$-1, for i = 1,...,p+1.

  mpcmove does not calculate optimal control moves at time $k+p$ and therefore it sets $Uopt$(p+1,:) to NaN.

- Yopt — p+1-by-n_y array containing the predicted output variable sequence, where p is the prediction horizon and n_y is the number of outputs.

  The first row contains the current outputs at time k after state estimation. Yopt(i,:) contains the values at time $k+i$-1, for i = 1,...,p+1.

- Xopt — p+1-by-n_x array containing the predicted state variable sequence, where p is the prediction horizon and n_x is the number of states.

  The first row contains the current states at time k as determined by state estimation.Xopt(i,:) contains the values at time $k+i$-1, for i = 1,...,p+1.

- Topt — p+1-by-1 vector of time intervals where Topt(1)=0 (representing the current time) and Topt(i)=Ts*(i-1), where Ts=MPCobj.Ts, the controller sample time and for i = 1,...,p+1.

  Use when plotting Uopt, Yopt and/or Xopt sequences.

- Slack — Slack variable, ε, used in constraint softening.

  Slack is a scalar that may have the following values:

  - 0 — All constraints were satisfied for the entire prediction horizon

  - >0 — At least one soft constraint is violated and represents the worst-case soft constraint violation (scaled by your ECR values for each constraint) when more than one constraints are violated.

See "Optimization Problem" for details.

- Iterations — QP solution result.

  Iterations is a scalar integer that may have the following values:

  - \>0 — Number of iterations needed to solve the quadratic programming (QP) problem that determines the optimal sequences.

  - 0 — QP problem could not be solved in the allowed maximum number of iterations.

  - -1 — QP problem was infeasible. A QP problem is infeasible if no solution can satisfy all the hard constraints.

  - -2 — Numerical error occurred when solving the QP problem.

- QPCode — QP solution status.

  QPCode is a String that may have the following values:

  - 'feasible' — Optimal solution was obtained (Iterations > 0)

  - 'infeasible' — QP solver detected a problem with no feasible solution (Iterations = -1) or a numerical error occured (Iterations = -2)

  - 'unreliable' — QP solver failed to converge (Iterations = 0)

- Cost — Cost of the objective function.

  Cost quantifies the degree to which the controller has achieved its objectives and is a non-negative scalar value. Cost is only meaningful when QPCode is 'feasible'.

  See "Optimization Problem" for details.

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

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

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

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); %storage array for OV values
u = zeros(N,1); %storage array for MV values
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
```

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 8 seconds (the 5th 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 a scenario at a single time instance, plotting the predicted optimal MV and OV sequences over the prediction horizon.

Define a plant model.

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

Create a model predictive controller with MV and MVRate constraints. The prediction horizon is 10 intervals. The control horizon is blocked.

```
MPCobj = mpc(Plant, ts, 10, [2 3 5]);
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);
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 =
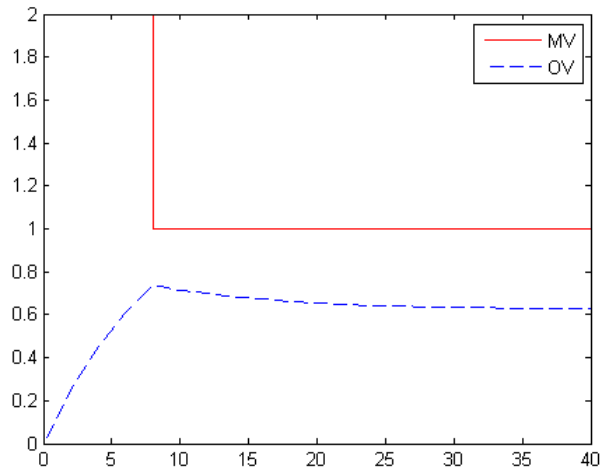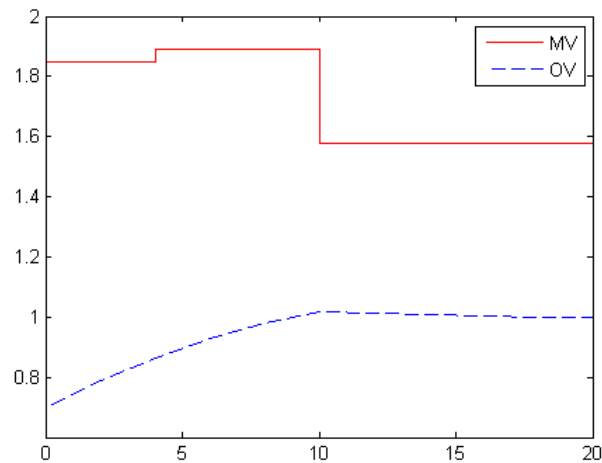
    0.0793
```

Alternatives
- Use `sim` for plant mismatch and noise simulation when not using run-time constraints or weight changes.

- Use `mpctool` to graphically and interactively combine model predictive design and simulation.

- Use the MPC Controller block in Simulink and for code generation.

See Also   mpc | mpcmoveopt | mpcstate | review | sim | setestim | getestim

Tutorials
- MPC Control with Anticipative Action (Look-Ahead)

- MPC Control with Input Quantization Based on Comparing the Optimal Costs

- Analysis of Control Sequences Optimized by MPC on a Double Integrator System

Purpose   Options set for mpcmove

Syntax   options = mpcmoveopt

Description options = mpcmoveopt creates an mpcmoveopt object, with default
                values for its properties. Use this object with mpcmove to allow run-time
                adjustment of the weights and constraints of the Model Predictive
                Controller, an mpc object, that is operating.

Tips
- The number of manipulated variables (n_u) and output variables (n_y)
  for the mpcmoveopt object must match that of the corresponding mpc
  object.

- If any weight property in options is set to [] (default), mpcmove uses
  the corresponding weight specified in the mpc object.

- In general, constraint specifications of options must be consistent
  with those of the corresponding mpc object.

  If all of the four constraint properties of options are set to []
  (default), mpcmove uses the existing constraints specified for the
  corresponding mpc object. The result will be the same as if there are
  no run-time constraint changes.

  Otherwise:

  - Constraints set to [] are treated as unbounded signals. The
    corresponding constraint settings for the mpc object must also be
    unbounded.

  - Constraints not set to [] are treated as bounded signals. The
    corresponding constraint settings for the mpc object must also be
    bounded.

    These requirements make the Model Predictive Controller object
    behave consistently with the corresponding MPC Controller block
    in Simulink

  A conflict may arise when you have a mixture of bounded and
  unbounded variables for one or more constraint properties of

`options`. It may be resolved by defining compatible constraints for the `mpc` object and corresponding `mpcmoveopt` object.

For example, suppose $n_y = 2$, and your `mpc` object defines a maximum for the first output variable but the second has no upper bound. If,

- `options.OutputMax = []`, then `mpcmove` interprets this as an attempt to remove the upper bound on the first output.

- `options.OutputMax` is not `[]`, then, because all entries must be finite, `mpcmove` interprets this as an attempt to impose a new upper bound on the second output.

To avoid this conflict, modify your `mpc` object to have a large but finite upper bound on the second output. It can then be paired with `options`, containing finite `OutputMax` values, without conflict.

Output Arguments

options

Options for the `mpcmove` command with the following fields:

- OutputWeights — 1-by-n_y vector of output variable tuning weights, where n_y is the number of output variables.`mpcmove` replaces the `Weight.OutputVariables` field of the corresponding `mpc` object with this vector. The weights must be finite and real values.

- MVRateWeights — 1-by-n_u vector of manipulated variable rate tuning weights, where n_u is the number of manipulated variables. `mpcmove` replaces the `Weight.ManipulatedVariablesRate` field of the corresponding `mpc` object with this vector. The weights must be finite and real values.

- ECRWeight — Scalar weight on the slack variable used for constraint softening. `mpcmove` replaces the `Weight.ECR` field of the corresponding `mpc` object with this value. The weight must be a finite and real value.

- OutputMin — 1-by-n_y vector of lower bounds on the output variables, where n_y is the number of output variables. `mpcmove` replaces the `OutputVariables(i).Min` field of the corresponding `mpc` object with this vector, for `i = 1,...,ny`.

- OutputMax — 1-by-n_y vector of upper bounds on the output variables, where n_y is the number of output variables. mpcmove replaces the OutputVariables(i).Max field of the corresponding mpc object with this vector, for i = 1,...,ny.

- MVMin — 1-by-n_u vector of lower bounds on the manipulated variables, where n_u is the number of manipulated variables. mpcmove replaces the ManipulatedVariables(i).Min field of the corresponding mpc object with this vector, for i = 1,...,nu.

- MVMax — 1-by-n_u vector of upper bounds on the manipulated variables, where n_u is the number of manipulated variables. mpcmove replaces the ManipulatedVariables(i).Max field of the corresponding mpc object with this vector, for i = 1,...,nu.

- OnlyComputeCost — Logical value to control whether the optimal sequence is to be calculated and exported.

  - 0 (default) sets mpcmove to compute and return the optimal cost and the optimal sequence of the Model Predictive Controller objective function.

  - 1 sets mpcmove to compute and return only the optimal cost of the Model Predictive Controller objective function.

Examples   Use an mpcmoveopt object to vary an MV upper bound during a simulation employing mpcmove. The upper bound decreases step-wise from 2 to 1 when elapsed time exceeds 4 seconds. Also, setting OnlyComputeCost = 1causes the Info object returned by mpcmove to contain the cost only.

Define an mpcmoveopt object and initialize some of its fields.

```
OPTobj = mpcmoveopt;
OPTobj.OnlyComputeCost = true;
OPTobj.MVMin = -2;
```

Define a plant model and a model predictive controller object.

```
ts = 2;
```

```
Plant = ss(0.8, 0.5, 0.25, 0, ts);
MPCobj = mpc(Plant, ts);
MPCobj.MV(1).Min = -2;
MPCobj.MV(1).Max =  2;
```

Perform mpcmove simulation.

```
x = mpcstate(MPCobj);
r = 1;
v = [];
t = [0:ts:10];
N = length(t);
y = zeros(N,1);
u = zeros(N,1);
for i = 1:N
    y(i) = 0.25*x.Plant;
    % Use the MPCMOVEOPT object to modify the MV upper bound in
    % real time.
    if t(i) <= 4
        OPTobj.MVMax = 2;
    else
        OPTobj.MVMax = 1;
    end
    [u(i), Info] = mpcmove(MPCobj, x, y(i), r, v, OPTobj);
end
```

Analyze the results.

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

Alternatives   When you use mpcmove, an mpcmoveopt object is optional. As an
alternative, you can modify the weight, constraint definitions, or both
before calling mpcmove. This approach is usually less computationally
efficient, but it avoids potential conflicts with constraint definitions
when mixed bounded and unbounded variables are present.

See Also   mpc | mpcmove | setconstraint | setterminal

mpcprops

Purpose   Provide help on MPC controller's 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   `set` | `get` | `mpchelp`

Purpose   MPC simulation options

Syntax   SimOptions=mpcsimopt(mpcobj)

Description   mpcsimopt creates an mpcsimopt object for specifying additional
                   parameters for simulation with sim.

                   SimOptions=mpcsimopt(mpcobj) creates an empty object SimOptions
                   which is compatible with the MPC object mpcobj. You must use set /
                   get to change simulation options.

Properties   **MPC Simulation Options Properties**

Property	Description
PlantInitialState	Initial state vector of the plant model generating the data.
ControllerInitialState	Initial condition of the MPC controller. This must be a valid @mpcstate object. **Note** Nonzero values of ControllerInitialState.LastMove are only meaningful if there are constraints on the increments of the manipulated variables.
UnmeasuredDisturbance	Unmeasured disturbance signal entering the plant. An array with as many columns as unmeasured disturbances.
InputNoise	Noise on manipulated variables. An array with as many columns as manipulated variables.

MPC Simulation Options Properties (Continued)

Property	Description
OutputNoise	Noise on measured outputs.
	An array with as many columns as measured outputs. The last sample of the array is extended constantly over the horizon to obtain the correct size.
RefLookAhead	Preview on reference signal ('on' or 'off').
MDLookAhead	Preview on measured disturbance signal ('on' or 'off').
Constraints	Use MPC constraints ('on' or 'off').
Model	Model used in simulation for generating the data.
	This property is useful for simulating the MPC controller under model mismatch. The LTI object specified in Model can be either a replacement for Model.Plant, or a structure with fields Plant, Nominal. By default, Model is equal to MPCobj.Model (no model mismatch). If Model is specified, then PlantInitialState refers to the initial state of Model.Plant and is defaulted to Model.Nominal.x.
	If Model.Nominal is empty, Model.Nominal.U and Model.Nominal.Y are inherited from MPCobj.Model.Nominal. Model.Nominal.X/DX is only inherited if

MPC Simulation Options Properties (Continued)

Property	Description
	both plants are state-space objects with the same state dimension.
StatusBar	Display the wait bar ('on' or 'off').
MVSignal	Sequence of manipulated variables (with offsets) for open-loop simulation (no MPC action).
	An array with as many columns as manipulated variables.
OpenLoop	Perform open-loop simulation.

Examples
We want to simulate the MPC control of a multi-input multi-output (MIMO) system under predicted / actual plant model mismatch. The system has two manipulated variables, two unmeasured disturbances, and two measured outputs.

```
% Open-loop system parameters
p1 = tf(1,[1 2 1])*[1 1; 0 1];
plant = ss([p1 p1]);

% Define I/O types
plant=setmpcsignals(plant,'MV',[1 2],'UD',[3 4]);

% Define I/O names (optional)
set(plant,'InputName',{'mv1','mv2','umd3','umd4'});

% Model for unmeasured input disturbances
distModel = eye(2,2)*ss(-.5,1,1,0);

% Create MPC object
mpcobj = mpc(plant,1,40,2);
mpcobj.Model.Disturbance = distModel;
```

```
% Closed-loop MPC simulation with model mismatch
% and unforeseen unmeasured disturbance inputs

% Define plant model generating the data
p2 = tf(1.5,[0.1 1 2 1])*[1 1; 0 1];
psim = ss([p2 p2 tf(1,[1 1])*[0;1]]);
psim=setmpcsignals(psim,'MV',[1 2],'UD',[3 4 5]);

% Closed-loop simulation
dist=ones(1,3); % Unmeasured disturbance trajectory
refs=[1 2];     % Output reference trajectory
Tf=100; % Total number of simulation steps

options=mpcsimopt(mpcobj);
options.unmeas=dist;
options.model=psim;

sim(mpcobj,Tf,refs,options);
```

See Also   sim

Purpose   Define MPC controller state

Syntax   xmpc=mpcstate(MPCobj,xp,xd,xn,u)
                 xmpc=mpcstate(MPCobj)

Description xmpc=mpcstate(MPCobj,xp,xd,xn,u) defines an mpcstate object for
                 state estimation and optimization in an MPC control algorithm based
                 on the MPC object MPCobj. The state of an MPC controller contains
                 the estimates of the states $x(k)$, $x_d(k)$, $x_m(k)$, where $x(k)$ is the state
                 of the plant model, $x_d(k)$ is the overall state of the input and output
                 disturbance model, $x_m(k)$ is the state of the measurement noise model,
                 and the value of the last vector $u(k\text{-}1)$ of manipulated variables. The
                 overall state is updated from the measured output $ym(k)$ by a linear
                 state observer (see "State Observer" in the Model Predictive Control
                 Toolbox User's Guide).

                 xmpc=mpcstate(MPCobj) returns a default extended initial state that is
                 compatible with the MPC controller MPCobj. Such a default state has
                 plant state and previous input initialized at nominal values, and the
                 states of the disturbance and noise models at zero.

                 Note that mpcstate objects are updated by mpcmove through the
                 internal state observer based on the extended prediction model.

Properties   The mpcstate object type contains the state of an MPC controller. Its
                 properties are listed in MPC State Object Properties on page 3-16.

MPC State Object Properties

Property	Description
Plant	Array of plant states. Values are absolute, i.e., they include possible state offsets (cf.Model.Nominal.X).
Disturbance	Array of states of unmeasured disturbance models. This contains the states of the input disturbance model and, appended below, the states of the unmeasured output disturbances model.

MPC State Object Properties (Continued)

Property	Description
Noise	Array of states of measurement noise model.
LastInput	Array of previous manipulated variables $u(k\text{-}1)$. Values are absolute, i.e., they include possible input offsets (cf. Model.Nominal.U).

The command

```
mpcstate(mpcobj)
```

returns a zero extended initial state compatible with the MPC object mpcobj, and with mpcobj.Plant and mpcobj.LastInput initialized at the nominal values specified in mpcobj.Model.Nominal.

See Also   getoutdist | setoutdist | setindist | getestim | setestim | ss | mpcmove

Purpose   Start Model Predictive Controller GUI

Syntax
```
mpctool
mpctool(MPCobj)
mpctool(MPCobj,'objname')
mpctool(MPCobj1, MPCobj2, ...)
mpctool(MPCobj1, 'objname1', MPCobj2, 'objname2', ...)
mpctool('TaskName')
```

Description   mpctool starts the GUI. For more information about designing and testing model predictive controllers, see "Working with the Design Tool".

mpctool(MPCobj) starts the GUI and loads MPCobj, which is an existing controller object.

mpctool(MPCobj,'objname') assigns objname (specified as a string) to the controller you are loading into the GUI. If you do not specify a name, the GUI uses the name of the variable that stores the controller object.

mpctool(MPCobj1, MPCobj2, ...) loads the specified list of controllers.

mpctool(MPCobj1, 'objname1', MPCobj2, 'objname2', ...) loads the specified list of controllers and assigns each controller the specified name.

mpctool('TaskName') starts the GUI and creates a new Model Predictive Control design task with the name specified by the string 'TaskName'.

See Also   mpc

mpcverbosity

Purpose   Change toolbox verbosity level

Syntax   mpcverbosity on
                 mpcverbosity off
                 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.

                 mpcverbosity just shows the verbosity status.

                 By default, messages are turned on.

                 See also "Construction and Initialization" on page 3-13 .

See Also   mpc

pack

Purpose   Reduce size of MPC object in memory

> **Note** pack will be removed in a future version.

Syntax   `pack(MPCobj)`

Description   `pack(MPCobj)` cleans up information build at initialization and stored in the `MPCData` field of the MPC object `MPCobj`. This reduces the amount of bytes in memory required to store the MPC object. For MPC objects based on large prediction models, it is recommended to pack the object before saving the object to file, in order to minimize the size of the file.

See Also   `mpc` | `getmpcdata` | `setmpcdata` | `compare`

plot

Purpose   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   sim | mpc

Purpose   Solve convex quadratic program using Dantzig-Wolfe's algorithm

> **Note** qpdantz will be removed in a future version. Use quadprog (requires Optimization Toolbox™) instead.

Syntax   [xopt,lambda,how]=qpdantz(H,f,A,b,xmin)
[xopt,lambda,how]=qpdantz(H,f,A,b,xmin,maxiter)

Description   [xopt,lambda,how]=qpdantz(H,f,A,b,xmin) solves the convex quadratic program

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

subject to $Ax \le b, x \ge x_{min}$

using Dantzig-Wolfe's active set method [2]. The Hessian matrix H should be positive definite. By default, xmin=1e-3. Vector xopt is the optimizer. Vector lambda contains the optimal dual variables (Lagrange multipliers).

The exit flag how is either 'feasible', 'infeasible' or 'unreliable'. The latter occurs when the solver terminates because the maximum number maxiter of allowed iterations was exceeded.

The solver is implemented in qpsolver.mex. Dantzig-Wolfe's algorithm uses the direction of the largest gradient, and the optimum is usually found after about $n+q$ iterations, where n=dim(x) is the number of optimization variables, and q=dim(b) is the number of constraints. More than $3(n+q)$ iterations are rarely required (see Chapter 7.3 of [2]).

Examples   Solve a random QP problem using quadprog from the Optimization Toolbox software and qpdantz.

```
n=50;    % Number of vars
H=rand(n,n);H=H'*H;H=(H+H')/2;
```

qpdantz

```
f=rand(n,1);
A=[eye(n);-eye(n)];
b=[rand(n,1);rand(n,1)];
x1=quadprog(H,f,A,b,[],[],-100,[],[],...
optimset('LargeScale','off','Algorithm','active-set'));
[x2,how]=qpdantz(H,f,A,b,-100*ones(n,1));
```

References   [1] Fletcher, R. Practical Methods of Optimization, John Wiley & Sons, Chichester, UK, 1987.

[2] Dantzig, G.B. Linear Programming and Extensions, Princeton University Press, Princeton, 1963.

Purpose	Examine MPC controller for design errors and stability problems at run-time
Syntax	review(mpcobj)

Description   review(mpcobj) checks for potential design issues in the Model Predictive Controller mpcobj and generates a report. review performs the following diagnostic tests:

- Is the optimization problem to be solved online well defined?

- Is the controller internally stable?

- Is the closed loop system stable when no constraints are active and there is no model mismatch?

- Is the controller able to eliminate steady-state tracking error when no constraints are active?

- Is there a likelihood that constraint definitions will result in an ill-conditioned or infeasible optimization problem?

Tips
- Use review iteratively to check your initial MPC design or whenever you make substantial changes to mpcobj. Make the recommended changes to your controller to eliminate potential problems.

- If you design your controller using MPC Design Tool, export the controller to the MATLAB Workspace, and analyze it using review.

- review does not modify mpcobj.

- review cannot detect all possible performance factors. So, additionally test your design using techniques such as simulations.

Input Arguments

mpcobj

Non-empty Model Predictive Controller (mpc) object

Examples   Create a Model Predictive Controller with hard upper and lower bounds on the manipulated variable and its rate-of-change.

Create a discrete Model Predictive Controller.

```
% Create a Model Predictive Controller
Plant = tf(1, [10 1]);
ts = 2;
MPCobj = mpc(Plant,ts);
```

Specify hard bounds on the MV 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 design.

```
review(MPCobj)
```

review flags the potential constraint conflict that could result if you applied this controller to a real process.

Examine the warning by clicking **Hard MV Constraints**.

Alternatives review automates certain tests that you could perform yourself.

To test for steady-state tracking errors, use cloffset.

To test the internal stability of a controller, check the eigenvalues of the mpc object. Use ss to convert the mpc object to a state-space model and call isstable.

See Also cloffset | mpc | ss

Tutorials • Reviewing Model Predictive Controller Design for Potential Stability and Robustness Issues

Purpose   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,...)
```
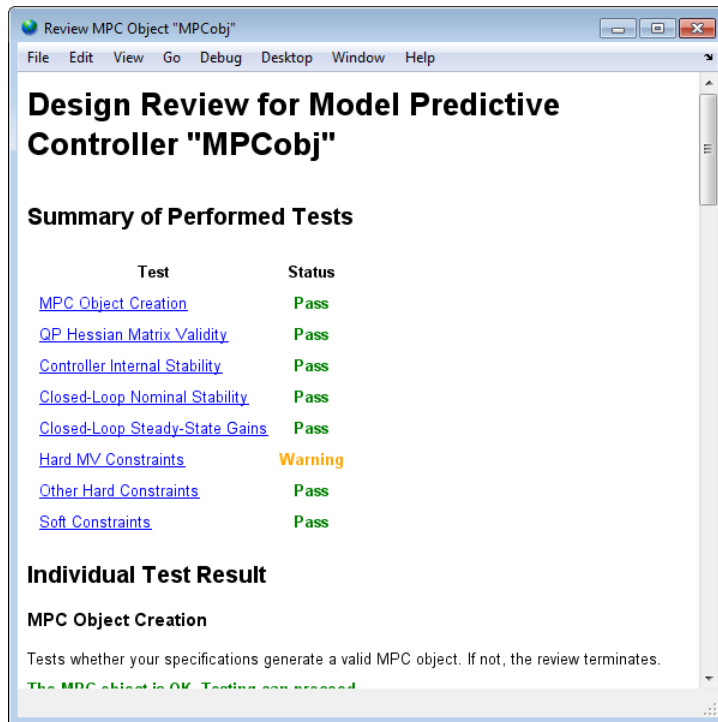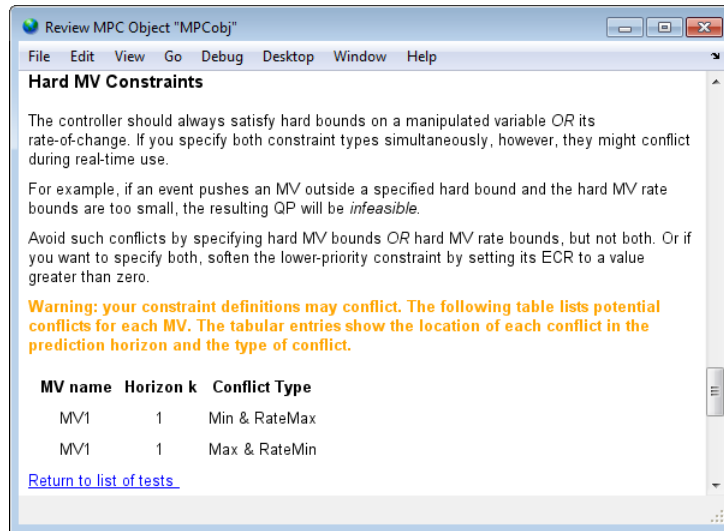
**Description**     The sensitivity function is a controller tuning aid. *J* specifies a
                    scalar performance metric. sensitivity computes *J* and its partial
                    derivatives with respect to the controller tuning weights. These
                    *sensitivities* suggest tuning weight adjustments that should improve
                    performance, i.e., 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 strings:

                    'ISE' (integral squared error) for which the performance metric is

$$J = \sum_{i=1}^{Tstop}\left( \sum_{j=1}^{n_y} (w_j^y e_{yij})^2 + \sum_{j=1}^{n_u} [(w_j^u e_{uij})^2 + (w_j^{\Delta u} \Delta u_{ij})^2] \right)$$

                    'IAE' (integral absolute error) for which the performance metric is

$$J = \sum_{i=1}^{Tstop}\left( \sum_{j=1}^{n_y} | w_j^y e_{yij} | + \sum_{j=1}^{n_u} (| w_j^u e_{uij} | + | w_j^{\Delta u} \Delta u_{ij} |) \right)$$

                    'ITSE' (integral of time-weighted squared error) for which the
                    performance metric is

$$J = \sum_{i=1}^{Tstop} i\Delta t\left( \sum_{j=1}^{n_y} (w_j^y e_{yij})^2 + \sum_{j=1}^{n_u} [(w_j^u e_{uij})^2 + (w_j^{\Delta u} \Delta u_{ij})^2] \right)$$

$$J = \sum_{i=1}^{Tstop} i\Delta t \left( \sum_{j=1}^{n_y} |w_j^y e_{yij}| + \sum_{j=1}^{n_u} (|w_j^u e_{uij}| + |w_j^{\Delta u} \Delta u_{ij}|) \right)$$

'ITAE' (integral of time-weighted absolute error) for which the performance metric is

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 non-negative performance weights defined by the structure PerfWeights, which contains the following fields:

'OutputVariables':    1 by $n_y$ vector containing the $w_j^y$ values

'ManipulatedVariables':    1 by $n_u$ vector containing the $w_j^u$ values

'ManipulatedVariablesRate':    1 by $n_u$ vector containing 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 $\Delta t$ 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. $\Delta u_{ij}$ 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'` | (1 by $n_y$) sensitivities with respect to `MPCobj.Weights.OutputVariables` |
| `'ManipulatedVariables'` | (1 by $n_u$) sensitivities with respect to `MPCobj.Weights.ManipulatedVariables` |
| `'ManipulatedVariablesRate'` | (1 by $n_u$) sensitivities with respect to `MPCobj.Weights.ManipulatedVariablesRate` |

See "Weights" on page 3-7 for details on the tuning weights contained in `MPCobj`.

`[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, ...)`

i.e., it must compute J for the given controller and optional parameters `param1`, `param2`, ... and it must be on the MATLAB path.

**Examples**  Suppose variable `MPCobj` contains a default controller definition for a plant with two controlled outputs, three manipulated variables, and no measured disturbances. Compute its performance and sensitivities as follows:

```
PerfFunc = 'IAE';
PerfWts.OutputVariables = [1 0.5];
PerfWts.ManipulatedVariables = zeros(1,3);
PerfWts.ManipulatedVariablesRate = zeros(1,3);
Tstop = 20;
r = [1 0];
v = [];
simopt = mpcsimopt;
utarget = zeros(1,3);
[J, sens] = sensitivity(MPCobj, PerfFunc, PerfWts, Tstop, ...
```

```
 r, v, simopt, utarget)
```

The simulation scenario in the above example uses a constant $r = 1$ for output 1 and $r = 0$ for output 2. In other words, the scenario is a unit step in the output 1 setpoint.

See Also   mpc | sim

Purpose   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 Controller Object" on page 3-2 for background on MPC properties). Like its Handle Graphics® counterpart, set uses property name/property 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 string 'Property'. This string 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/property value pair updates one particular property.

set(MPCobj,'Property') displays admissible values for the property specified by 'Property'. See "MPC Controller Object" on page 3-2 for an overview of legitimate MPC property values.

set(sys) displays all assignable properties of sys and their admissible values.

See Also   mpc | get

setconstraint

Purpose   Custom constraints on plant inputs and outputs

Syntax   setconstraint(MPCobj,E,F,G)
                   setconstraint(MPCobj,E,F,G,V)
                   setconstraint(MPCobj,E,F,G,V,S)

Description   setconstraint(MPCobj,E,F,G) adds constraints of the following form
                   to an MPC controller MPCobj:

$$Eu(k + j \mid k) + Fy(k + j \mid k) \leq G$$

where:

$j = 0, \ldots, p$
p is the prediction horizon length
y are the measured and unmeasured outputs
u are the manipulated variables
E, F, and G are constants. Each row of E, F, and G represents a
linear constraint to be imposed at each prediction horizon step.

setconstraint(MPCobj,E,F,G,V) adds constraints of the following
form:

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

where,

V is a constant representing the Equal Concern for the Relaxation
(ECR)
ε is the slack variable used for constraint softening (as in Equation
2-3 of "Standard Form")

setconstraint(MPCobj,E,F,G,V,S) adds constraints of the following
form:

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

where:

v are the measured disturbances
S is a constant

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.
- Because $u(k + p \mid k)$ is not optimized by the MPC controller, the last constraint at time $k + p$ assumes that $u(k+p \mid k) = u(k+p-1 \mid k)$.

Input Arguments

MPCobj

MPC controller, specified as an MPC Controller object

E

Constant used in custom constraints, specified as a matrix with:

n_u columns, where n_u is the number of manipulated variables
Same number of rows as F, G, V, and S

To remove all the mixed constraints, use [ ] or zero matrix for both the *E* and *F* matrices.

F

Constant used in custom constraints, specified as a matrix with:

n_y columns, where n_y is the number of controlled outputs (measured and unmeasured)
Same number of rows as E, G, V, and S

To remove all the mixed constraints, use [ ] or zero matrix for both the *E* and *F* matrices.

G

Constant used in custom constraints, specified as a column vector with the same number of rows as E, F, V, and S.

V

Constant used in custom constraints, specified as a column vector with the same number of rows as E, F, G, and S.

If V is not specified, the default of 1 is applied to all constraint inequalities and all constraints are soft (default behavior for output bounds as described in "Standard Form").

To make the ith constraint hard, specify $V(i) = 0$.

To make the ith 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 decreases the allowed constraint violation, i.e., the constraint becomes harder.

Note If a constraint is difficult to satisfy, reducing its $V(i)$ value (to make it harder) may be counter-productive, and can lead to erratic control action, instability, or failure of the QP solver that determines the control action.

Default: vector of 1s

S

Constant used in custom constraints, specified as a matrix with:

n_v columns, where n_v is the number of measured disturbances
Same number of rows as E, F, G and V

Examples   This example shows how to specify the custom constraint $0 \le u_2 - 2u_3 + y_2 \le 15$ on an MPC controller. The controller has three manipulated variables and two controlled outputs.

The constraint imposes upper and lower bounds on $u_2 - 2u_3 + y_2$.

1 Formulate this constraint in the required form:

$$\begin{bmatrix} 0 & -1 & 2 \\ 0 & 1 & -2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} + \begin{bmatrix} 0 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \leq \begin{bmatrix} 0 \\ 15 \end{bmatrix}$$

2 Specify the constraints on the plant inputs and outputs:

```
E = [0 -1 2; 0 1 -2];
F = [0 -1; 0 1];
G = [0; 15];
setconstraint(MPCobj, E, F, G);
```

Alternatively, you can use:

```
E = [0 -1 2; 0 1 -2];
F = [0 -1; 0 1];
G = [0; 15];
V = [1; 1];
S = [];
setconstraint(MPCobj, E, F, G, V, S);
```

See Also   setterminal

Tutorials   • MPC Control with Constraints on a Combination of Input and Output Signals

   • MPC Control of a Nonlinear Blending Process

How To   • "Custom Constraints on Inputs and Outputs"

setestim

Purpose   Modify MPC object's linear state estimator

Syntax   `setestim(MPCobj,M)`
                `setestim(MPCobj,'default')`

Description   The `setestim` function modifies the linear estimator gain of an MPC object. The state estimator is based on the linear model (see "State Estimation" in the Model Predictive Control Toolbox User's Guide.)

$$x(k + 1) = Ax(k) + B_u u(k) + B_v v(k)$$

$$y_m(k) = C_m x(k) + D_{vm} v(k)$$

where $v(k)$ are the measured disturbances, $u(k)$ are the manipulated plant inputs, $y_m(k)$ are the measured plant outputs, and $x(k)$ is the overall state vector collecting states of plant, unmeasured disturbance, and measurement noise models. The order of the states in x is the following: plant states; disturbance models states; noise model states.

`setestim(MPCobj,M)`, where `MPCobj` is an MPC object, changes the default Kalman estimator gain stored in `MPCobj` to that specified by matrix `M`.

`setestim(MPCobj,'default')` restores the default Kalman gain.

The estimator used in Model Predictive Control Toolbox software is described in "State Estimation" in the Model Predictive Control Toolbox User's Guide. The estimator's equations are as follows.

Predicted Output Computation:

$$\hat{y}_m(k|k-1) = C_m \hat{x}(k|k-1) + D_{vm} v(k)$$

Measurement Update:

$$\hat{x}(k|k) = \hat{x}(k|k-1) + M\left(y_m(k) - \hat{y}_m(k|k-1)\right)$$

Time Update:

$$\hat{x}(k+1|k) = A\hat{x}(k|k) + B_u u(k) + B_v v(k)$$

By combining these three equations, the overall state observer is

$$\hat{x}(k+1|k) = (A - LC_m)\hat{x}(k|k-1) + Ly_m(k) + B_u u(k) + (B_v - LD_{vm})v(k)$$

where $L = AM$.

Note The estimator gain M has the same meaning as the gain M in function DKALMAN in Control System Toolbox software.

Matrices A, B$_u$, B$_v$, C$_m$, D$_{vm}$ can be retrieved using getestim as follows:

```
[M,A,Cm,Bu,Bv,Dvm]=getestim(MPCobj)
```

Examples   To design an estimator by pole placement, you can use the commands assuming that the linear system $AM = L$ is solvable.

```
[M,A,Cm]=getestim(MPCobj);
L=place(A',Cm',observer_poles)';
M=A\L;
setestim(MPCobj,M);
```

setestim

See Also   getestim | mpc | mpcstate

Purpose   Modify unmeasured input disturbance model

Syntax   ```
setindist(MPCobj,'integrators')
setindist(MPCobj,'model',model)
```

Description `setindist(MPCobj,'integrators')` imposes the default disturbance model for unmeasured inputs, that is, for each unmeasured input disturbance channel, an integrator is added unless there is a violation of observability, otherwise the input is treated as white noise with unit variance (this is equivalent to `MPCobj.Model.Disturbance=[]`).

setindist(MPCobj,'model',model) sets the input disturbance model to `model` (this is equivalent to `MPCobj.Model.Disturbance=model`).

See Also   mpc | getindist | setestim | getestim | setoutdist

setmpcdata

Purpose	Set private MPC data structure

> **Note** setmpcdata will be removed in a future version. Use set, setconstraint, setestim, setindist andsetoutdist instead.

Syntax	setmpcdata(MPCobj,mpcdata)
Description	setmpcdata(MPCobj,mpcdata) changes the private field MPCData of the MPC object MPCobj, where all internal QP matrices, models, estimator gains are stored at initalization of the object. You may only need this for very advanced use of Model Predictive Control Toolbox software.

> **Note** Changes to the data structure may easily lead to unpredictable results.

See Also	getmpcdata	set	get	pack

Purpose   Set signal types in MPC plant model

Syntax   P=setmpcsignals(P,SignalType1,Channels1,SignalType2,Channels2,...)

Description   The purpose of setmpcsignals is to set I/O channels of the MPC
                  plant model P. P must be an LTI object. Valid signal types, their
                  abbreviations, and the channel type they refer to are listed below.

Signal Type	Abbreviation	Channel
Manipulated	MV	Input
MeasuredDisturbances	MD	Input
UnmeasuredDisturbances	UD	Input
MeasuredOutputs	MO	Output
UnmeasuredOutputs	UO	Output

Unambiguous abbreviations of signal types are also accepted.

P=setmpcsignals(P) sets channel assignments to default, namely all
inputs are manipulated variables (MVs), all outputs are measured
outputs (MOs). More generally, input signals that are not explicitly
assigned are assumed to be MVs, while unassigned output signals are
considered as MOs.

Examples   We want to define an MPC object based on the LTI discrete-time plant
                  model sys with four inputs and three outputs. The first and second
                  input are measured disturbances, the third input is an unmeasured
                  disturbance, the fourth input is a manipulated variable (default), the
                  second output is an unmeasured, all other outputs are measured.

```
sys=setmpcsignals(sys,'MD',[1 2],'UD',[3],'UO',[2]);
mpc1=mpc(sys);
```

setmpcsignals

Note When using `setmpcsignals` to modify an existing MPC object, be sure that the fields `Weights`, `MV`, `OV`, `DV`, `Model.Noise`, and `Model.Disturbance` are consistent with the new I/O signal types.

See Also   `mpc` | `set`

Purpose   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. 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. 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

setoutdist

Purpose　Modify unmeasured output disturbance model

Syntax
```
setoutdist(MPCobj,'integrators')
setoutdist(MPCobj,'remove',channels)
setoutdist(MPCobj,'model',model)
```

Description　`setoutdist(MPCobj,'integrators')` specifies the default method output disturbance model, based on the specs stored in `MPCobj.OutputVariables.Integrator` and `MPCobj.Weights.OutputVariables`. Output integrators are added according to the following rules:

1　Outputs are ordered by decreasing output weight (in case of time-varying weights, the sum of the absolute values over time is considered for each output channel. In case of equal output weight, the order within the output vector is followed).

2　By following such order, an output integrator is added per measured outputs, unless there is a violation of observability or the corresponding value in `MPCobj.OutputVariables.Integrator` is zero. A warning message is given when an integrator is added on an unmeasured output channel.

`setoutdist(MPCobj,'remove',channels)` removes integrators from the output channels specified in vector `channels`. This corresponds to setting `MPCobj.OutputVariables(channels).Integrator=0`. The default for `channels` is `(1:ny)`, where ny is the total number of outputs, that is, all output integrators are removed.

`setoutdist(MPCobj,'model',model)` replaces the array of output integrators designed by default according to `MPCobj.OutputVariables.Integrator` with the LTI model `model`. The model must have ny outputs. If no `model` is specified, then the default model based on the specs stored in `MPCobj.OutputVariables.Integrator` and `MPCobj.Weights.OutputVariables` is used (same as `setoutdist(MPCobj, 'integrators')`.

See Also   mpc | getestim | setestim | setoutdist | setindist

setterminal

Purpose	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.

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.

Input Arguments

MPCobj

MPC controller, specified as an MPC controller object

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 in Equation 2-3 of "Standard Form"). To apply non-zero off-diagonal terminal weights, you must augment the plant model. See Implementing Infinite-Horizon LQR by Setting Terminal Weights in a Finite-Horizon MPC Formulation.

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.

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.

setterminal

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 in Equation 2-3 of "Standard Form"). To apply non-zero off-diagonal terminal weights, you must augment the plant model. See Implementing Infinite-Horizon LQR by Setting Terminal Weights in a Finite-Horizon MPC Formulation.

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.

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   This example shows how to specify constraints and a penalty weight at the last step of the prediction horizon of an MPC controller. The controller has three output variables and two manipulated variables.

1 Specify a prediction horizon of 8.

```
MPCobj.PredictionHorizon = 8;
```

2 Define a penalty weight and constraints:

```
Y=struct('Weight',[1,10,0],'Min',[0,-Inf,-1],...
    'Max',[Inf,2,Inf]);
U=struct('Min',[1,-Inf]);
```

The constraints and weights include:

- Diagonal penalty weights of 1 and 10 on the first two output variables

- Lower bounds of 0 and –1 on outputs 1 and 3, none on output 2

- Upper bound at 2 on output 2, none on outputs 1 and 3

- Lower bound at 1 on manipulated variable 1

- No other conditions (weights or bounds) on the manipulated variables

3 Specify the constraints and weight at the last step (step 8) of the prediction horizon:

```
setterminal(MPCobj,Y,U);
```

This example shows how to specify constraints and a penalty weight beginning with step 5 and ending at the last step of the prediction horizon of an MPC controller, The controller has three output variables and two manipulated variables.

1 Specify a prediction horizon of 8.

```
MPCobj.PredictionHorizon = 8;
```

2 Define a penalty weight and constraints:

```
Y=struct('Weight',[1,10,0],'Min',[0,-Inf,-1],...
    'Max',[Inf,2,Inf]);
U=struct('Min',[1,-Inf]);
```

The constraints and weights include:

- Diagonal penalty weights of 1 and 10 on the first two output variables

- Lower bounds of 0 and –1 on outputs 1 and 3, none on output 2

- Upper bound at 2 on output 2, none on outputs 1 and 3

- Lower bound at 1 on manipulated variable 1

- No other conditions (weights or bounds) on the manipulated variables

3 Specify the constraints and weight beginning with step 5 and ending at the last step of the prediction horizon:

```
setterminal(MPCobj,Y,U,5);
```

See Also | mpc | mpcprops | setconstraint

Tutorials   • "Providing LQR Performance Using Terminal Penalty"

                      • Implementing Infinite-Horizon LQR by Setting Terminal Weights in a Finite-Horizon MPC Formulation

How To   • "Terminal Weights and Constraints"

Purpose   Simulate closed-loop/open-loop response to arbitrary reference and disturbance signals

Syntax   sim(MPCobj,T,r)
sim(MPCobj,T,r,v)
sim(MPCobj,T,r,SimOptions) or sim(MPCobj,T,r,v,SimOptions)
[y,t,u,xp,xmpc,SimOptions]=sim(MPCobj,T,...)

Description The purpose of sim is to simulate the 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 between the prediction plant model and the model of the process generating the output data.

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 object MPCobj, and plots the simulation results. T is the number of simulation steps. r is the reference signal array with as many columns as the number of output variables.

sim(MPCobj,T,r,v) also specifies the measured disturbance signal v, that has as many columns as the number of measured disturbances.

Note The last sample of r/v is extended constantly over the simulation horizon, to obtain the correct size.

sim(MPCobj,T,r,SimOptions) or sim(MPCobj,T,r,v,SimOptions) specifies the simulation options object SimOptions, such as initial states, input/output noise and unmeasured disturbances, plant mismatch, etc. See mpcsimopt for details.

Without output arguments, sim automatically plots input and output trajectories.

[y,t,u,xp,xmpc,SimOptions]=sim(MPCobj,T,...) instead of plotting closed-loop trajectories returns the sequence of plant outputs y, the

time sequence t (equally spaced by MPCobj.Ts), the sequence u of manipulated variables 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 options object SimOptions used for the simulation.

The descriptions of the input arguments and their default values are shown in the table below.

Input Argument	Description	Default
MPCobj	MPC object specifying the parameters of the MPC control law	None
T	Number of simulation steps	Largest row-size of r,v,d,n
r	Reference signal	MPCobj.Model.Nominal.Y
v	Measured disturbance signal	Entries from MPCobj.Model.Nominal.U
SimOptions	Object of class @mpcsimopt containing the simulation parameters (See mpcsimopt)	[]

r is an array with as many columns as outputs, v is an array with as many columns as measured disturbances. The last sample of r/v/d/n is extended constantly over the horizon, to obtain the correct size.

The output arguments of sim are detailed below.

Output Argument	Description
y	Sequence of controlled plant outputs (without noise added on measured ones)
t	Time sequence (equally spaced by MPCobj.Ts)

Output Argument	Description
u	Sequence of manipulated variables generated by MPC
xp	Sequence of states of plant model (from `Model` or `SimOptions.Model`)
xmpc	Sequence of states of MPC controller (estimates of the extended state). This is a structure with the same fields as the `mpcstate` object.

Examples   We want to simulate the MPC control of a multi-input single-output system. The system has one manipulated variable, one measured disturbance, one unmeasured disturbance, and one output.

```
%Plant model and initial state
sys=ss(tf({1,1,1},{[1 .5 1],[1 1],[.7 .5 1]}));

% MPC object setup
Ts=.2;            % sampling time
sysd=c2d(sys,Ts); % prediction model

% Define type of input signals
sysd=setmpcsignals(model,'MV',1,'MD',2,'UD',3);

MPCobj=mpc(sysd); % Default weights and horizons

% Define constraints on manipulated variable
MPCobj.MV=struct('Min',O,'Max',1);

Tstop=30;         % Simulation time

Tf=round(Tstop/Ts); % Number of simulation steps
r=ones(Tf,1);      % Reference trajectory
v=[zeros(Tf/3,1);ones(2*Tf/3,1)]; % Measured dist. trajectory
sim(MPCobj,Tf,r,v);
```

sim

See Also   mpcsimopt | mpc | mpcmove

Purpose   Display model output/input/disturbance dimensions

Syntax   sizes=size(MPCobj)

Description sizes=size(MPCobj) returns the row vector sizes = $[n_{ym}\ n_u\ n_{yu}\ n_v\ n_d]$ associated with the MPC object MPCobj, where n_{ym} is the number of measured controlled outputs, n_u is the number of manipulated inputs, n_{yu} is the number of unmeasured controlled outputs, n_v is the number of measured disturbances, and n_d is the number of unmeasured disturbances.

size(MPCobj) by itself makes a nice display.

See Also   mpc | set

Purpose   Convert unconstrained MPC controller to state-space linear form

Syntax   sys=ss(MPCobj)
[sys,Br,Dr,Bv,Dv,Boff,Doff,But,Dut]=ss(MPCobj)
[sys,Br,Dr,Bv,Dv,Boff,Doff,But,Dut]=ss(MPCobj,ref_preview,
md_preview,name_flag)

Description   The ss utility returns the linear controller sys as an LTI system in ss
form corresponding to the MPC controller MPCobj when the constraints
are not active. The purpose is to use the linear equivalent control in
Control System Toolbox software for sensitivity analysis and other
linear analysis.

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.

[sys,Br,Dr,Bv,Dv,Boff,Doff,But,Dut]=ss(MPCobj) returns the
linearized MPC controller in its full version, that has the following
structure

$$x(k + 1) = Ax(k) + By_m(k) + B_r r(k) + B_v v(k) + B_{ut} u_{target}(k) + B_{off}$$

$$u(k) = Cx(k) + Dy_m(k) + D_r r(k) + D_v v(k) + D_{ut} u_{target}(k) + D_{off}$$

Note Vector x includes the states of the observer
(plant+disturbance+noise model states) and the previous
manipulated variable $u(k\text{-}1)$.

In the general case of nonzero offsets, y_m (as well as r, v, u_{target}) must be interpreted as the difference between the vector and the corresponding offset. Vectors B_{off}, D_{off} are constant terms due to nonzero offsets, in particular 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). Note that when Nominal.X is 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,ref_preview,md_preview,name_flag) allows you to specify 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:

$x(k + 1) = Ax(k) + By_m(k) + B_r[r(k);r(k + 1);...;r(k + p - 1)] +...$

$u(k) = Cx(k) + Dy_m(k) + D_r[r(k);r(k + 1);...;r(k + p- 1)] +...$

Similarly if the flag md_preview='on', then matrices B_r and D_r multiply the whole measured disturbance sequence:

$x(k + 1) = Ax(k) +...+ B_v[v(k);v(k + 1);...;v(k + p)] +...$

$u(k) = Cx(k) +...+ D_v[v(k);v(k + 1);...;v(k + p)] +...$

The optional input argument name_flag='names' adds state, input, and output names to the created LTI object.

Examples   To get the transfer function LTIcon from (y_m, r) to u,

```
[sys,Br,Dr]=ss(MPCobj);
set(sys,'B',[sys.B,Br],'D',[sys.D,Dr]);
```

See Also   mpc | set | tf | zpk

Purpose	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`

Purpose   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 vector
                    such that $x=Ax+Bu$, $y=Cx+Du$, or the best approximation of such an x in
                    a least squares sense, sets noise and disturbance model states at zero,
                    and forms the extended state vector.

See Also   mpc | mpcstate

zpk

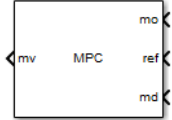|	
Purpose	Convert unconstrained MPC controller to zero/pole/gain form
Syntax	`sys=zpk(MPCobj)`
Description	The `zpk` function computes the zero-pole-gain form of the linear controller `ss(MPCobj)` as an LTI system in `zpk` form corresponding to the MPC controller when the constraints are not active. The purpose is to use the linear equivalent control in Control System Toolbox software for sensitivity and other linear analysis.
See Also	`ss` | `tf`

Block Reference

MPC Controller

Purpose   Compute MPC control law

Library   MPC Simulink Library

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 variables (`mv`) by solving a quadratic program (QP).

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 will control.

Because the MPC Controller block uses MATLAB Function blocks to implement the QP solver, 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.

Dialog Box

The MPC Controller block has the following parameter groupings:

- "Parameters" on page 2-4
- "Required Inports" on page 2-5
- "Required Outports" on page 2-6
- "Optional Inports" on page 2-6
- "Optional Outports" on page 2-10
- "Online Tuning Inports" on page 2-12

MPC Controller

Parameters

MPC controller

You must provide an `mpc` object that defines your controller using one of the following methods:

- Enter the name of an `mpc` object in the **MPC Controller** edit box. This object must be present in the base workspace.

  Clicking **Design** opens the MPC design tool where you can modify the controller settings in a graphical environment. 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 base workspace.

  To see how well the controller works for the nonlinear plant, run a closed-loop Simulink simulation.

- If you do not have an existing `mpc` object in the base workspace, leave the **MPC controller** field empty and, with the MPC Controller block connected to the plant, click **Design**. This action constructs a default `mpc` controller by obtaining a linearized model from the Simulink diagram at the default operating point. Continue your controller design in the MPC design tool.

  To use this design approach, you must have Simulink Control Design™ software.

Initial controller state

Specifies the initial controller state. If this parameter is left blank, the block uses the nominal values that are defined in the `Model.Nominal` property of the `mpc` object. To override the default, create an `mpcstate` object in your workspace that represents the initial state, and enter its name in the field.

Required Inports

Measured output

At each control instant, the mo signal must contain the current output variable measurements. Let n_{ym} be the number of measured output variables (MO) defined in your predictive controller. If n_{ym}=1, connect a scalar signal to the mo inport. Otherwise, connect a row or column vector signal containing n_{ym} real, double-precision elements.

Reference

At each control instant, the ref signal must contain the current reference values (targets or setpoints) for the n_y output variables (ny = n_{ym}+ number of unmeasured outputs). You have the option to specify future reference values (previewing).

The ref signal must be size N by n_y, where $N(1 \leq N \leq p)$ is the number of time steps for which you are specifying reference values and p is the prediction horizon. Each element must be a real double-precision number. The ref dimension must not change from one control instant to the next.

When N=1, you cannot preview. To specify future reference values, choose N such that $1 < N \leq p$ to enable previewing. Doing so usually improves performance via feedforward information. The first row specifies the n_y references for the first step in the prediction horizon (at the next control interval k=1), and so on for N steps. If N<p, the last row designates constant reference values to be used for the remaining p-N steps.

For example, suppose n_y=2 and p=6. At a given control instant, the signal connected to the controller's ref inport is

```
[2 5      k=1
 2 6      k=2
 2 7      k=3
 2 8]      k=4
```

The signal informs the controller that:

- Reference values for the first prediction horizon step (k=1) are 2 and 5.

- The first reference value remains at 2, but the second increases gradually.

- The second reference value becomes 8 at the beginning of the fourth step (k=4) in the prediction horizon.

- Both values remain constant at 2 and 8 respectively for steps 5–6 of the prediction horizon.

mpcpreview shows how to use reference previewing in a specific case. For calculation details on the use of the reference signal, see "Optimization Problem".

Required Outports

Manipulated Variables

The mv outport provides a signal defining the $n_u \geq 1$ manipulated variables, which are to be implemented in the plant. The controller updates its mv outport by solving a quadratic program at each control instant. The elements are real, double-precision values.

Optional Inports

Measured disturbance

Add an inport (md) to which you can connect a measured disturbance signal.

Your measured disturbance signal (MD) must be size $N \times n_{md}$, where

$n_{md}(\geq 1)$ is the number of measured disturbances defined in your

Model Predictive Controller and $N \ (1 \leq N \leq p+1)$ is the number of time steps for which the MD is known. Each element must be a real, double-precision number. The signal dimensions must not change from one control instant to the next.

If N=1 you cannot preview. At each control instant, the MD signal must contain the most recent measurements at the current time k=0 (as a row vector, length n_{md}). The controller assumes that the MDs remain constant at their current values for the entire prediction horizon.

If you are able to predict future MD values, choose N such that $1 < N \leq p+1$ to enable previewing. Doing so usually improves performance via feedforward. In this case, the first row must contain the n_{md} current values at k=0, and the remaining rows designate variations over the next N-1 control instants. If N<p+1, the last row designates constant MD values to be used for the remaining p+1-N steps of the prediction horizon.

For example suppose n_{md}=2 and p=6. At a given control instant, the signal connected to the controller's md inport is:

```
[2 5      k=0
 2 6      k=1
 2 7      k=2
 2 8]     k=3
```

This signal informs the controller that:

- The current MDs are 2 and 5 at k=0.

- The first MD remains at 2, but the second increases gradually.

- The second MD becomes 8 at the beginning of the step 3 (k=3) in the prediction horizon.

- Both values remain constant at 2 and 8 respectively for steps 4–6 of the prediction horizon.

mpcpreview shows how to use MD previewing in a specific case.

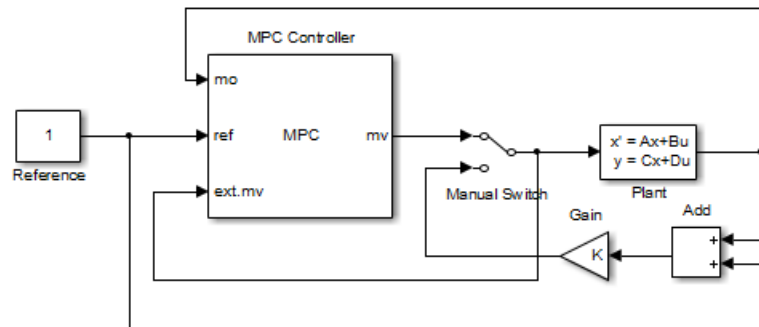For calculation details, see "Prediction Model" and "QP Matrices".

Externally supplied MV signals

Add an inport (ext.mv), which you can connect to the actual manipulated variables (MV) used in the plant. The block uses these to

update its internal state estimates. For example, suppose the actual signals saturate at physical limits or the MV is under manual control. In both cases, feeding the actual value back to the MPC Controller block can improve performance significantly, because the prediction model's state estimates are updated more accurately.

The following example shows how a manual switch may override the controller's output. Also see Turning Controller Online and Offline with Bumpless Transfer.

Do not connect this option to leave the ext.mv inport unconnected. In either case, the model predictive controller assumes that the plant uses the MV signals sent by the MPC Controller block. In the preceding example, the external MV signal always provides the model predictive controller that the control signal actually used in the plant. Otherwise, the model predictive controller's internal state estimate would be inaccurate.

Note The MPC Controller block is a discrete-time block with sampling time inherited from the MPC object. The MPC block has direct feedthrough from measured outputs (`mo`), output references (`ref`), and measured disturbances (`md`) to MPC-manipulated variables (`mv`). There is no direct feedthrough from externally supplied manipulated variables (`ext.mv`) to MPC-manipulated variables (`mv`).

Input and output limits

Add inports (umin,umax,ymin,ymax), which you can connect to run-time constraint signals. If this check box is not selected, the block uses the constant constraint values stored within its mpc object. Example connections appear in the following model. See Varying Input and Output Constraints for an example of using this option.

Each unconnected limit inport, such as ymin in the following model, is treated as an unbounded signal. The corresponding constraint settings in the mpc object must also be unbounded. For connected limit inports, such as ymax, the signals must be finite and the corresponding variables in the mpc object must also be bounded.

All constraint signals connected to the block must be finite. Also, you cannot change the number or identity of constrained and unconstrained variables. For example, if your mpc object specifies that your first MV has a lower bound, you must supply a umin signal for it.

Optimization enabling switch

Add an inport (QP Switch) whose input specifies whether the controller performs optimization calculations. If the input signal is zero, the

controller behaves normally. If the input signal becomes nonzero, the MPC Controller block turns off the controller's optimization calculations and sets the controller output to zero. These actions save computational effort when the controller output is not needed, such as when the system has been placed in manual operation or another controller has taken over. The controller, however, continues to update its internal state estimate in the usual way. Thus, it is ready to resume optimization calculations whenever the QP Switch signal returns to zero.

If you select this option, the mask automatically selects the **Externally supplied MV signal** option. Connect this option to the current MV value in the plant. Otherwise, there would be a "bump" each time the QP Switch signal reactivates optimization.

Optional Outports
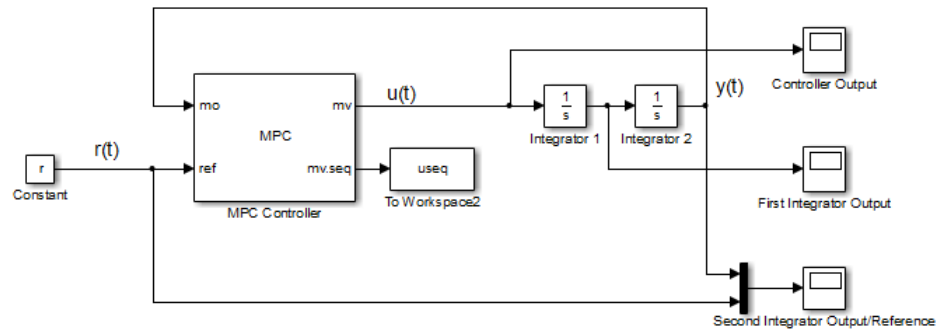
Optimal cost

Add an outport (cost) that provides the calculated optimal cost (scalar) of the quadratic program during operation. The computed value is an indication of controller performance. If the controller is performing well, the value is low. However, if the optimization problem is infeasible, this value is meaningless. (See qp.status.)

Optimal control sequence

Add an outport (mv.seq) that provides the controller's computed optimal MV sequence for the entire prediction horizon from k=0 to k=p-1. If n_u is the number of MVs and p is the length of the prediction horizon, this signal is a p by n_u matrix. The first row represents k=0 and duplicates the block's MV outport.

The following block diagram (from Analysis of Control Sequences Optimized by MPC on a Double Integrator System) illustrates how to use this option. The diagram shows how to collect diagnostic data and send it to the To Workspace2 block, which creates the variable, useq, in the workspace. Run the example to see how the optimal sequence evolves with time.

Optimization status

Add an outport (`qp.status`) that allows you to monitor the status of the QP solver.

If a QP problem is solved successfully at 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. Thus, a large value means a relatively slow block execution at this time interval.
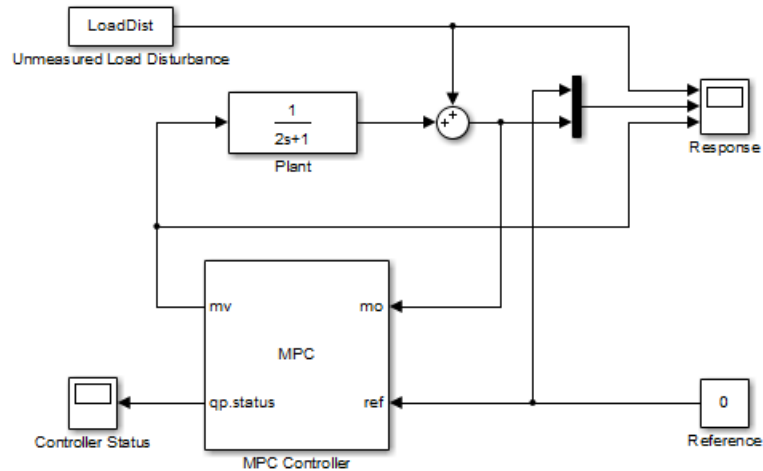
The QP solver may fail to find an optimal solution for the following reasons:

- `qp.status = 0` — The QP solver cannot find a solution within the maximum number of iterations specified in the `mpc` object.

- `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 OV outside its specified bounds.

- `qp.status = -2` — The QP solver has encountered numerical difficulties in solving a severely ill-conditioned QP problem.

For all the previous three failure modes, the MPC block holds its `mv` output at the most recent successful solution. In a real-time application, you can use status indicator to set an alarm or take other special action.

MPC Controller

The next diagram shows how to use the status indicator to monitor the MPC Controller block in real time. See Monitoring Optimization Status to Detect Controller Failures for more details.
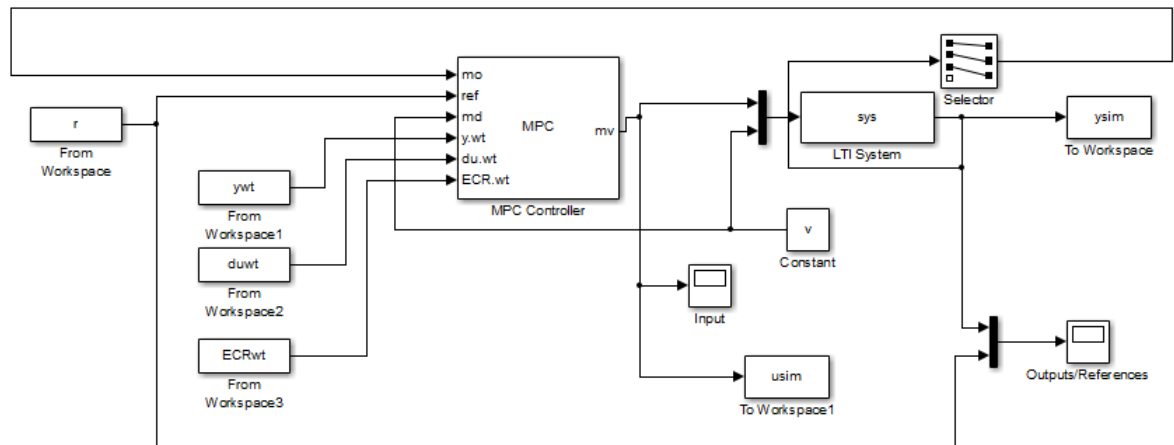

Online Tuning Inports

A controller intended for real-time applications should have "knobs" you can use to tune its performance when it operates with the real plant. This group of optional inports serves that purpose.

The diagram shown below displays the MPC Controller block's three tuning knobs. In this simulation context, the knobs are being tuned by prestored signals (the ywt, duwt, and ECRwt variables in the From Workspace blocks). In practice, you would connect a knob or similar manual adjustment.

Weights on plant outputs

Add an inport (y.wt) whose input is a vector signal defining a nonnegative weight for each controlled output variable (OV). This signal overrides the MPCobj.Weights.OV property, which establishes the relative importance of OV reference tracking.

For example, if the preceding controller defined 3 OVs, the signal connected to the y.wt inport should be a vector with 3 elements. If the second element is relatively large, the controller would place a relatively high priority on making OV(2) track the r(2) reference signal. Setting a y.wt signal to zero turns off reference tracking for that OV.

If you do not connect a signal to the y.wt inport, the block uses the OV weights specified in your MPC object, and these values remain constant.

Weights on manipulated variables rate

Add an inport (du.wt), whose input is a vector signal defining nu nonnegative weights, where nu is the number of manipulated variables (MVs). The input overrides the MPCobj.Weights.MVrate property stored in the mpc object.

For example, if your controller defines four MVs and the second du.wt element is relatively large, the controller would use relatively small

changes in the second MV. Such move suppression makes the controller less aggressive. However, too much suppression makes it sluggish.

If you do not connect a signal to the `du.wt` inport, the block uses the `MVrate` weights property specified in your `mpc` object, and these values remain constant.

Weight on overall constraint softening

Add an inport (`ECR.wt`), whose input is a scalar nonnegative signal that overrides the MPC Controller block's `MPCobj.Weights.ECR` property. This inport 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.

You may not be able to avoid violations of an output variable constraint. Thus, increasing the `ECR.wt` value is often counterproductive. Such an increase causes the controller to pay less attention to its other objectives and does not help reduce constraint violations. You usually need to tune `ECR.wt` to achieve the proper balance in relation to the other control objectives.

See Also   `mpc`, `mpcstate` , Multiple MPC Controllers block

Tutorials
- MPC Control with Input Quantization Based on Comparing the Optimal Costs

- Analysis of Control Sequences Optimized by MPC on a Double Integrator System
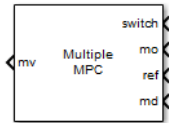
Purpose   Simulate switching between multiple MPC controllers

Library   MPC Simulink Library

Description   The Multiple MPC Controllers block receives the current measured
output, reference signal, and measured disturbance signal. It then
solves a quadratic program to calculate the optimal manipulated
variables. It also receives a switching signal that designates which one
of two or more controllers is to perform the calculation (i.e., the active
controller). The block contains these controllers as MPC objects, each of
which is designed for a particular operating region of a nonlinear plant.
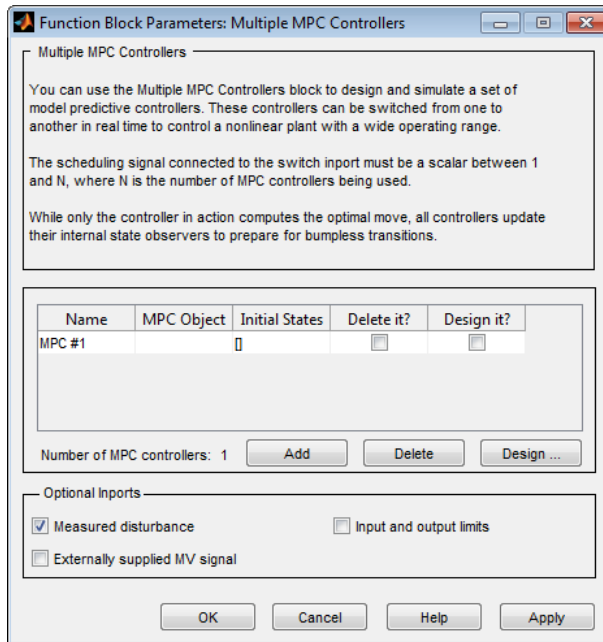
The Multiple MPC Controllers block allows you to achieve better control
of a nonlinear plant over a range of operating conditions. A controller
that works well initially can degrade if the plant is nonlinear and its
operating point changes. In conventional feedback control, you might
compensate for this degradation by gain scheduling. In a similar
manner, the Multiple MPC Controllers block allows you to transition
between multiple MPC controllers in real time in a preordained
manner. You design each controller to work well in a particular region
of the operating space. When the plant moves away from this region,
you instruct another MPC controller to take over.

The Multiple MPC Controllers block does not provide all the optional
features found in the MPC Controller block. The following ports are
currently not available:

- Optional outports such as optimal cost, optimal control sequence,
  and optimization status

- Optional inports for online tuning

Multiple MPC Controllers

The MPC Controller block has the following parameter groupings:

- "Parameters" on page 2-16
- "Required Inports" on page 2-17
- "Required Outports" on page 2-19
- "Optional Inports" on page 2-19

Parameters

MPC Object List

> The table is an ordered list of MPC objects. The first row designates the controller to be used when the `switch` input equals a certain number. The first designates which controller is used when the switch input equals 1, the second when the switch input

equals 2, and so on. These controllers must refer to objects that already exist in your base workspace.

Note After entering each MPC object name, press **Enter**. Also press **Enter** after editing an object name.

Use **Add** and **Delete** to add and remove rows. When deleting, indicate any rows to delete using the **Delete It** check box.

When the edit box is empty, and the block is connected to the plant, clicking the **Design** button constructs a default MPC controller. This controller is constructed using a linearized plant model from the Simulink diagram. This action also opens the design tool so you can modify the default behavior.

You can also start the design tool by selecting one or more MPC objects using the **Design It** check box and then clicking **Design**. All selected MPC objects are loaded into the design tool where you can review and edit their properties.

Initial controller state

Initial state of each MPC object in the ordered list. Each must be a valid mpcstate object. If no value is supplied, the default is the nominal value defined in the Model.Nominal property of the mpc object.

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 controllers listed in your block mask. At each control instant, this signal designates the controller that will be used.

Measured output

At each control instant, the mo signal must contain the current output variable measurements. Let n_{ym} be the number of measured output variables (MO) defined in your predictive controller. If n_{ym}=1, connect a scalar signal to the mo inport. Otherwise, connect a row or column vector signal containing n_{ym} real, double-precision elements.

Reference

At each control instant, the ref signal must contain the current reference values (targets or setpoints) for the n_y output variables (ny = n_{ym}+ number of unmeasured outputs). You have the option to specify future reference values (previewing).

The ref signal must be size N by n_y, where $N(1 \leq N \leq p)$ is the number of time steps for which you are specifying reference values and p is the prediction horizon. Each element must be a real, double-precision number. The ref dimension must not change from one control instant to the next.

When N=1, you cannot preview. To specify future reference values, choose N such that $1 < N \leq p$ to enable previewing. Doing so usually improves performance via feedforward information. The first row specifies the n_y references for the first step in the prediction horizon (at the next control interval k=1), and so on for N steps. If N<p, the last row designates constant reference values to be used for the remaining p-N steps.

For example, suppose n_y=2 and p=6. At a given control instant, the signal connected to the controller's ref inport is

```
[2 5      k=1
 2 6      k=2
 2 7      k=3
 2 8]      k=4
```

The signal informs the controller that:

- Reference values for the first prediction horizon step (k=1) are 2 and 5.

- The first reference value remains at 2, but the second increases gradually.

- The second reference value becomes 8 at the beginning of the fourth step (k=4) in the prediction horizon.

- Both values remain constant at 2 and 8 respectively for steps 5–6 of the prediction horizon.

Required Outports

Manipulated Variables

The mv outport provides a signal defining the $n_u \geq 1$ manipulated variables, which are to be implemented in the plant. The controller updates its mv outport by solving a quadratic program at each control instant. The elements are real, double-precision values.

Optional Inports

Measured disturbance

Add an inport (md) to which you can connect a measured disturbance signal.

Your measured disturbance signal (MD) must be size Nxn$_{md}$, where $n_{md} (\geq 1)$ is the number of measured disturbances defined in your Model Predictive Controller and N $(1 \leq N \leq p+1)$ is the number of time steps for which the MD is known. Each element must be a real, double-precision number. The signal dimensions must not change from one control instant to the next.

If N=1 you cannot preview. At each control instant, the MD signal must contain the most recent measurements at the current time k=0 (as a row vector, length n$_{md}$). The controller assumes that the MDs remain constant at their current values for the entire prediction horizon.

If you are able to predict future MD values, choose N such that $1 < N \leq p+1$ to enable previewing. Doing so usually improves performance via feedforward. In this case, the first row must contain the n$_{md}$ current

values at $k=0$, and the remaining rows designate variations over the next $N-1$ control instants. If $N<p+1$, the last row designates constant MD values to be used for the remaining $p+1-N$ steps of the prediction horizon.

For example suppose $n_{md}=2$ and $p=6$. At a given control instant, the signal connected to the controller's md inport is:

```
[2 5      k=0
 2 6      k=1
 2 7      k=2
 2 8]     k=3
```

This signal informs the controller that:

- The current MDs are 2 and 5 at k=0.

- The first MD remains at 2, but the second increases gradually.

- The second MD becomes 8 at the beginning of the step 3 (k=3) in the prediction horizon.

- Both values remain constant at 2 and 8 respectively for steps 4–6 of the prediction horizon.

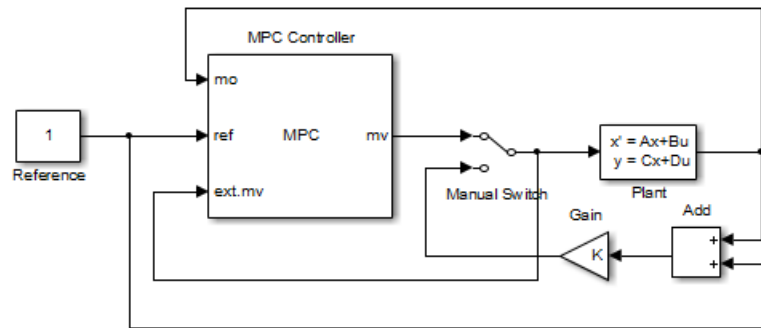mpcpreview shows how to use MD previewing in a specific case.

For calculation details, see "Prediction Model" and "QP Matrices".

Externally supplied MV signals

Add an inport (ext.mv), which you can connect to the actual manipulated variables (MV) used in the plant. The block uses these to update its internal state estimates. For example, suppose the actual signals saturate at physical limits or the MV is under manual control. In both cases, feeding the actual value back to the MPC Controller block can improve performance significantly, because the prediction model's state estimates are updated more accurately.

The following example shows how a manual switch may override the controller's output. Also see Turning Controller Online and Offline with Bumpless Transfer.

Do not connect this option to leave the ext.mv inport unconnected. In either case, the model predictive controller assumes that the plant uses the MV signals sent by the MPC Controller block. In the preceding example, the external MV signal always provides the model predictive controller that the control signal actually used in the plant. Otherwise, the model predictive controller's internal state estimate would be inaccurate.

Note The MPC Controller block is a discrete-time block with sampling time inherited from the MPC object. The MPC block has direct feedthrough from measured outputs (`mo`), output references (`ref`), and measured disturbances (`md`) to MPC-manipulated variables (`mv`). There is no direct feedthrough from externally supplied manipulated variables (`ext.mv`) to MPC-manipulated variables (`mv`).

Input and output limits

Add inports (`umin,umax,ymin,ymax`), which you can connect to run-time constraint signals. If this check box is not selected, the block uses the constant constraint values stored within its `mpc` object. Example connections appear in the following model. See Varying Input and Output Constraints for an example of using this option.

Each unconnected limit inport, such as `ymin` in the following model, is treated as an unbounded signal. The corresponding constraint settings

Multiple MPC Controllers

in the `mpc` object must also be unbounded. For connected limit inports, such as `ymax`, the signals must be finite and the corresponding variables in the `mpc` object must also be bounded.

All constraint signals connected to the block must be finite. Also, you cannot change the number or identity of constrained and unconstrained variables. For example, if your `mpc` object specifies that your first MV has a lower bound, you must supply a `umin` signal for it.

See Also   mpc | mpcmove | mpcstateMPC Controller |

Related Examples
- Scheduling Controllers for a Plant with Multiple Operating Points
- Chemical Reactor with Multiple Operating Points

3

Object Reference

- "MPC Controller Object" on page 3-2
- "MPC Simulation Options Object" on page 3-14
- "MPC State Object" on page 3-16

MPC Controller Object

All the parameters defining the MPC control law (prediction horizon, weights, constraints, etc.) are stored in an MPC object, whose properties are listed in the following table (MPC Controller Object on page 3-2).

MPC Controller Object

Property	Description
ManipulatedVariables (or MV or Manipulated or Input)	Input and input-rate upper and lower bounds, ECR values, names, units, and input target
OutputVariables (or OV or Controlled or Output)	Output upper and lower bounds, ECR values, names, units
DisturbanceVariables (or DV or Disturbance)	Disturbance names and units
Weights	Weights defining the performance function
Model	Plant, input disturbance, and output noise models, and nominal conditions.
Ts	Controller's sampling time
Optimizer	Parameters for the QP solver
PredictionHorizon	Prediction horizon
ControlHorizon	Number of free control moves or vector of blocking moves
History	Creation time
Notes	Text or comments about the MPC controller object
UserData	Any additional data

MPC Controller Object (Continued)

Property	Description
MPCData (private)	Matrices for the QP problem and other accessorial data
Version (private)	Model Predictive Control Toolbox version number

ManipulatedVariables

ManipulatedVariables (or MV or Manipulated or Input) is an n_u-dimensional array of structures (n_u = number of manipulated variables), one per manipulated variable. Each structure has the fields described in the following table (Structure ManipulatedVariables on page 3-3), where p denotes the prediction horizon.

Structure ManipulatedVariables

Field Name	Content	Default
Min	1 to p dimensional vector of lower constraints on a manipulated variable u	-Inf
Max	1 to p dimensional vector of upper constraints on a manipulated variable u	Inf
MinECR	1 to p dimensional vector describing the equal concern for the relaxation of the lower constraints on u	0
MaxECR	1 to p dimensional vector describing the equal concern for the relaxation of the upper constraints on u	0
Target	1 to p dimensional vector of target values for the input variable u	'nominal'

Structure ManipulatedVariables (Continued)

Field Name	Content	Default
RateMin	1 to p dimensional vector of lower constraints on the rate of a manipulated variable u	-Inf if problem is unconstrained, otherwise -10
RateMax	1 to p dimensional vector of upper constraints on the rate of a manipulated variable u	Inf
RateMinECR	1 to p dimensional vector describing the equal concern for the relaxation of the lower constraints on the rate of u	0
RateMaxECR	1 to p dimensional vector describing the equal concern for the relaxation of the upper constraints on the rate of u	0
Name	Name of input signal. This is inherited from InputName of the LTI plant model.	InputName of LTI plant model
Units	String specifying the measurement units for the manipulated variable	''

Note Rates refer to the difference $\Delta u(k)=u(k)-u(k\text{-}1)$. 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 $du/dt \cong \Delta u(k)/T_s$.

OutputVariables

OutputVariables (or OV or Controlled or Output) is an n_y-dimensional array of structures (n_y = number of outputs), one per output signal. Each structure has the fields described in the following table (Structure OutputVariables on page 3-5), where p denotes the prediction horizon.

Structure OutputVariables

Field Name	Content	Default
Min	1 to p dimensional vector of lower constraints on an output y	-Inf
Max	1 to p dimensional vector of upper constraints on an output y	Inf
MinECR	1 to p dimensional vector describing the equal concern for the relaxation of the lower constraints on an output y	1
MaxECR	1 to p dimensional vector describing the equal concern for the relaxation of the upper constraints on an output y	1
Name	Name of output signal. This is inherited from OutputName of the LTI plant model.	OutputName of LTI plant model
Units	String specifying the measurement units for the measured output	''
Integrator	Magnitude of integrated white noise on the output channel (0=no integrator)	[]

In order to reject constant disturbances due for instance to gain nonlinearities, the default output disturbance model used in Model Predictive Control Toolbox software is a collection of integrators driven by white noise on measured outputs (see "Output Disturbance Model"in the Model Predictive Control Toolbox User's Guide). Output integrators are added according to the following rule:

1 Measured outputs are ordered by decreasing output weight (in case of time-varying weights, the sum of the absolute values over time is considered for each output channel, and in case of equal output weight, the order within the output vector is followed).

    2 By following such order, an output integrator is added per measured outputs, unless there is a violation of observability, or you force it by zeroing the corresponding value in `OutputVariables.Integrators`).

By default, `OutputVariables.Integrators` is empty on all outputs. This enforces the default action of Model Predictive Control Toolbox software, namely add integrators on measured outputs, do not add integrators on unmeasured outputs. By setting the entry of `OutputVariables(i).Integrators` to zero, no attempt will be made to add integrated white noise on the `i`-th output . On the contrary, by setting the entry of `OutputVariables(i).Integrators` to one, an attempt will be made to add integrated white noise on the `i`-th output (see `getoutdist`).

DisturbanceVariables

`DisturbanceVariables` (or `DV` or `Disturbance`) is an $(n_v + n_d)$-dimensional array of structures (n_v = number of measured input disturbances, n_d = number of unmeasured input disturbances), one per input disturbance. Each structure has the fields described in the following table (Structure DisturbanceVariables on page 3-6).

Structure DisturbanceVariables

Field Name	Content	Default
Name	Name of input signal. This is inherited from `InputName` of the LTI plant model.	`InputName` of LTI plant model
Units	String specifying the measurement units for the manipulated variable	`' '`

The order of the disturbance signals within the array `DisturbanceVariables` is the following: the first n_v entries relate to measured input disturbances, the last n_d entries relate to unmeasured input disturbances.

> **Note** The `Name` properties of `ManipulatedVariables`, `OutputVariables`, and `DisturbanceVariables` are read only. You can set signal names in the `Model.Plant.InputName` and `Model.Plant.OutputName`properties of the MPC object, for instance by using the method `setname`.

Weights

`Weights` is the structure defining the QP weighting matrices. Unlike the `InputSpecs` and `OutputSpecs`, which are arrays of structures, `weights` is a single structure containing four fields. The values of these fields depend on whether you are using the standard quadratic cost function (Equation (2–3)) or the alternative cost function (Equation (2–5)).

Standard Cost Function

The table below, Weights for the Standard Cost Function (MATLAB® Structure) on page 3-7, lists the content of the four fields where p denotes the prediction horizon, n_u the number of manipulated variables, n_y the number of output variables.

The fields `ManipulatedVariables`, `ManipulatedVariablesRate`, and `OutputVariables` are arrays with n_u, n_u, and n_y columns, respectively. If weights are time invariant, then `ManipulatedVariables`, `ManipulatedVariablesRate`, and `OutputVariables` are row vectors. However, for time-varying weights, each field is a matrix with up to p rows. If the number of rows is less than the prediction horizon, p, the object constructor duplicates the last row to create a matrix with p rows.

Weights for the Standard Cost Function (MATLAB Structure)

Field Name	Content	Default
`ManipulatedVariables` (or MV or `Manipulated` or `Input`)	(1 to p)-by-n_u dimensional array of input weights	`zeros(1,nu)`
`ManipulatedVariablesRate` (or `MVRate` or `ManipulatedRate` or `InputRate`)	(1 to p)-by-n_u dimensional array of input-rate weights	`0.1*ones(1,nu)`

Weights for the Standard Cost Function (MATLAB Structure) (Continued)

Field Name	Content	Default
OutputVariables (or OV or Controlled or Output)	(1 to p)-by-n_y dimensional array of output weights	1 (The default for output weights is the following: if $n_u \geq n_y$, all outputs are weighted with unit weight; if $n_u < n_y$, n_u outputs are weighted with unit weight (with preference given to measured outputs), while the remaining outputs receive zero weight.)
ECR	Weight on the slack variable ε used for softening the constraints	1e5*(max weight)

The default ECR weight is 10^5 times the largest weight specified in ManipulatedVariables, ManipulatedVariablesRate, and OutputVariables.

Note All weights must be greater than or equal to zero. If all weights on manipulated variable increments are strictly positive, the resulting QP problem is always strictly convex. If some of those weights are zero, the Hessian matrix of the QP problem may become only positive semidefinite. In order to keep the QP problem always strictly convex, if the condition number of the Hessian matrix $K_{\Delta U}$ is larger than 10^{12}, the quantity 10*sqrt(eps) is added on each diagonal term. This may only occur when all input rates are not weighted ($W^{\Delta u}=0$) (see "Cost Function" in the *Model Predictive Control Toolbox User's Guide*).

Alternative Cost Function

You can specify off-diagonal Q and R weight matrices in the cost function. To accomplish this, you must define the fields ManipulatedVariables, ManipulatedVariablesRate, and OutputVariables as cell arrays, each containing a single positive-semi-definite matrix of the appropriate size. Specifically, OutputVariables must be a cell array containing the n_y-by-n_y Q

matrix, `ManipulatedVariables` must be a cell array containing the n_u-by-n_u R_u matrix, and `ManipulatedVariablesRate` must be a cell array containing the n_u-by-n_u $R_{\Delta u}$ matrix (see Equation (2–5)) and the `mpcweightsdemo` example). You can abbreviate the field names as shown in Weights for the Standard Cost Function (MATLAB® Structure) on page 3-7. You can also use diagonal weights (as defined in Weights for the Standard Cost Function (MATLAB® Structure) on page 3-7) for one or more of these fields. If you omit a field, the object constructor uses the defaults shown in Weights for the Standard Cost Function (MATLAB® Structure) on page 3-7.

For example, you can specify off-diagonal weights, as follows

```
MPCobj.Weights.OutputVariables={Q};
MPCobj.ManipulatedVariables={Ru};
MPCobj.ManipulatedVariablesRate={Rdu};
```

where `Q`=Q. `Ru`=R_u, and $Rdu = R_{\Delta u}$ are positive semidefinite matrices.

Note You cannot specify off-diagonal time-varying weights.

Model

The property `Model` specifies plant, input disturbance, and output noise models, and nominal conditions, according to the model setup described in "Model Used for State Estimation" in the Model Predictive Control Toolbox User's Guide. It is specified through a structure containing the fields reported in Structure Model Describing the Models Used by MPC on page 3-9.

Structure Model Describing the Models Used by MPC

Field Name	Content	Default
Plant	LTI model or identified linear model of the plant	No default
Disturbance	LTI model describing color of input disturbances	An integrator on each Unmeasured input channel

Structure Model Describing the Models Used by MPC (Continued)

Field Name	Content	Default
Noise	LTI model describing color of plant output measurement noise	Unit white noise on each measured output = identity static gain
Nominal	Structure containing the state, input, and output values where Model.Plant is linearized	See Nominal Values at Operating Point on page 3-11.

Note Direct feedthrough from manipulated variables to any output in Model.Plant is not allowed. See "Prediction Model" in the Model Predictive Control Toolbox User's Guide.

The type of input and output signals is assigned either through the InputGroup and OutputGroup properties of Model.Plant, or, more conveniently, through function setmpcsignals, according to the nomenclature described in Input Groups in Plant Model on page 3-10 and Output Groups in Plant Model on page 3-11.

Input Groups in Plant Model

Name	Value
ManipulatedVariables (or MV or Manipulated or Input)	Indices of manipulated variables
MeasuredDisturbances (or MD or Measured)	Indices of measured disturbances
UnmeasuredDisturbances (or UD or Unmeasured)	Indices of unmeasured disturbances

Output Groups in Plant Model

Name	Value
MeasuredOutputs (or MO or Measured)	Indices of measured outputs
UnmeasuredOutputs (or UO or Unmeasured)	Indices of unmeasured outputs

By default, all inputs are manipulated variables, and all outputs are measured.

Note With this current release, the InputGroup and OutputGroup properties of LTI objects are defined as structures, rather than cell arrays (see the Control System Toolbox documentation for more details).

The structure Nominal contains the nominal values for states, inputs, outputs and state derivatives/differences at the operating point where Model.Plant was linearized. The fields are reported in Nominal Values at Operating Point on page 3-11 (see "Offsets" in the Model Predictive Control Toolbox User's Guide).

Nominal Values at Operating Point

Field	Description	Default
X	Plant state at operating point	0
U	Plant input at operating point, including manipulated variables, measured and unmeasured disturbances	0
Y	Plant output at operating point	0
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.	0

Ts

Sampling time of the MPC controller. By default, if `Model.Plant` is a discrete-time model, `Ts=Model.Plant.ts`. For continuous-time plant models, you must specify a sampling time for the MPC controller.

Optimizer

Parameters for the QP optimization. Optimizer is a structure with the fields reported in the following table (Optimizer Properties on page 3-12).

Optimizer Properties

Field	Description	Default
MaxIter	Maximum number of iterations allowed in the QP solver	200
Trace	On/off	'off'
Solver	QP solver used (only 'ActiveSet')	'ActiveSet'
MinOutputECR	Minimum positive value allowed for OutputMinECR and OutputMaxECR	1e-10

`MinOutputECR` is a positive scalar used to specify the minimum allowed ECR for output constraints. If values smaller than `MinOutputECR` are provided in the `OutputVariables` property of the MPC objects a warning message is issued and the value is raised to `MinOutputECR`.

PredictionHorizon

`PredictionHorizon` is an integer value expressing the number p of sampling steps of prediction.

ControlHorizon

`ControlHorizon` is either a number of free control moves, or a vector of blocking moves (see "Optimization Variables" in the Model Predictive Control Toolbox User's Guide).

History

`History` stores the time the MPC controller was created.

Notes

`Notes` stores text or comments as a cell array of strings.

UserData

Any additional data stored within the MPC controller object.

MPCData

`MPCData` is a private property of the MPC object used for storing intermediate operations, QP matrices, internal flags, etc.

Version

`Version` is a private property indicating the Model Predictive Control Toolbox version number.

Construction and Initialization

An MPC object is built in two steps. The first step happens *at construction* of the object when the object constructor `mpc` is invoked, or properties are changed by a `set` command. At this first stage, only basic consistency checks are performed, such as dimensions of signals, weights, constraints, etc. The second step happens *at initialization* of the object, namely when the object is used for the first time by methods such as `mpcmove` and `sim`, that require the full computation of the QP matrices and the estimator gain. At this second stage, further checks are performed, such as a test of observability of the overall extended model.

Informative messages are displayed in the command window in both phases, you can turn them on or off using the `mpcverbosity` command.

MPC Simulation Options Object

The `mpcsimopt` object type contains various simulation options for simulating an MPC controller with the command `sim`. Its properties are listed in the following table (MPC Simulation Options Properties on page 3-14).

MPC Simulation Options Properties

Property	Description
`PlantInitialState`	Initial state vector of the plant model generating the data.
`ControllerInitialState`	Initial condition of the MPC controller. This must be a valid `@mpcstate` object.
`UnmeasuredDisturbance`	Unmeasured disturbance signal entering the plant.
`InputNoise`	Noise on manipulated variables.
`OutputNoise`	Noise on measured outputs.
`RefLookAhead`	Preview on reference signal (`'on'` or `'off'`).
`MDLookAhead`	Preview on measured disturbance signal (`'on'` or `'off'`).
`Constraints`	Use MPC constraints (`'on'` or `'off'`).
`Model`	Model used in simulation for generating the data.
`StatusBar`	Display the wait bar (`'on'` or `'off'`).
`MVSignal`	Sequence of manipulated variables (with offsets) for open-loop simulation (no MPC action).
`OpenLoop`	Perform open-loop simulation.

The command

```
SimOptions=mpcsimopt(mpcobj)
```

returns an empty @mpcsimopt object. You must use set / get to change simulation options.

UnmeasuredDisturbance is an array with as many columns as unmeasured disturbances, InputNoise and MVSignal are arrays with as many columns as manipulated variables, OutputNoise is an array with as many columns as measured outputs. The last sample of the array is extended constantly over the horizon to obtain the correct size.

Note Nonzero values of ControllerInitialState.LastMove are only meaningful if there are constraints on the increments of the manipulated variables.

The property Model is useful for simulating the MPC controller under model mismatch. The LTI object specified in Model can be either a replacement for Model.Plant, or a structure with fields Plant, Nominal. By default, Model is equal to MPCobj.Model (no model mismatch). If Model is specified, then PlantInitialState refers to the initial state of Model.Plant and is defaulted to Model.Nominal.x.

If Model.Nominal is empty, Model.Nominal.U and Model.Nominal.Y are inherited from MPCobj.Model.Nominal. Model.Nominal.X/DX is only inherited if both plants are state-space objects with the same state dimension.

MPC State Object

The mpcstate object type contains the state of an MPC controller. Its properties are listed in MPC State Object Properties on page 3-16.

MPC State Object Properties

Property	Description
Plant	Array of plant states. Values are absolute, i.e., they include possible state offsets (cf.Model.Nominal.X).
Disturbance	Array of states of unmeasured disturbance models. This contains the states of the input disturbance model and, appended below, the states of the unmeasured output disturbances model.
Noise	Array of states of measurement noise model.
LastInput	Array of previous manipulated variables $u(k\text{-}1)$. Values are absolute, i.e., they include possible input offsets (cf. Model.Nominal.U).

The command

```
mpcstate(mpcobj)
```

returns a zero extended initial state compatible with the MPC object mpcobj, and with mpcobj.Plant and mpcobj.LastInput initialized at the nominal values specified in mpcobj.Model.Nominal.

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