

# Optimizing Process Economic Performance with Model Predictive Control

James B. Rawlings

Department of Chemical and Biological Engineering



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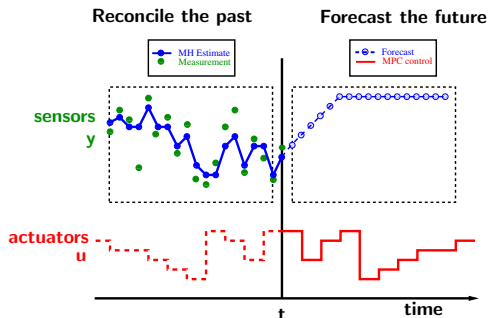
Systems and Control Seminar

Institute for Systems Theory and Automatic Control

University of Stuttgart

- 1 Optimal control, optimal feedback control, and model predictive control (MPC)
- 2 Industrial impact of these ideas
- 3 Using MPC to optimize plant economics

# Predictive control



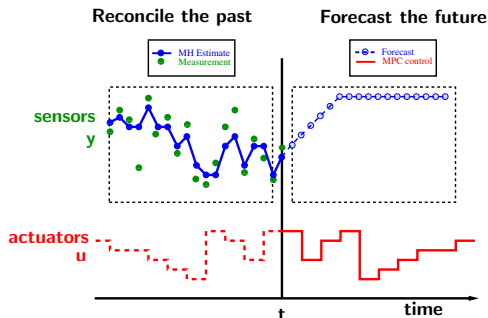
$$\min_{u(t)} \int_0^T |y_{sp} - g(x, u)|_Q^2 + |u_{sp} - u|_R^2 dt$$

$$\dot{x} = f(x, u)$$

$$x(0) = x_0 \quad (\text{given})$$

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

# State estimation



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

$$\dot{x} = f(x, u) + w \quad (\text{process noise})$$

$$y = g(x, u) + v \quad (\text{measurement noise})$$

## From optimal control to optimal *feedback* control

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- Optimal feedback control sees limited industrial application during this period.

## So what unchained optimal control?

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— Lee and Markus (1967)  
*Foundations of Optimal Control Theory*

Our notion of **very rapidly** changed radically from 1960 to 1985.

# Large industrial success story!

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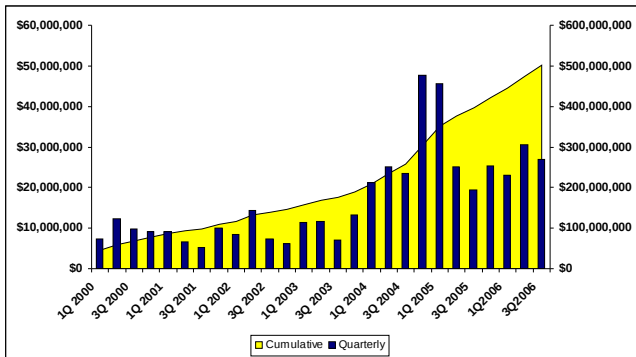
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## We're Doing it For the Money



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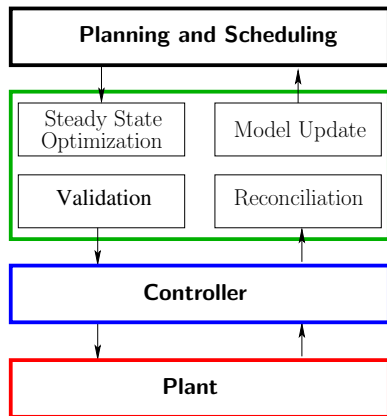
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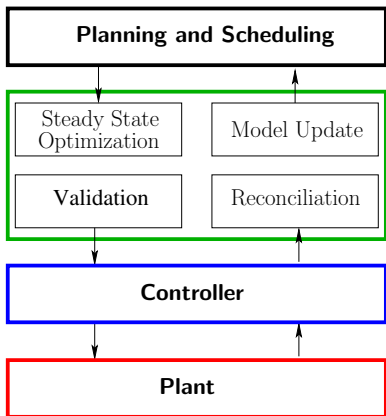
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- Do we have tools to optimize dynamic *economic* operation?

# Optimizing economics: Current industrial practice



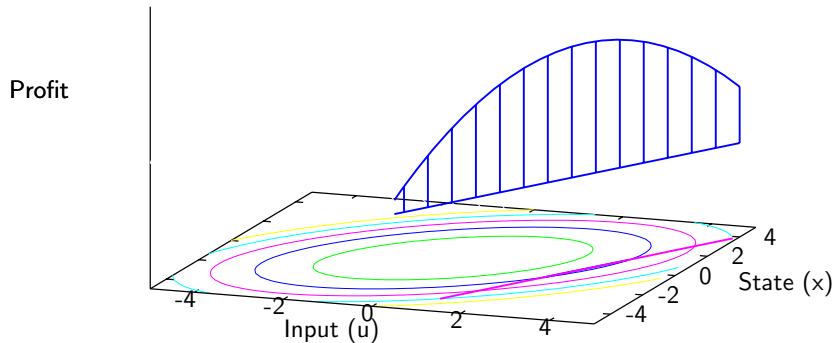
- Two layer structure
- Drawbacks

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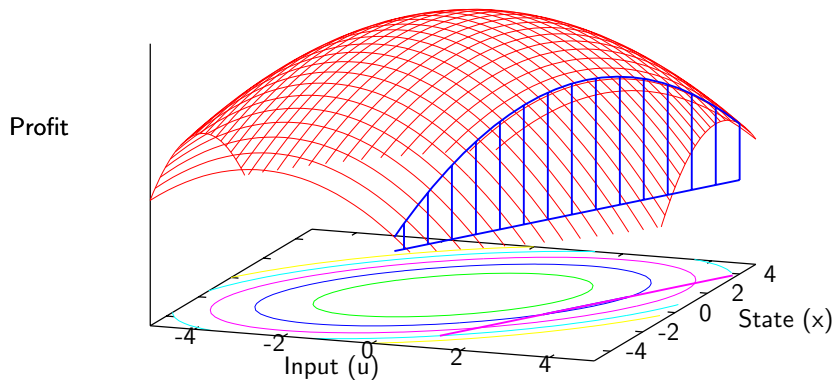


- Two layer structure
- Drawbacks
  - ▶ Inconsistent models
  - ▶ Re-identify linear model as setpoint changes
  - ▶ Time scale separation may not hold
  - ▶ Economics unavailable in dynamic layer

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subject to:  $x = f(x, u) \quad x \in \mathbb{X} \quad u \in \mathbb{U}$

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- Solution:  $(x_s, u_s)$

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- Stage cost:

std-MPC:  $\tilde{\ell}(x, u) = |x - x_s|_Q^2 + |u - u_s|_R^2$       –or–

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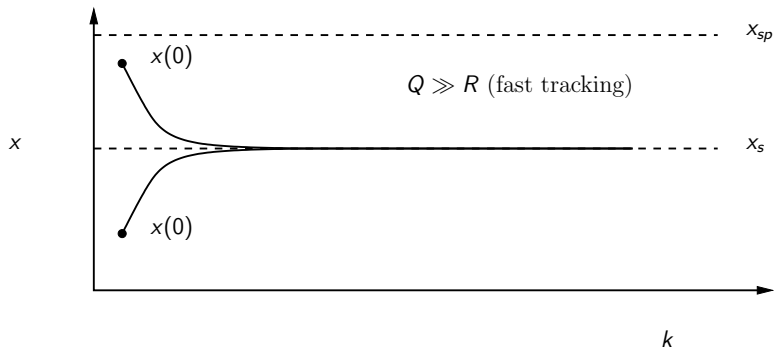
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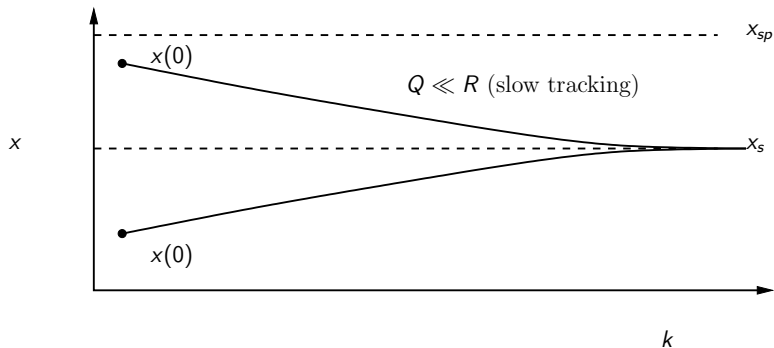
$$\text{eco-MPC: } \tilde{\ell}(x, u) = \ell(x, u)$$

- Control law:  $u^0(x) = \mathbf{u}^0(0; x)$

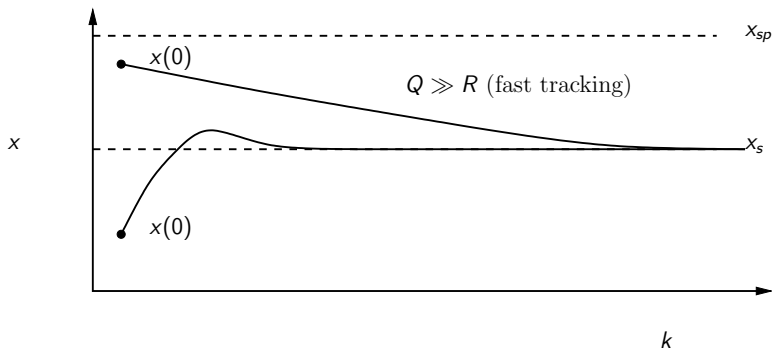
# What closed-loop behavior is desirable? Fast tracking



# What closed-loop behavior is desirable? Slow tracking



# What closed-loop behavior is desirable? Asymmetric tracking



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- Standard nominal MPC stability arguments do not apply
- Simulations indicate the closed loop *is* stable
- How can we be sure?

- The economic MPC for **linear dynamics**,  $f(x, u) = Ax + Bu$ , and **convex cost** is asymptotically stabilizing (Rawlings, Bonn , J rgensen, Venkat, and J rgensen, 2008)

## Recent results for economic MPC

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- Proof based on convexity of stage cost
- No Lyapunov function was found

- Stability results extended to nonlinear systems satisfying **strong duality**. There exists constant  $\lambda \in \mathbb{R}^n$  such that

$$\min_{(x,u) \in \mathbb{Z}} \ell(x, u) + \lambda'(x - f(x, u)) \geq \ell(x_s, u_s)$$

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- The Lyapunov function is based on **rotated stage cost**

$$L(x, u) = \ell(x, u) - \ell(x_s, u_s) + \lambda'(x - f(x, u))$$

- Diehl, Amrit, and Rawlings (2011)

## Generalization to dissipative systems

- Stability results generalized to **dissipative systems**. There exists function  $\lambda : \mathbb{X} \rightarrow \mathbb{R}$  and supply rate  $s : \mathbb{X} \times \mathbb{U} \rightarrow \mathbb{R}$  such that

$$\lambda(f(x, u)) - \lambda(x) \leq s(x, u) \quad (x, u) \in \mathbb{Z}$$

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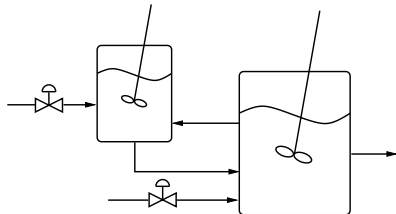
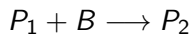
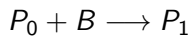
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- Rotated stage cost

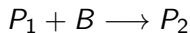
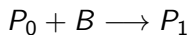
$$L(x, u) = \ell(x, u) - \ell(x_s, u_s) + \lambda(x) - \lambda(f(x, u))$$

- **MPC also shown to outperform optimal steady performance**
- Angeli, Amrit, and Rawlings (2011)

# Nonlinear chemical reactor example



# Nonlinear chemical reactor example



Species mass balances:

$$\dot{x}_1 = u_1 - x_1 - \sigma_1 x_1 x_2$$

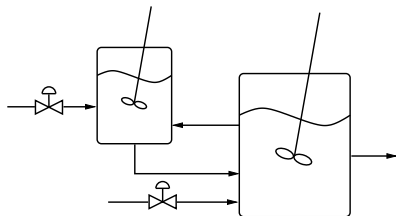
$$\dot{x}_2 = u_2 - x_2 - \sigma_1 x_1 x_2 - \sigma_2 x_2 x_3$$

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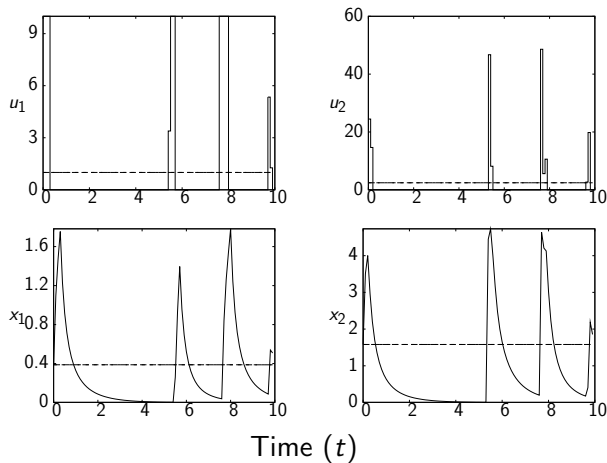
$$\dot{x}_4 = -x_4 + \sigma_2 x_2 x_3$$

$x_1, x_2, x_3, x_4$ : concentrations of  $P_0, B, P_1, P_2$

$u_1, u_2$ : inflow rates of  $P_0$  and  $B$



# Nonlinear chemical reactor example: Unstable system



- System initialized at the best steady state
- Steady solution not optimal: Unstable system !

# Average performance

- Asymptotic average of any function of states and inputs ( $y = h(x, u)$ ):

$$\text{Av}[y] := \lim_{T \rightarrow \infty} \frac{\sum_{k=0}^T h(x(k), u(k))}{T + 1}$$

- Asymptotic average performance along the closed loop

$$\text{Av}[\ell(x, \mathbf{u})] := \lim_{T \rightarrow \infty} \frac{\sum_{k=0}^T \ell(x(k), u(k))}{T + 1}, \quad x^+ = f(x, u)$$

## Nonsteady operation: Average constraints

- Auxiliary output variable  $y = h(x, u)$
- Closed and convex set  $\mathbb{Y}$ , such that  $h(x_s, u_s) \in \mathbb{Y}$
- Receding horizon control strategy such that

$$(x(k), u(k)) \in \mathbb{Z} \quad k \in \mathbb{I}_{\geq 0}$$
$$\text{Av}[y] \subseteq \mathbb{Y}$$

# Average constraints: Algorithm

- 1 At each time  $t$  solve the following optimization problem

$$\min_{\mathbf{v}} \sum_{k=0}^{N-1} \ell(z(k), v(k))$$

$$z^+ = f(z, v)$$

$$(z(k), v(k)) \in \mathbb{Z}, \quad k \in \mathbb{I}_{0:N-1}$$

$$z(N) = x_s, \quad z(0) = x$$

$$\sum_{k=0}^{N-1} h(z(k), v(k)) \in \mathbb{Y}_t$$

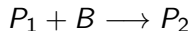
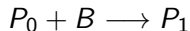
- 2 The time-varying output constraint set defined recursively

$$\mathbb{Y}_{i+1} = \mathbb{Y}_i \oplus \mathbb{Y} \ominus h(x(i), u(i)) \quad \text{for } i \in \mathbb{I}_{\geq 0}$$

$$\mathbb{Y}_0 = N\mathbb{Y} + \mathbb{Y}_{00}, \quad \mathbb{Y}_{00} \subset \mathbb{R}^{N_y}$$

- 3 Inject the first move of the optimal solution into the system and goto step 1

# Nonlinear chemical reactor example



Constraint:  $Av[u_1] \in [0, 1]$

Economic objective: Maximize  $P_1(x_3)$

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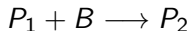
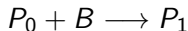
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Economic objective: Maximize  $P_1(x_3)$

- Unstable solution
- $Av[u_1] = 1$
- Average performance beats best steady state  
 $Av[x_3] = 0.44 \geq x_{3s} = 0.37$

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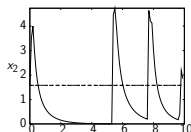
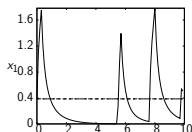
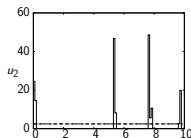
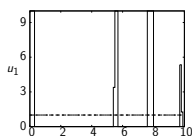
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Time (t)

# Nonsteady operation: Periodic operation

- Economics optimizing MPC may not be stable
  - ▶ Nonsteady operation outperforms best steady state solution

$$Av[\ell(x, \mathbf{u}^0)] \leq \ell(x_s, u_s), \quad \forall x \in \mathcal{X}_N$$

- Periodic operation

- ▶ Known period of operation:  $Q$
- ▶ Periodic constraint:  $x(0) = x(Q)$
- ▶ Optimal periodic solution  $x^*(k)$ ,  $k \in \mathbb{I}_{0:Q-1}$

$$\min_{x(0), \mathbf{u}} V_Q(x(0), \mathbf{u}) = \sum_{k=0}^{Q-1} \ell(x(k), u(k))$$
$$\text{subject to } \begin{cases} x^+ = f(x, u) \\ (x(k), u(k)) \in \mathbb{Z}, & k \in \mathbb{I}_{0:Q-1} \\ x(Q) = x(0) \end{cases}$$

## Nonsteady operation: Periodic MPC

- Open loop dynamic regulation problem at time  $t$

$$\min_{\mathbf{v}} \sum_{k=0}^{N-1} \ell(z(k), v(k))$$
$$z^+ = f(z, v), \quad z(0) = x$$
$$(z(k), v(k)) \in \mathbb{Z}, \quad k \in \mathbb{I}_{0:N-1}$$
$$z(N) = x^*(t \bmod Q)$$

Closed loop control law:  $u_P^0(x) = u^0(0; x)$

- Periodic MPC outperforms optimal periodic solution

$$\text{Av}[\ell(x, \mathbf{u}_P^0)] \leq \frac{\sum_{k=0}^{Q-1} \ell(x^*(k), u^*(k))}{Q}$$

## Chemical reactor example: Parallel reactions

CSTR with parallel reactions



Economic objective: Maximize  $P_1$  ( $x_2$ )

$$\dot{x}_1 = 1 - 10^4 x_1^2 e^{-1/x_3} - 400 x_1 e^{-0.55/x_3} - x_1$$

$$\dot{x}_2 = 10^4 x_1^2 e^{-1/x_3} - x_2$$

$$\dot{x}_3 = u - x_3$$

$x_1, x_2$ : Concentrations of  $R, P_1$

$x_3$ : Temperature in the reactor.

$u$ : Heat flux through the reactor wall

# Chemical reactor example: Parallel reactions

CSTR with parallel reactions



Economic objective: Maximize  $P_1$  ( $x_2$ )

- Optimal steady state  $x_{2s} = 0.084$
- Optimal periodic solution:  
 $Av[x_2^*(k)] = 0.092$

$$\dot{x}_1 = 1 - 10^4 x_1^2 e^{-1/x_3} - 400 x_1 e^{-0.55/x_3} - x_1$$

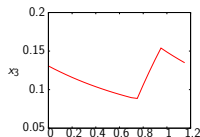
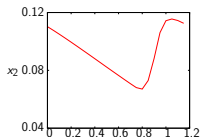
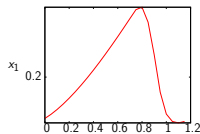
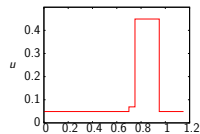
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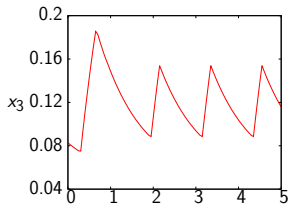
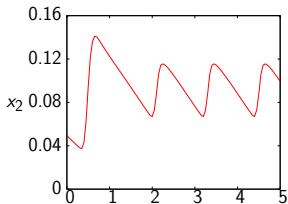
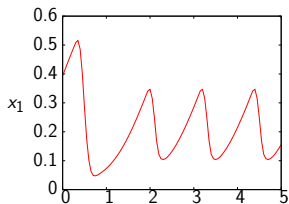
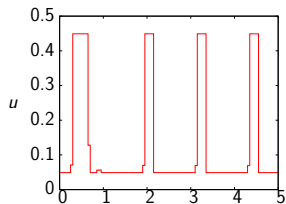
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- System under closed loop settles to the recurring periodic solution
- Asymptotic average performance  $Av[x_2] = 0.093$
- Average performance beats average periodic solution

# Enforcing convergence

- Optimizing economic performance may not give stability
- Tradeoff between stability and performance
- Convergence may be enforced by modifying the dynamic problem
  - ▶ Convex regularization terms in the objective

$$\tilde{\ell}(x, u) = \ell(x, u) + |\Delta u|_S^2 + |x - x_s|_Q^2 + |u - u_s|_R^2$$

- ▶ Zero variance constraint

$$\text{Av}[|x - x_s|^2] \in \{0\}$$

## Chemical reactor example: Parallel reactions

CSTR with parallel reactions



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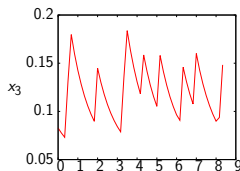
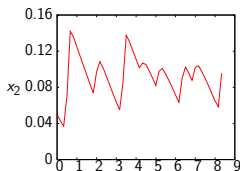
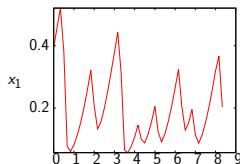
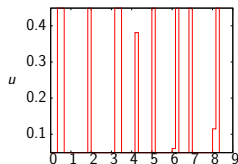
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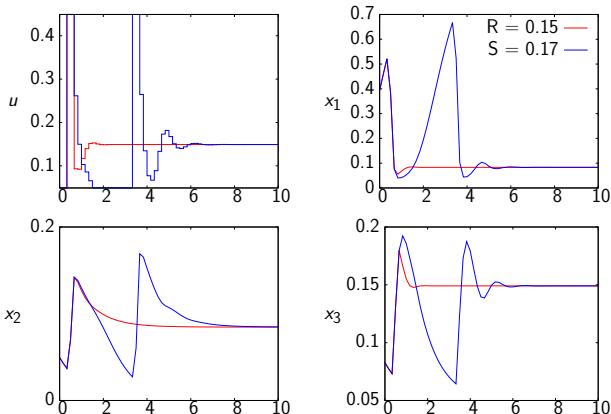
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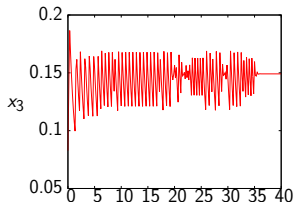
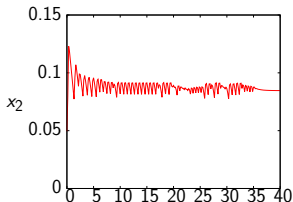
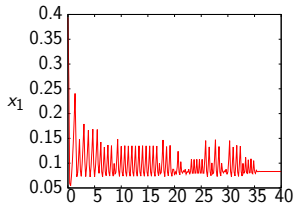
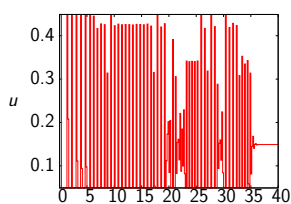
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  - ▶ Understanding the interplay between nonlinearity of model and convexity of objective

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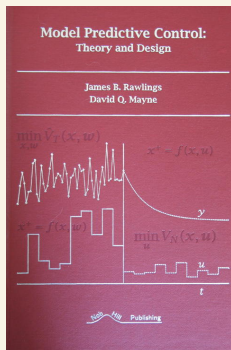
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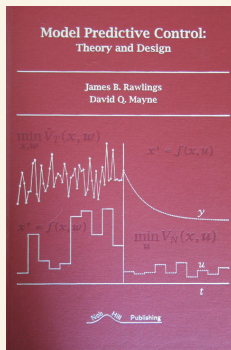
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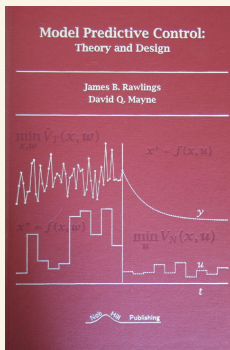
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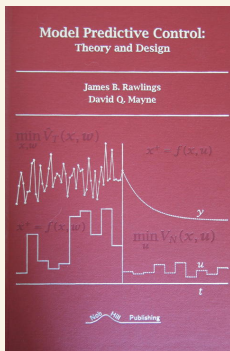
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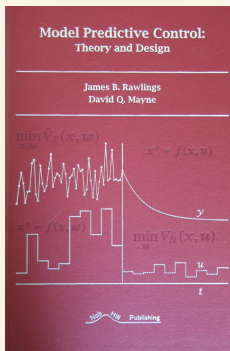
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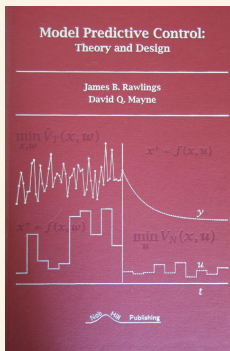
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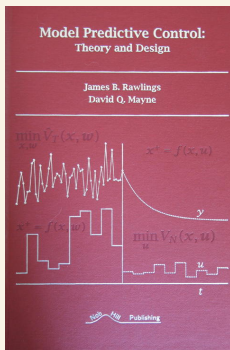
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