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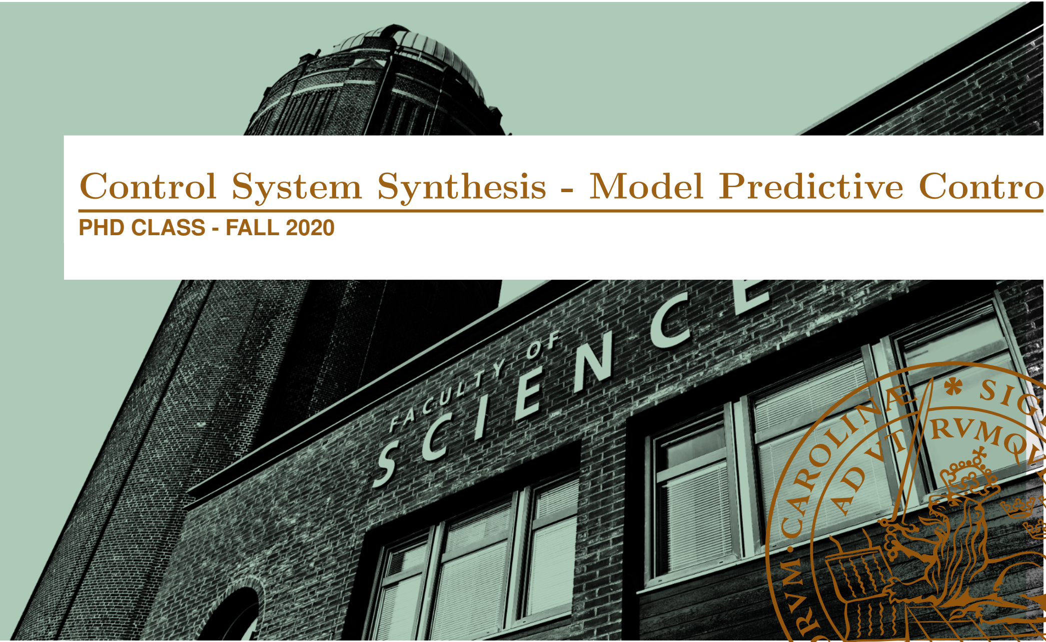
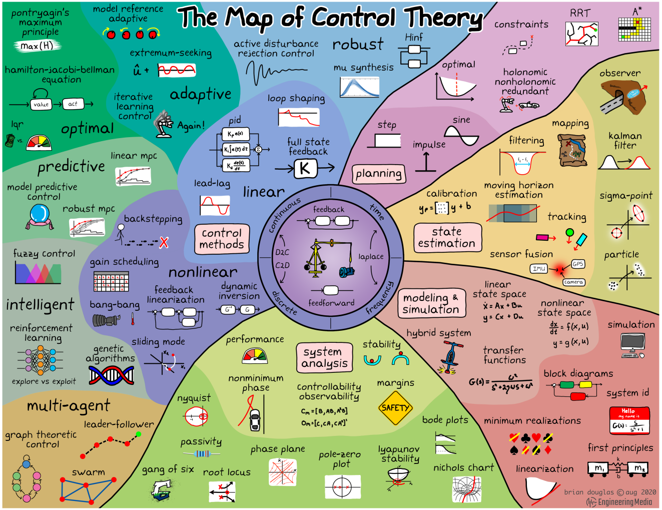
Control System Synthesis - Model Predictive Control

PHD CLASS - FALL 2020

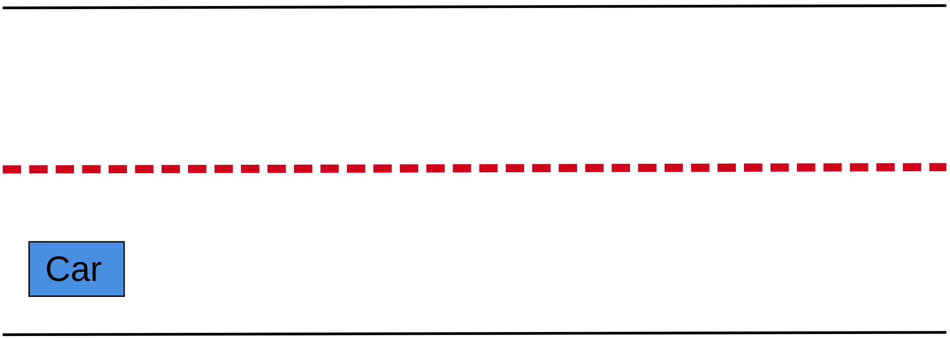



The Map of Control Theory
pontryagin's maximum principle
max(H)
model reference adaptive
extremum-seeking
hamilton-jacobi-bellman equation
value
act
iterative learning control
adaptive
Again!
lqr
optimal
active disturbance rejection control
robust
Hinf
mu synthesis
loop shaping
pid
full state feedback
K
lead-lag
linear
control methods
predictive
linear mpc
model predictive control
robust mpc
backstepping
fuzzy control
gain scheduling
nonlinear
intelligent
bang-bang
feedback linearization
dynamic inversion
reinforcement learning
genetic algorithms
sliding mode
explore vs exploit
multi-agent
leader-follower
graph theoretic control
swarm
constraints
RRT
A*
optimal
holonomic
nonholonomic
redundant
observer
step
sine
impulse
planning
filtering
mapping
kalman filter
calibration
moving horizon estimation
state estimation
tracking
sigma-point
sensor fusion
IMU
GPS
camera
particle
feedback
time
continuous
D2C
C2D
laplace
discrete
feedforward
frequency
modeling & simulation
linear state space
nonlinear state space
simulation
hybrid system
transfer functions
block diagrams
system id
performance
system analysis
stability
nonminimum phase
controllability observability
margins
SAFETY
nyquist
passivity
phase plane
pole-zero plot
lyapunov stability
bode plots
nichols chart
minimum realizations
first principles
linearization
gang of six
root locus
Hello
brian douglas © aug 2020
Engineering Media

Content overview

MPC design

Basic idea



MPC design

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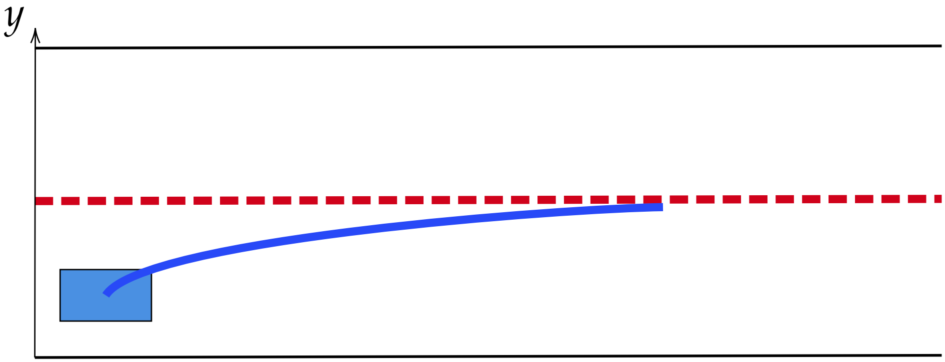

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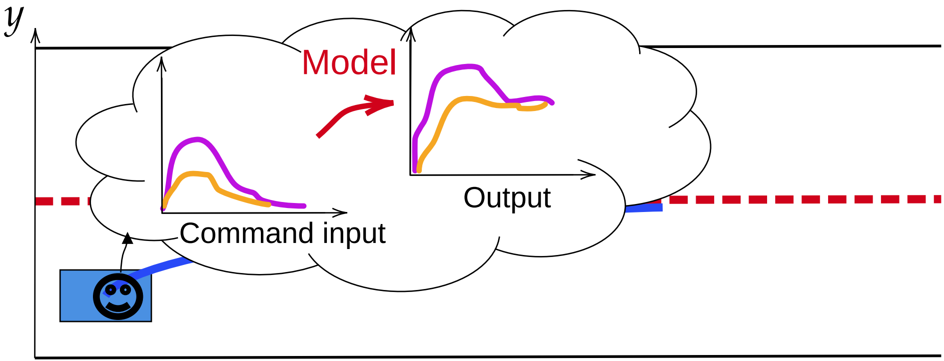
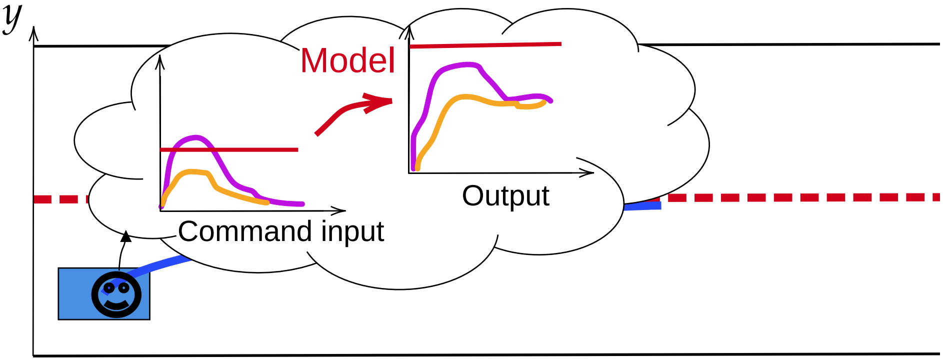
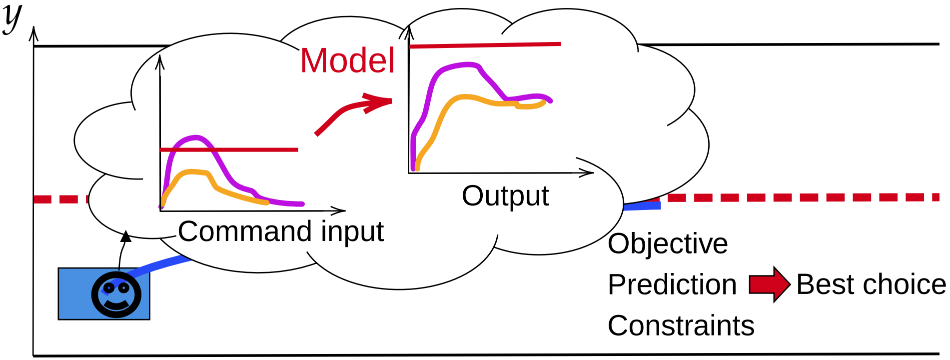



y
Model
Command input
Output

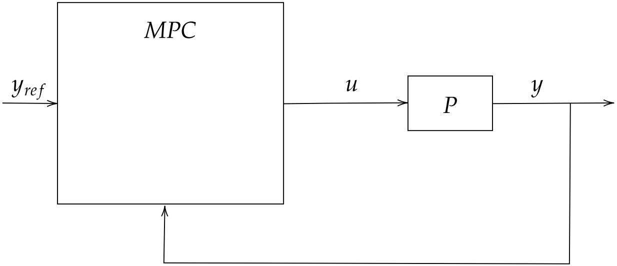
MPC design

Basic idea



MPC design

How does MPC work?



- MPC is a form of feedback control

MPC design

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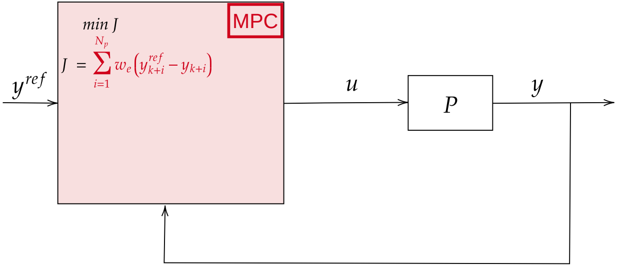

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- that solves an optimization problem to select the optimal control at each time step

MPC design

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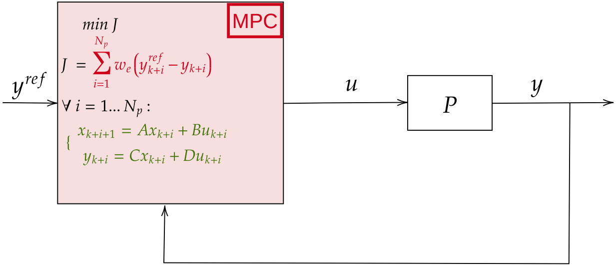

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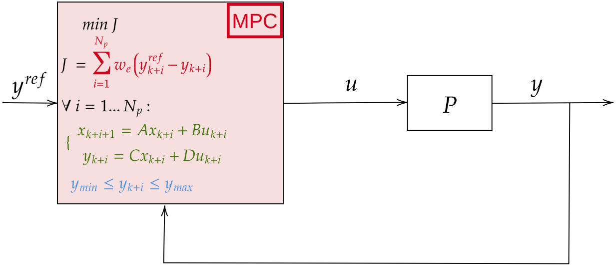

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MPC design

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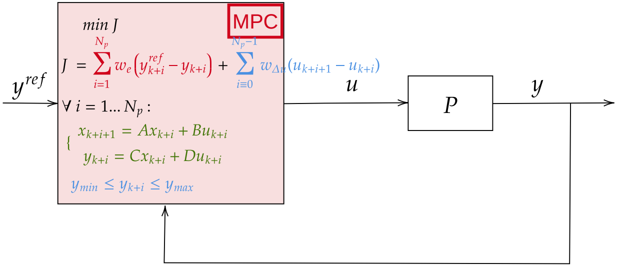

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MPC design

Design parameters

- sample time
- prediction horizon
- control horizon
- constraints
- weights

MPC design
Design parameters

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$\rightarrow$ influence the controller performances

MPC design
Design parameters

- sample time
- prediction horizon
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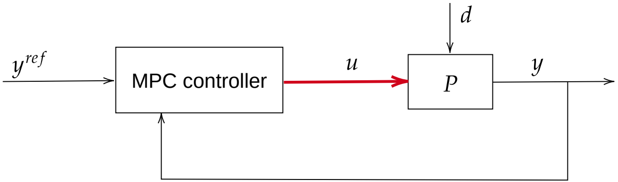
$\rightarrow$ influence the controller performances

$\rightarrow$ influence computational complexity

Sample time T_s



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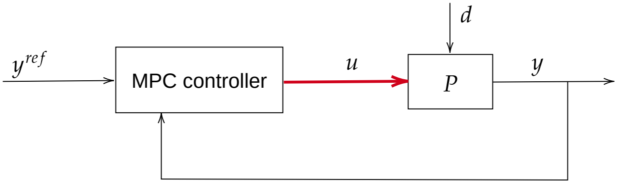
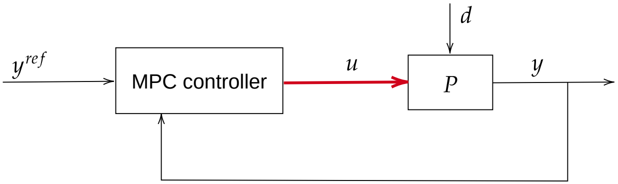


- T_s too big $\Rightarrow$ slow response to disturbances/setpoint changes

Sample time T_s



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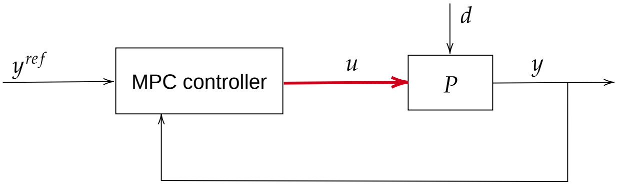
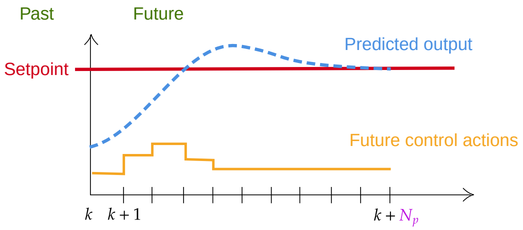


- T_s too big $\Rightarrow$ slow response to disturbances/setpoint changes
- T_s too small $\Rightarrow$ faster response but computational load increase
- **Recommendation:** $\frac{T_r}{20} \leq T_s \leq \frac{T_r}{10}$

Prediction horizon N_p



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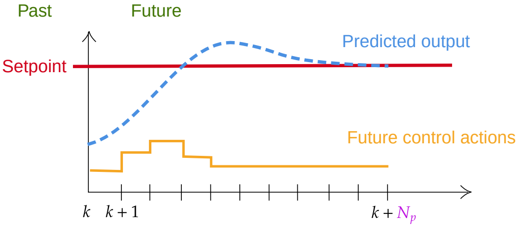
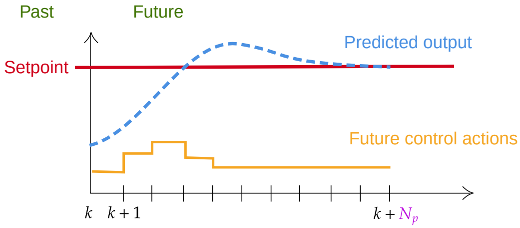


- N_p too small $\Rightarrow$ may be too late to react to disturbances

Prediction horizon N_p



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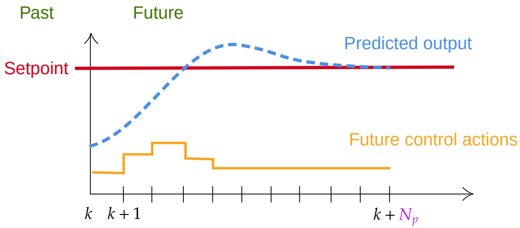
Prediction horizon N_p

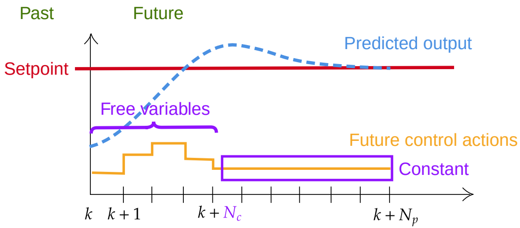


- N_p too small $\Rightarrow$ may be too late to react to disturbances
- N_p too big $\Rightarrow$ computational load increase (potentially unnecessary due to potential disturbances)
- **Recommendation:** Choose N_p to cover the significant dynamics of the system

$$N_p T_s \approx T_{settling}$$

Control horizon N_c

$\rightarrow$ usually only the first couple of control moves have a significant effect on the predicted output behavior



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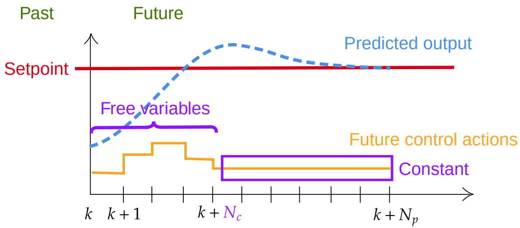

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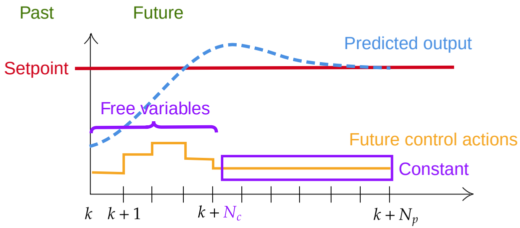

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MPC design

Design parameters

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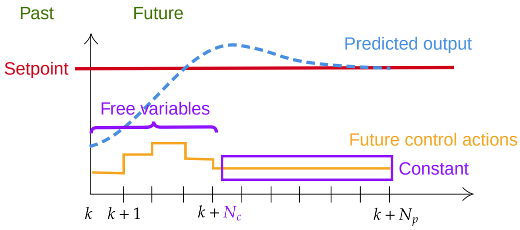

- N_c too small $\Rightarrow$ not enough degrees of freedom to reach the objective
- N_c too big $\Rightarrow$ computational load increase
- **Recommendation:** 10 to 20% of N_p, minimum 2-3 steps

MPC design
Design parameters

Constraints

- on the inputs, outputs or inputs variations
- **Soft constraints**
- **Hard constraints**

MPC design

Design parameters

Constraints

- on the inputs, outputs or inputs variations
- **Soft constraints**: can be violated
- **Hard constraints**: cannot be violated

MPC design

Design parameters

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Constraints

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- **Soft constraints**
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MPC design

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- Output constraints as soft constraints

$$y_{min} - \varepsilon V_{max} \leq y \leq y_{max} + \varepsilon V_{max}$$

$$\min_{u,\varepsilon} \cdots + \rho\varepsilon$$

MPC design
Design parameters

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$$y_{min} - \varepsilon V_{max} \leq y \leq y_{max} + \varepsilon V_{max}$$

$$\min_{u,\varepsilon} \cdots + \rho\varepsilon$$

- Avoid having hard constraints on both inputs and inputs variations

$$J = \sum_{i=1}^{N_p} \omega_e (y_{k+1}^{ref} - y_{k+1})^2 + \sum_{i=0}^{N_p-1} \omega_{\Delta u} (u_{k+i+1} - u_{k+i})^2$$

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Weights

- The MPC controller may have different objectives

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→ affect the controller performances

- Linear system

MPC design

Summary

- Linear system
- Linear constraints

MPC design
Summary

- Linear system
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- Quadratic cost function

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→ **LTI MPC**

MPC design
Summary

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$\rightarrow$ **LTI MPC**

- convex optimization problem

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- Linear system
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→ **LTI MPC**
  - convex optimization problem
  - single global optimum of the cost function

MPC design

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- Linear system
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$\rightarrow$ **LTI MPC**

- convex optimization problem
- single global optimum of the cost function
- well-studied problem, many numerical methods and software to solve it

- Linear system
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$\rightarrow$ **LTI MPC**

- convex optimization problem
- single global optimum of the cost function
- well-studied problem, many numerical methods and software to solve it

Compared to LQR:

- MPC solves the optimization problem in a smaller time window $\Rightarrow$ suboptimal solution
- MPC is an online technique and can handle deviations of the system from the model

- Linear system
- Linear constraints
- Quadratic cost function

$\rightarrow$ **LTI MPC**

  - convex optimization problem
  - single global optimum of the cost function
  - well-studied problem, many numerical methods and software to solve it

The state is often used in the cost function $\rightarrow$ state estimator may be needed

MPC design
Important issues

- **Feasibility**

- **Feasibility** $\rightarrow$ soft state or output constraints introducing a slack variable ε

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MPC design

Important issues

- **Feasibility** $\rightarrow$ soft state or output constraints introducing a slack variable ε
- **Stability** $\rightarrow$ either use the minimizer of the cost function as a Lyapunov function or require the norm of the state x to shrink
  - Terminal constraint $x(k+N_p)=0$ or set (involves the LQ gain) or terminal cost
  - Infinite Output Prediction Horizon $N_p=\infty$
  - Contraction Constraint $\|x(t+1)\| \leq \alpha\|x(t)\|$ with $\alpha<1$

MPC design
Important issues

- **Feasibility** $\rightarrow$ soft state or output constraints introducing a slack variable ε
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- **Computational cost** $\rightarrow$ design parameters and stability constraints (in the LTI MPC case)

Basic MPC:

- the system and the prediction model are the same
- no unmeasured noise/disturbance

Going further

Robust MPC

Basic MPC:

- the system and the prediction model are the same
- no unmeasured noise/disturbance

Fundamental question: what about robustness to model uncertainty and noise?

Bemporad, A., and Morari, M. (1999). *Robust model predictive control: A survey.*, in *Robustness in identification and control*, Springer.

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Robustness:

- specific uncertainty range: $P \in \mathcal{P}$, $w \in \mathcal{W}$
- robust stability, robust performance and robust constraints fulfillment

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Nominal vs robust MPC

Nominal vs robust MPC

1. **Robust performances:** $\min_{U} \max_{\substack{P \in \mathcal{P} \\ w \in \mathcal{W}}} J(U, x, P, w)$

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   $\rightarrow$ include a feedback term into the prediction model

$$u = Fx + v$$

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3. **Open-loop or a closed-loop prediction scheme ?**
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4. **Robust stability enforcement**
   - indirectly: performance objective and uncertainty description
   - directly: type of robust contraction constraint

Going further

Stochastic MPC

A. Mesbah, *Stochastic Model Predictive Control: An Overview and Perspectives for Future Research*, in IEEE Control Systems Magazine, 2016.

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- Noise and disturbances are stochastic variables, making the prediction model stochastic
- **Chance constraints**: constraints satisfied with at least a priori specified probability level
- rooted in stochastic programming and chance-constrained optimization

Going further

1 MPC design
- Basic idea
- How does MPC work?
- Design parameters
- Important issues

2 Going further
- Robust MPC
- Stochastic MPC
- Running MPC faster and explicit MPC
- Adaptive and Gain-scheduled MPC
- Nonlinear MPC
- Data-driven MPC

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Going further

Running MPC faster and explicit MPC

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$\rightarrow$ design parameters

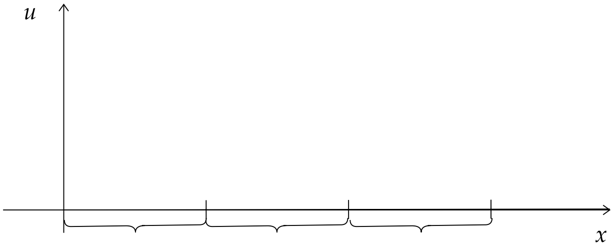
$\rightarrow$ model order reduction

$\rightarrow$ lower complexity

$\rightarrow$ maximum number of optimization iterations $\rightarrow$ suboptimal solution but still satisfies constraints

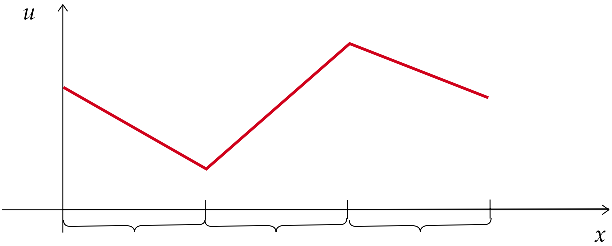
How to run MPC faster?

- Explicit MPC precomputes the optimal solution in different state-regions



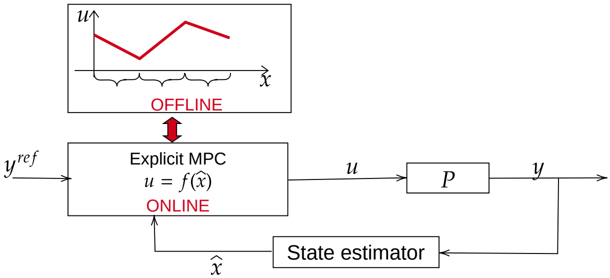
How to run MPC faster?

- Explicit MPC precomputes the optimal solution in different state-regions
- as linear functions that are piecewise affine and continuous in x



How to run MPC faster?

- Explicit MPC precomputes the optimal solution in different state-regions
- as linear functions that are piecewise affine and continuous in x
- Online evaluation the state region and of *u*



How to run MPC faster?

- Explicit MPC precomputes the optimal solution in different state-regions
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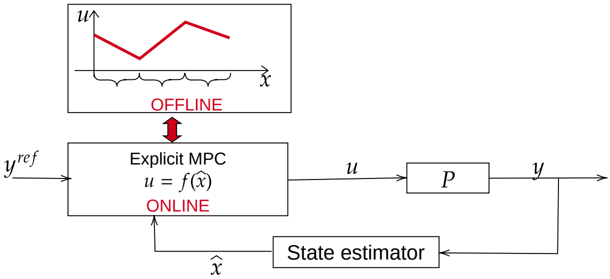
- Online evaluation the state region and of *u*
- Many regions $\rightarrow$ time consuming and memory needed



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Going further

Adaptive and Gain-scheduled MPC

Nonlinear systems + linear constraints + quadratic cost function

$\rightarrow$ linearization to benefit from the nice properties of linear MPC

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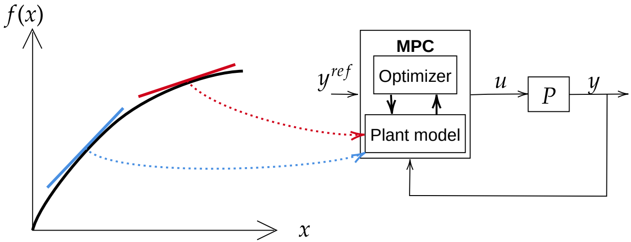


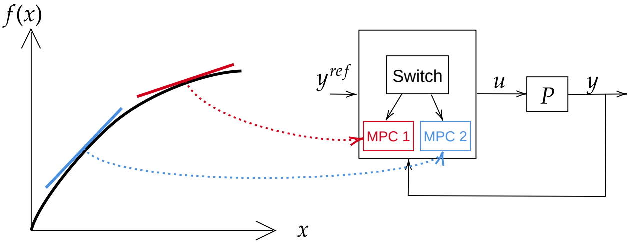
Going further

Adaptive and Gain-scheduled MPC

Nonlinear systems + linear constraints + quadratic cost function

$\rightarrow$ linearization to benefit from the nice properties of linear MPC

- **Adaptive MPC**: linearized model computed on the fly, updated at each time step
- **Gain-scheduled MPC**: switch between different MPC controllers for different operating points of interest



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Nonlinear MPC

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- economic MPC is part of nonlinear MPC

Going further

Dealing with non-linearities

Plant	L	NL $\approx$ L	highly NL	L
Constraints	L	L	L or NL	NL
Cost	L	L	L or NL	NL
	Linear MPC	Adaptive MPC or Gain-scheduled MPC	Non-linear MPC	

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Going further
Data-driven MPC

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- When no accurate model is available:

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Data-driven MPC

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Huang, B., Kadali, R. *Dynamic modeling, predictive control and performance monitoring: a data-driven subspace approach*, Springer, 2008.

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  - Learning for closed-loop performances