Optimal dynamic operation of chemical processes: Assessment of the last 20 years and current research opportunities

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Outline

1. The last 20 years — what tools have researchers developed
2. Industrial impact of these ideas
3. Have all the questions been answered?
   - Control of large-scale systems
   - Optimizing economics
4. Conclusions and future outlook

The power of abstraction

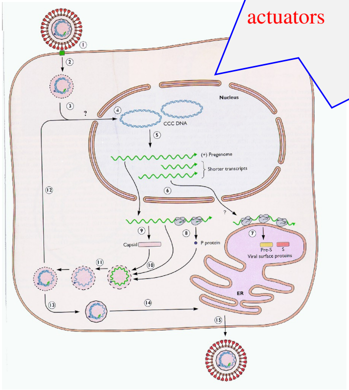
process

actuators

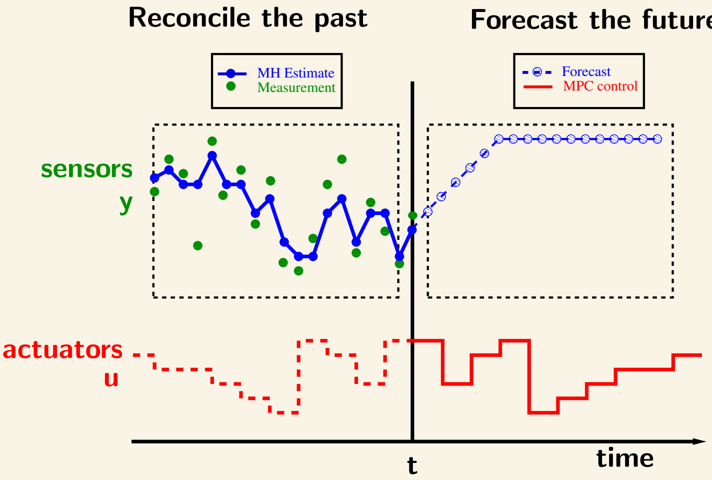
$$\frac{dx}{dt} = f(x, u)$$

$$y = g(x, u)$$

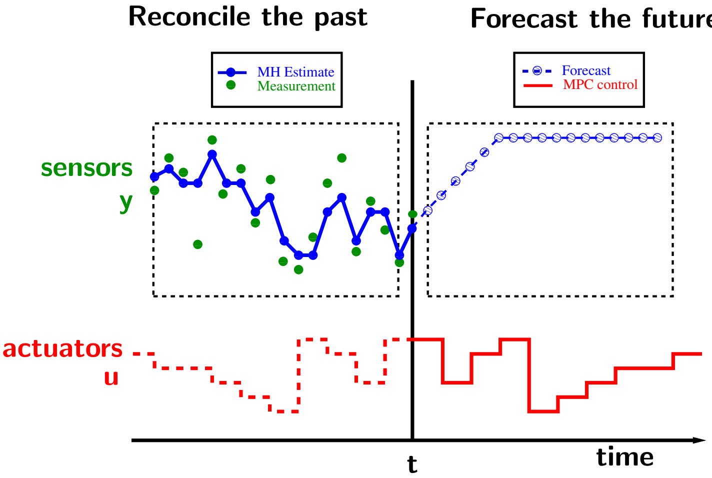
sensors



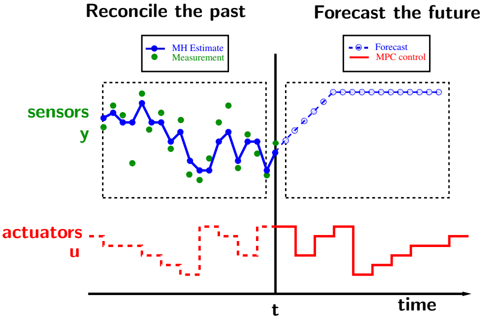
The model predictive control framework



The future influences the present just as much as the past does.



Predictive control

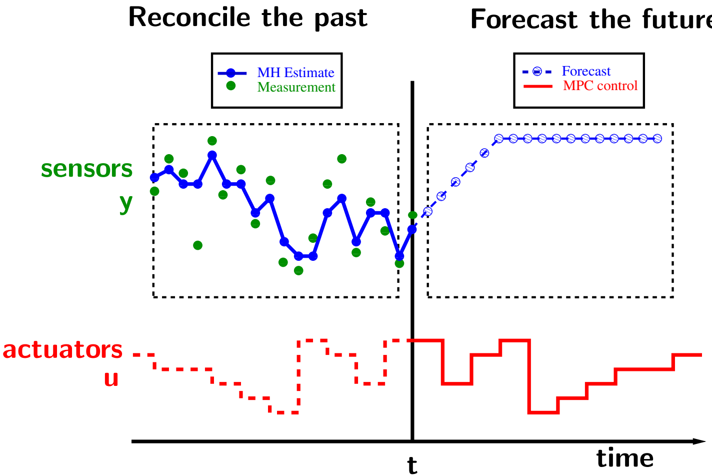


$$\min_{u(t)} \int_0^T |y_{sp} - g(x,u)|_Q^2 + |u_{sp} - u|_R^2 \, dt$$

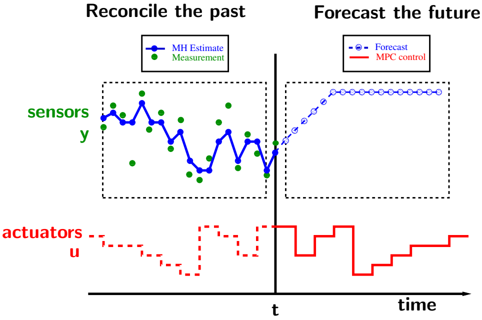
$$\dot{x} = f(x,u)$$
$$x(0) = x_0 \quad \text{(given)}$$
$$y = g(x,u)$$

State estimation

When I want to understand what is happening today or try to decide what will happen tomorrow, I look back.



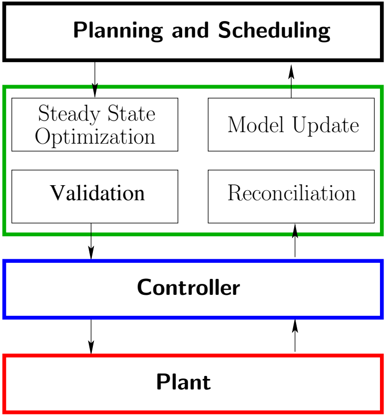
State estimation



$$\min_{x_0, w(t)} \int_{-T}^{0} |y - g(x,u)|_R^2 + |\dot{x} - f(x,u)|_Q^2 \, dt$$

$$\begin{aligned} \dot{x} &= f(x,u) + w \quad &\text{(process noise)} \\ y &= g(x,u) + v \quad &\text{(measurement noise)} \end{aligned}$$

Industrial impact of the research



Two layer structure

- Steady-state layer
  - RTO optimizes steady-state model
  - Optimal setpoints passed to dynamic layer

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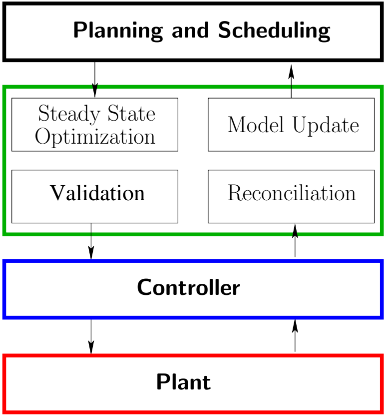

Two layer structure

- Steady-state layer
  - RTO optimizes steady-state model
  - Optimal setpoints passed to dynamic layer
- Dynamic layer
  - Controller tracks the setpoints
  - Linear MPC (replaces multiloop PID)

Large industrial success story!

Linear MPC and ethylene manufacturing

- Number of MPC applications in ethylene: 800 to 1200

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- 16 M$/year increased profit (2008)

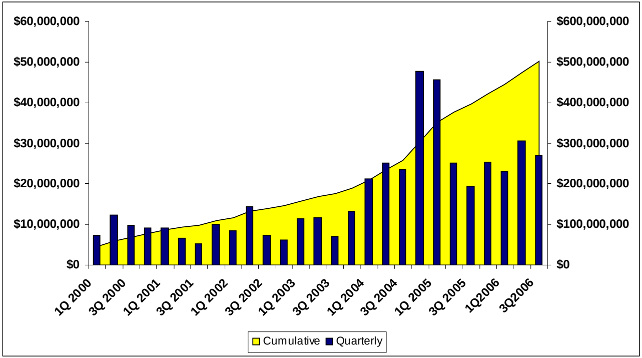
Impact for 13 ethylene plants (Starks and Arrieta, 2007)

Dow

Hydrocarbons AC&O

17

We're Doing it For the Money



Advanced Control & Optimization

Are all the problems solved?

Some questions to consider

- How do we best decompose *large-scale systems* into manageable problems?

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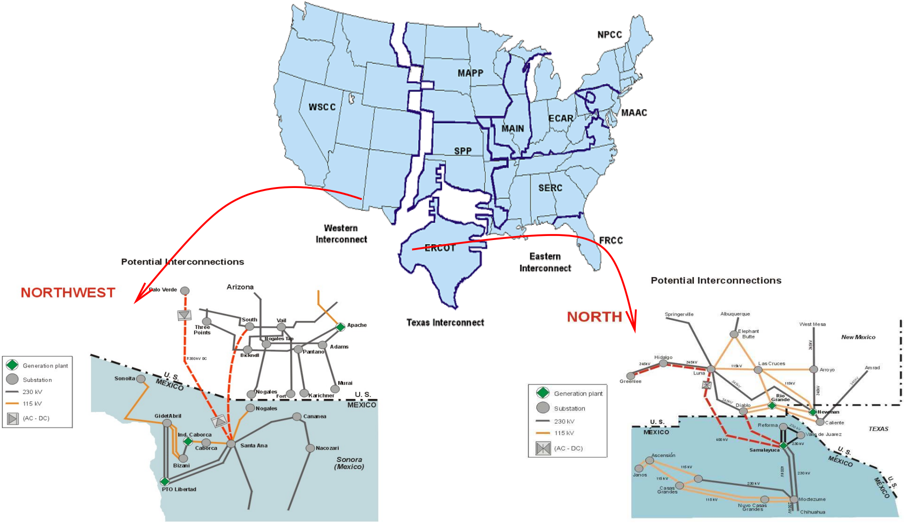
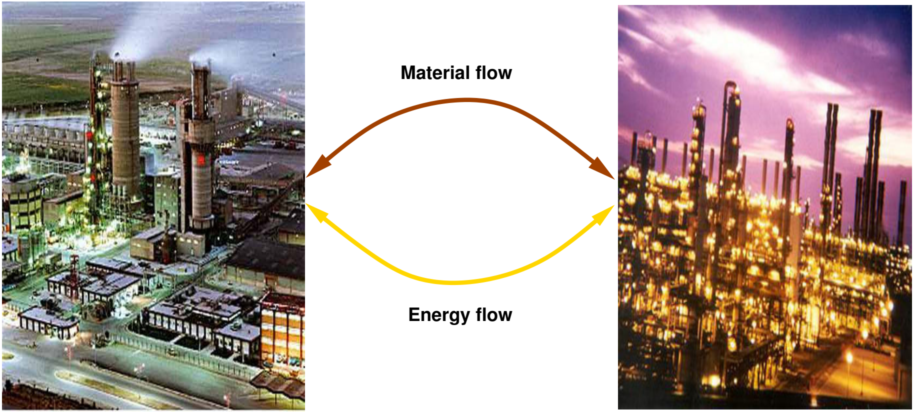
- How do we best decompose *large-scale systems* into manageable problems?
- How do we optimize dynamic *economic* operation?

Electrical power distribution



Chemical plant integration



MPC at the large scale

Decentralized Control

- Most large-scale systems consist of networks of interconnected/interacting subsystems
  - Chemical plants, electrical power grids, water distribution networks, ...

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Decentralized Control

- Most large-scale systems consist of networks of interconnected/interacting subsystems
  - Chemical plants, electrical power grids, water distribution networks, ...
- Traditional approach: Decentralized control
  - Wealth of literature from the early 1970's on improved decentralized control [a]
  - Well known that poor performance may result if the interconnections are not negligible

[a](Sandell Jr. et al., 1978; Šiljak, 1991; Lunze, 1992)

MPC at the large scale

Centralized Control

- Steady increase in available computing power has provided the opportunity for centralized control
- Most practitioners view centralized control of large, networked systems as impractical and unrealistic
- A divide and conquer strategy is essential for control of large, networked systems (Ho, 2005)
- Centralized control: A benchmark for comparing and assessing distributed controllers

Nomenclature: consider two interacting units

Objective functions	$V_1(u_1, u_2), \ V_2(u_1, u_2)$
and	$V(u_1, u_2) = w_1 V_1(u_1, u_2) + w_2 V_2(u_1, u_2)$
decision variables for units	$u_1 \in \Omega_1, \quad u_2 \in \Omega_2$

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Decentralized Control	$\min_{u_1 \in \Omega_1} \widetilde{V}_1(u_1) \quad \min_{u_2 \in \Omega_2} \widetilde{V}_2(u_2)$

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Noncooperative Control	$\min_{u_1 \in \Omega_1} V_1(u_1, u_2) \quad \min_{u_2 \in \Omega_2} V_2(u_1, u_2)$
(Nash equilibrium)	

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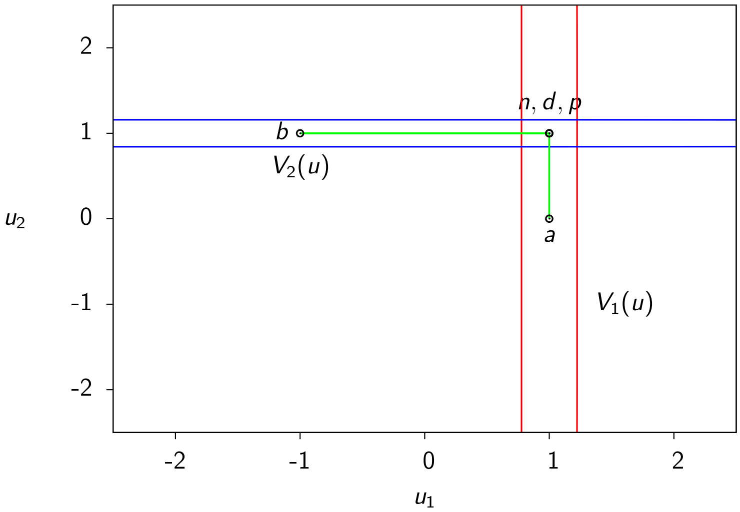
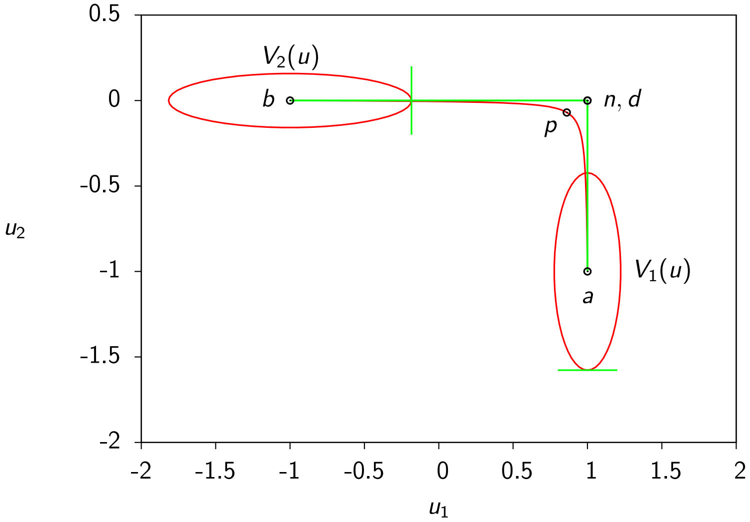
Cooperative Control	$\min_{u_1 \in \Omega_1} V(u_1, u_2) \quad \min_{u_2 \in \Omega_2} V(u_1, u_2)$
(Pareto optimal)	
Centralized Control	$\min_{u_1, u_2 \in \Omega_1 \times \Omega_2} V(u_1, u_2)$
(Pareto optimal)	

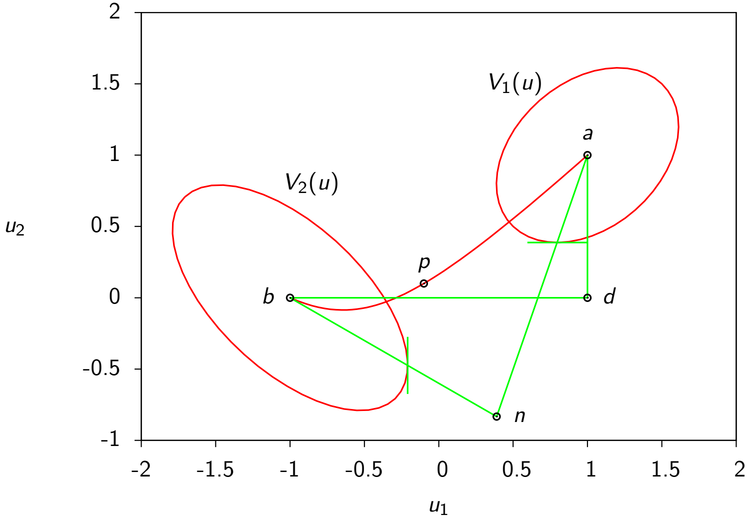
Noninteracting systems



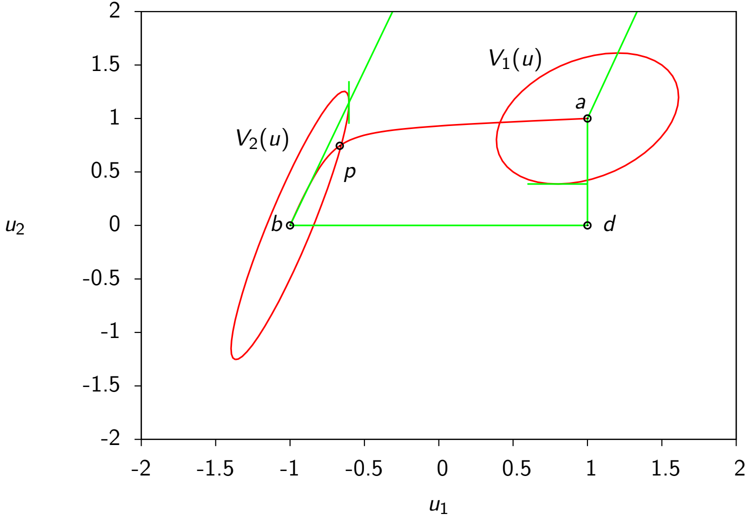
Weakly interacting systems



Moderately interacting systems



Strongly interacting (conflicting) systems



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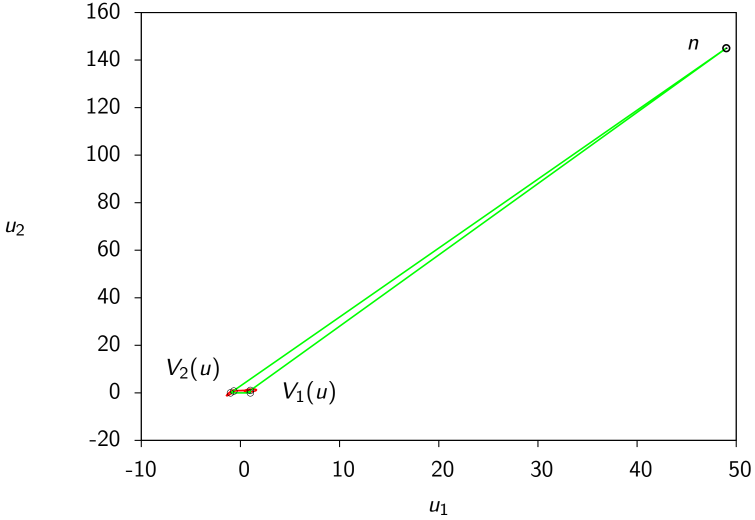
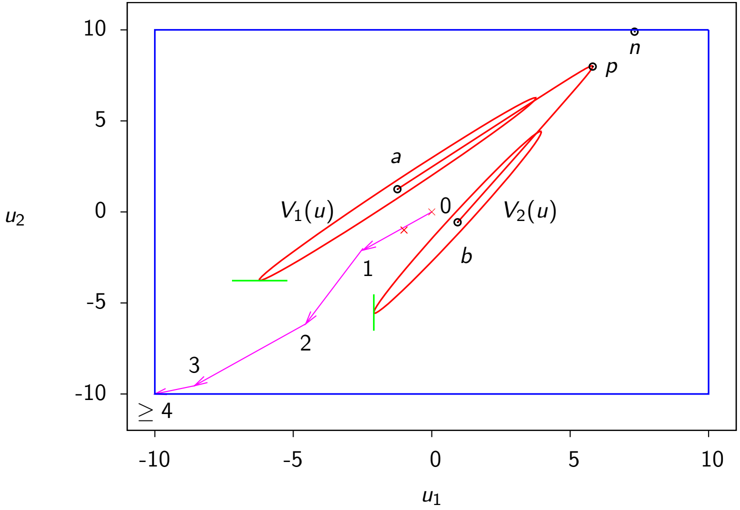


Geometry of cooperative vs. noncooperative MPC



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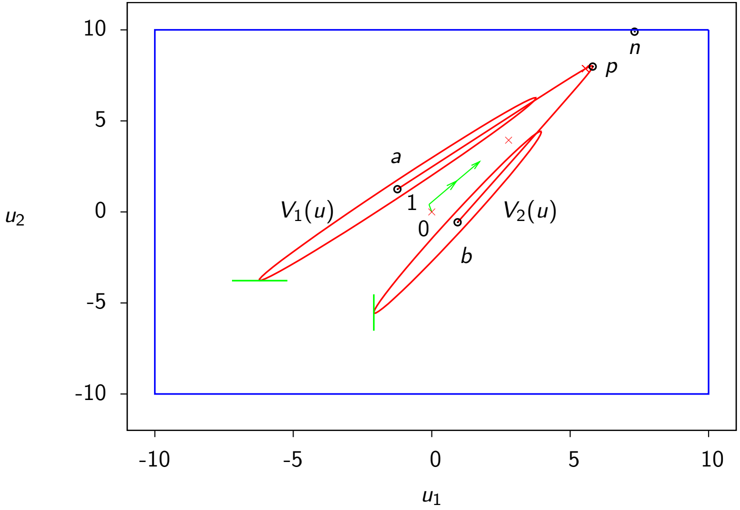
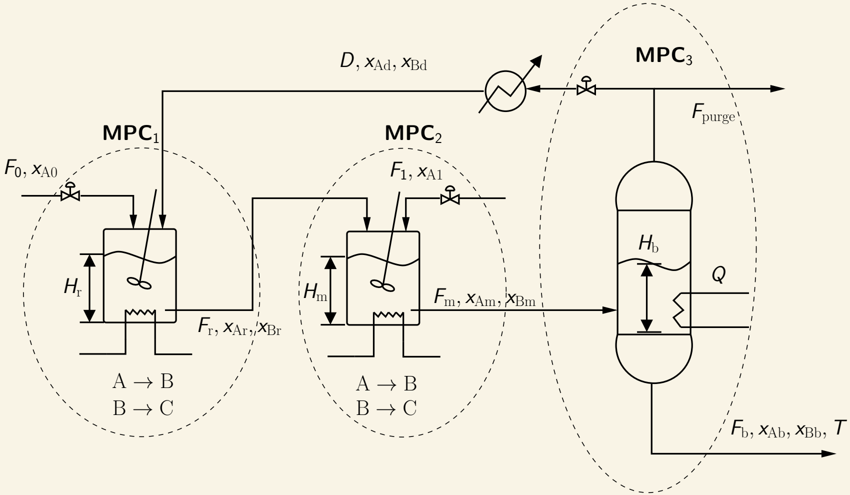


Two reactors with separation and recycle



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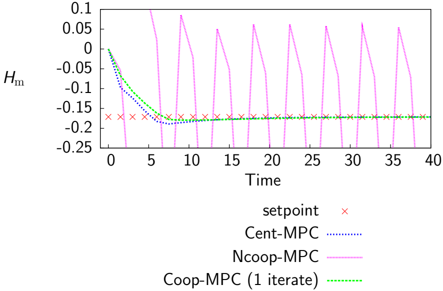
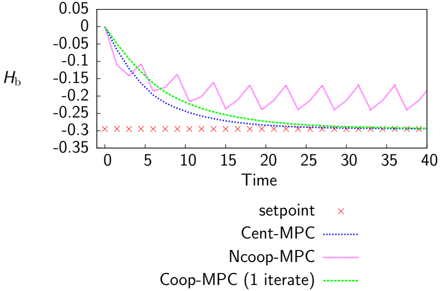
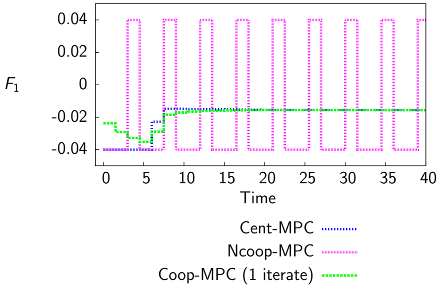
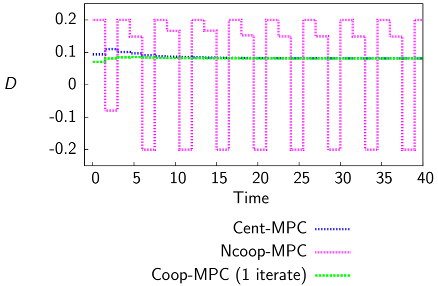






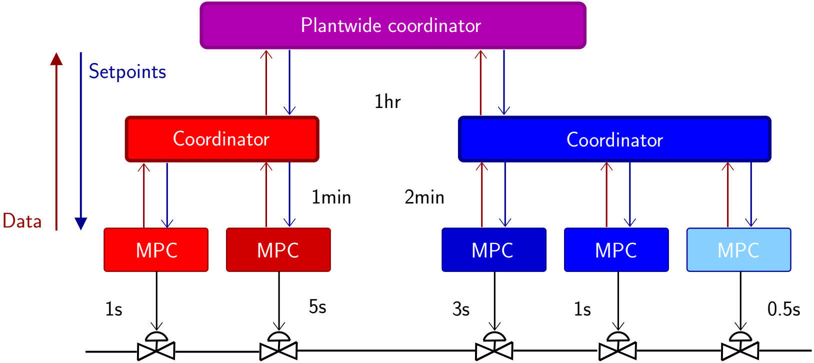


Two reactors with separation and recycle

Performance comparison

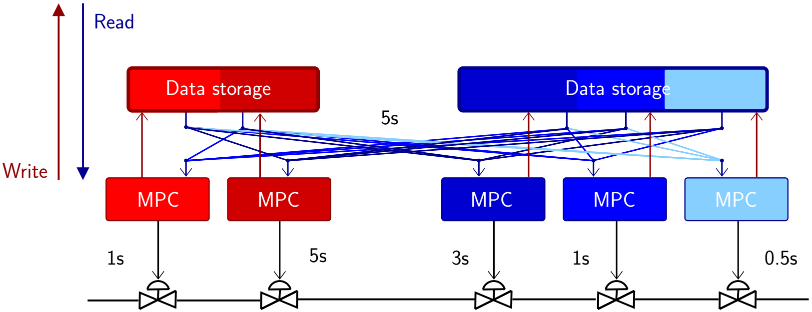
	Cost ($\times 10^{-2}$)	Performance loss
Centralized MPC	1.75	0
Decentralized MPC	∞	∞
Noncooperative MPC	∞	∞
Cooperative MPC (1 iterate)	2.2	25.7%
Cooperative MPC (10 iterates)	1.84	5%

Traditional hierarchical MPC



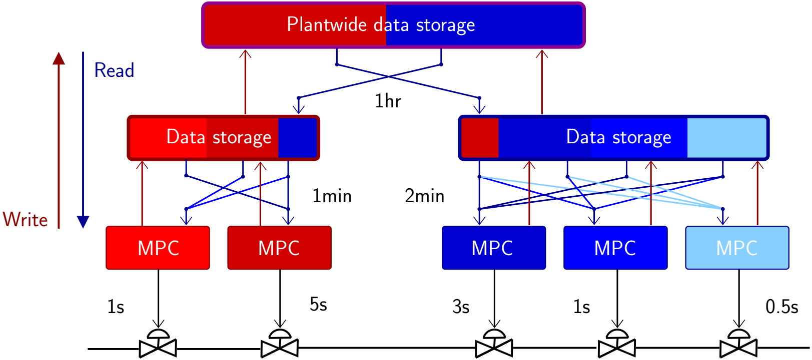
- Multiple dynamical time scales in plant
- Data and setpoints are exchanged on slower time scale
- Optimization performed at each layer

Cooperative MPC data exchange



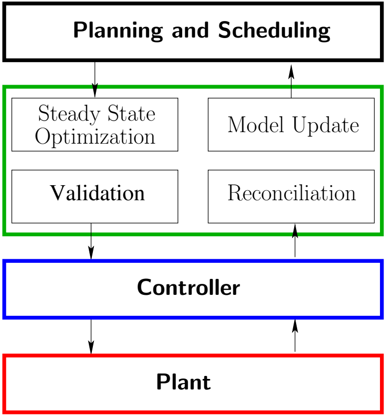
- All data exchanged plantwide
- Slowest MPC defines rate of data exchange

Cooperative hierarchical MPC



- Optimization at MPC layer only
- Only subset of data exchanged plantwide
- Data exchanged at slower time scale

Optimizing economics: Current industrial practice



- Two layer structure
- Drawbacks

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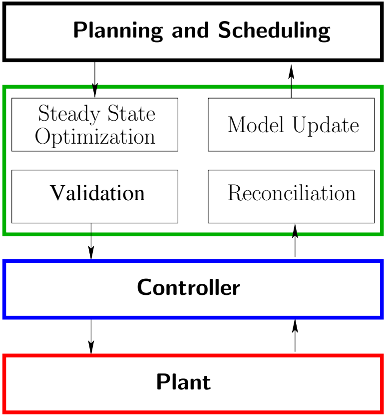
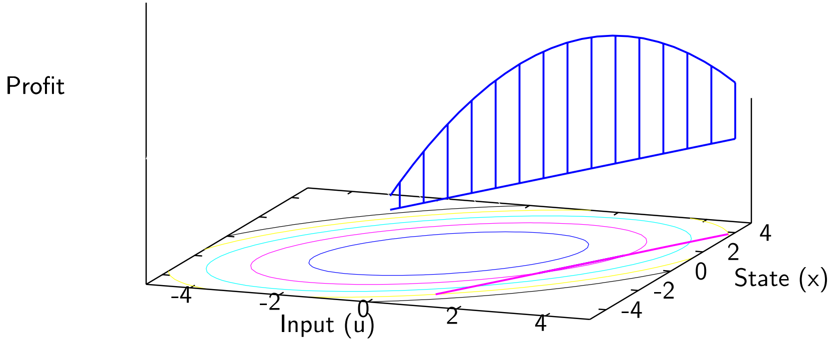


- Two layer structure
- Drawbacks
  - Inconsistent models
  - Re-identify linear model as setpoint changes
  - Time scale separation may not hold
  - Economics unavailable in dynamic layer

Motivating the idea



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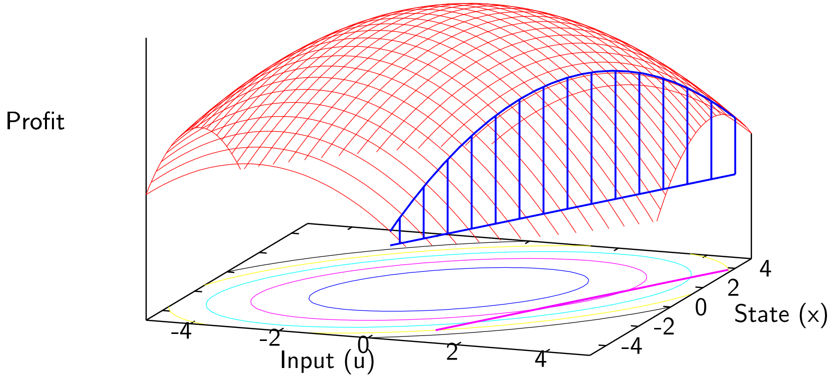

Economics controller

$$\min_{u(t)} \int_0^T L(x,u)dt \qquad \text{subject to:} \quad \begin{aligned} \dot{x} &= f(x,u) \\ y &= g(x,u) \end{aligned}$$

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- Target tracking (standard)

$$L(x,u) = |y_{sp} - g(x,u)|_Q^2 + |u_{sp} - u|_R^2$$

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- Target tracking (standard)

$$L(x,u) = |y_{sp} - g(x,u)|_Q^2 + |u_{sp} - u|_R^2$$

- Economic optimization (new)
  L is the negative of economic profit function

$$L(x,u) = -P(x,u)$$

Strong duality and asymptotic stability

Strong Duality

If there exists a λ such that the the following problems have the same solution

$$\min_{x,u} L(x,u) \qquad f(x,u) = 0 \qquad h(x,u) \leq 0$$

$$\min_{x,u} L(x,u) - \lambda(f(x,u)) \qquad h(x,u) \leq 0$$

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$$h(x,u) \leq 0$$

- Asymptotic stability of the closed-loop economics controller with a strictly convex cost and linear dynamics (Rawlings et al., 2008)
- Asymptotic stability of the closed-loop economics controller with strong duality in the steady-state problem (Diehl et al., 2010)

Example

$$x_{k+1} = \begin{bmatrix} 0.857 & 0.884 \\ -0.0147 & -0.0151 \end{bmatrix} x_k + \begin{bmatrix} 8.565 \\ 0.88418 \end{bmatrix} u_k$$

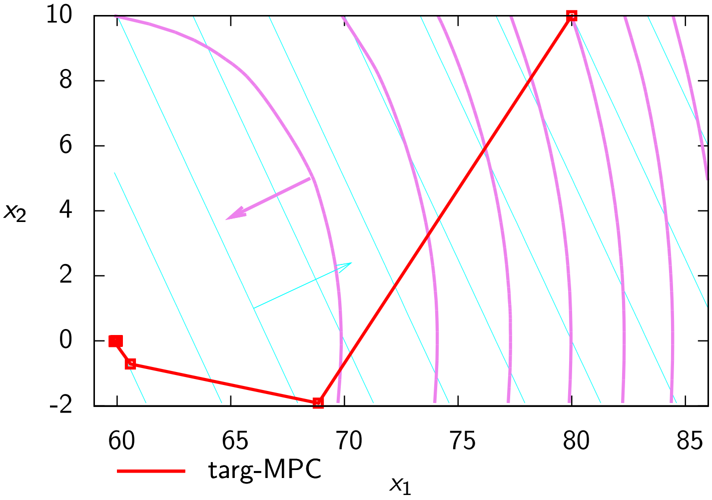
Input constraint: $-1 \leq u \leq 1$

Economics

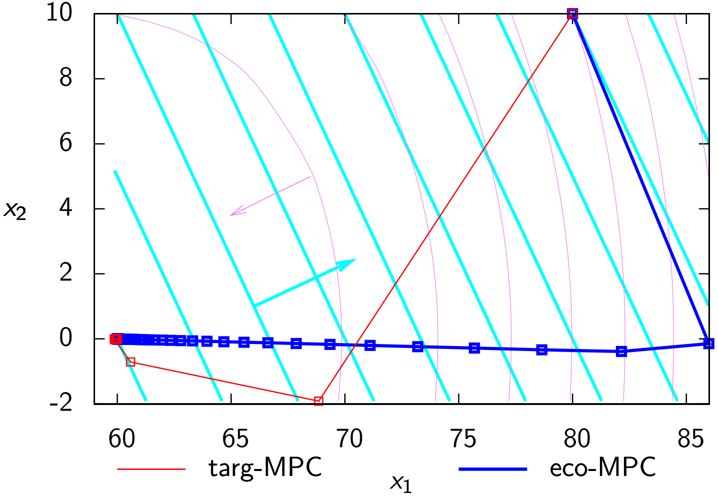
- $L_{eco} = \alpha' x + \beta' u$
- $\alpha = \begin{bmatrix} -3 & -2 \end{bmatrix}' \qquad \beta = -2$

Tracking

- $L_{targ} = |x - x^*|_Q^2 + |u - u^*|_R^2$
- $Q = 2I_2 \qquad R = 2$
- $x^* = \begin{bmatrix} 60 & 0 \end{bmatrix}' \qquad u^* = 1$



10
8
6
4
2
0
-2
x_2
60
65
70
75
80
85
x_1
targ-MPC



10
8
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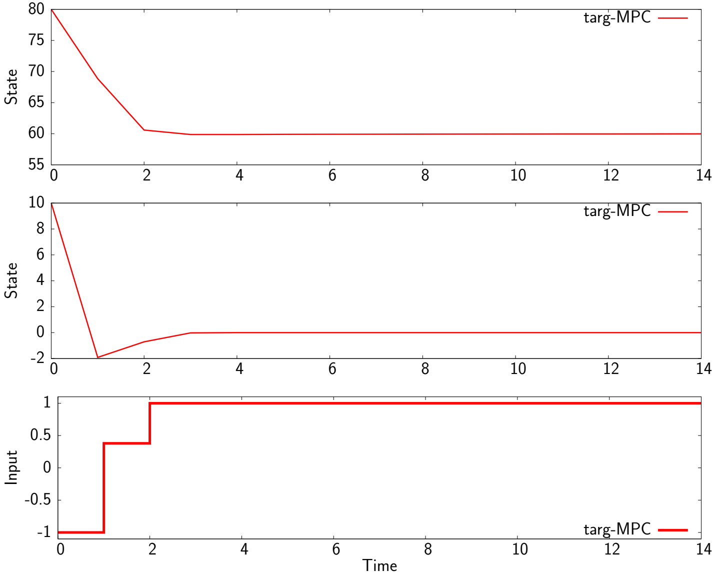
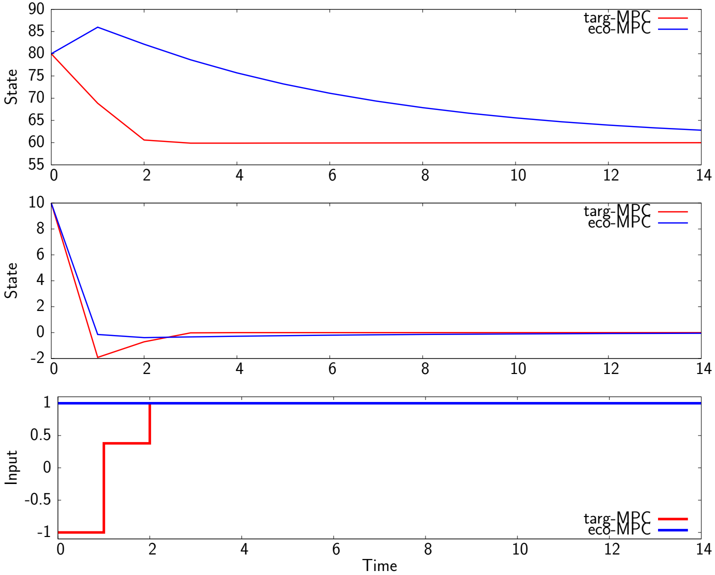
4
2
0
-2
x_2
60
65
70
75
80
85
x_1
targ-MPC
eco-MPC



State
targ-MPC
80
75
70
65
60
55
0
2
4
6
8
10
12
14
State
targ-MPC
10
8
6
4
2
0
-2
0
2
4
6
8
10
12
14
Input
targ-MPC
1
0.5
0
-0.5
-1
0
2
4
6
8
10
12
14
Time



90
85
80
75
70
65
60
55
State
targ-MPC
eco-MPC
0
2
4
6
8
10
12
14
10
8
6
4
2
0
-2
State
1
0.5
0
-0.5
-1
Input
Time

Conclusions

- Optimal dynamic operation of chemical processes has undergone a total transformation in the last 20 years.

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- The currently available theory splits the problem into state estimation and regulation. Both are posed and solved as online optimization problems.

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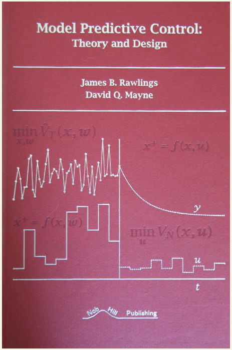

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