

# Optimal control unchained

James B. Rawlings

Department of Chemical and Biological Engineering

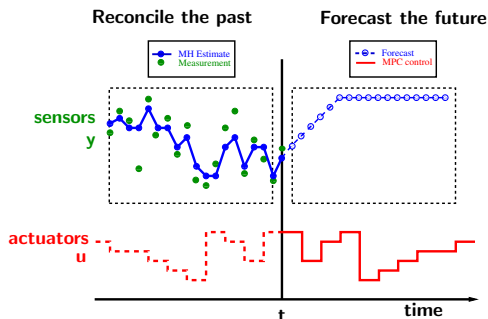


September 30, 2010

50 Years of Nonlinear Control and Optimization —  
A Historical Workshop  
Royal Society, London, UK

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

# Predictive control



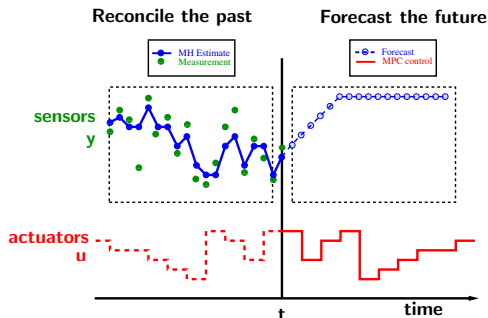
$$\min_{u(t)} \int_0^T |y_{sp} - g(x, u)|_Q^2 + |u_{sp} - u|_R^2 dt$$

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

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

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

# 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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- Industrial systems are either constrained or nonlinear or both. Optimal *feedback* control for these systems seems to lead to *intractable* dynamic programming problems. The curse of dimensionality. (Bellman and Dreyfus, 1962)
- 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.

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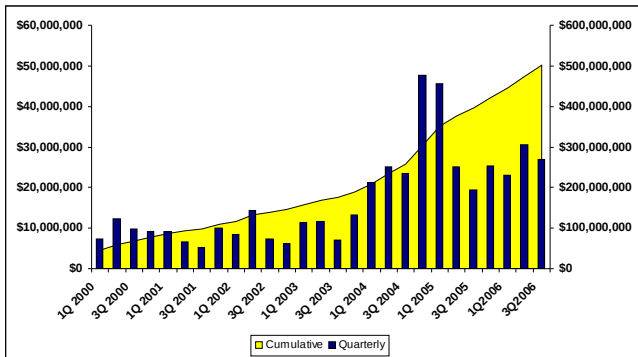
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## We're Doing it For the Money



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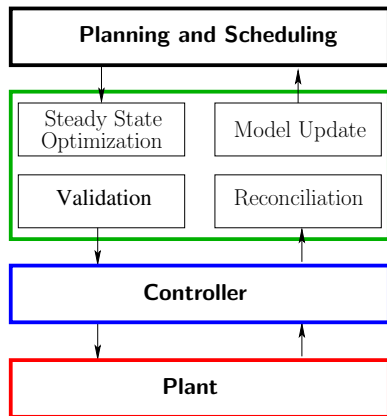
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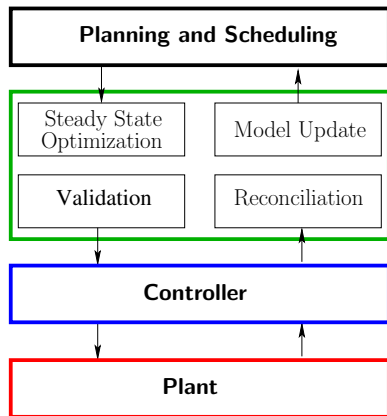
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- Do we have tools to optimize dynamic *economic* operation?

# Optimizing economics: Current industrial practice



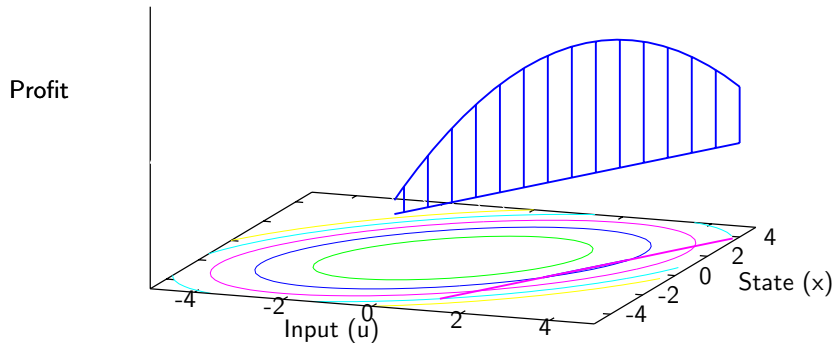
- Two layer structure
- Drawbacks

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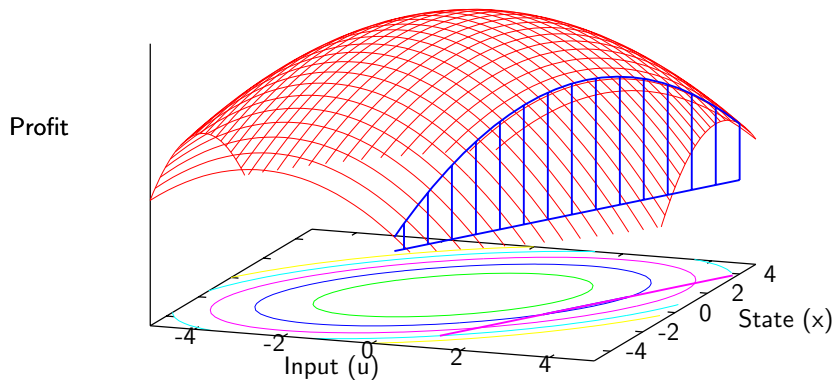


- Two layer structure
- Drawbacks
  - ▶ Inconsistent models
  - ▶ Re-identify linear model as setpoint changes
  - ▶ Time scale separation may not hold
  - ▶ Economics unavailable in dynamic layer

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

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

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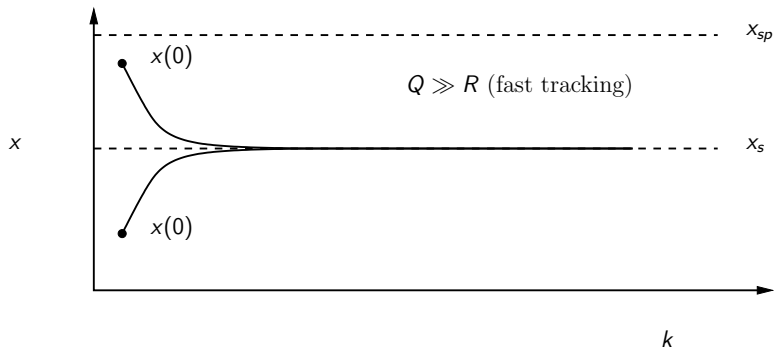
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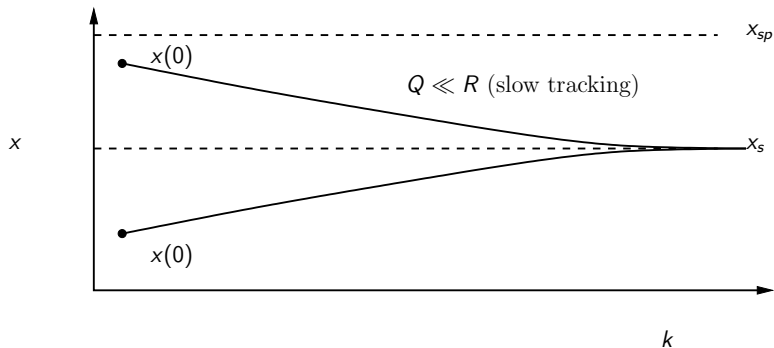
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- Control law:  $u^0(x) = \mathbf{u}^0(0; x)$

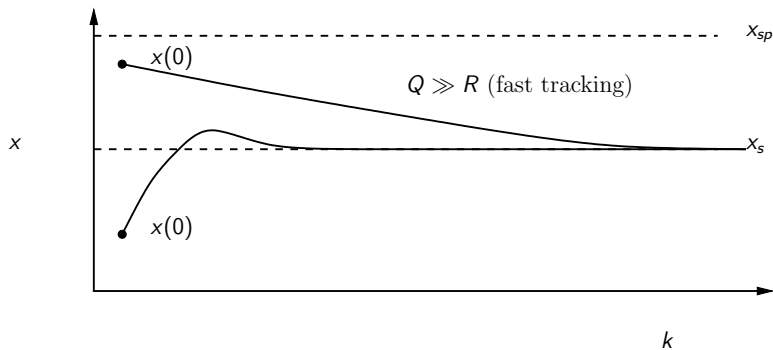
# What closed-loop behavior is desirable? Fast tracking



# What closed-loop behavior is desirable? Slow tracking



# What closed-loop behavior is desirable? Asymmetric tracking



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- 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)

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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

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

## Rotated cost and Lyapunov function

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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 (2010)

## Generalization to dissipative systems

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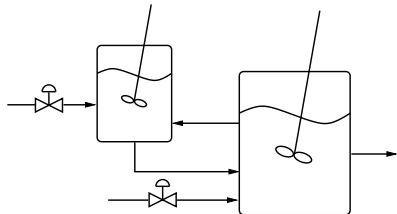
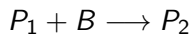
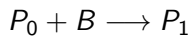
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- Rotated stage cost

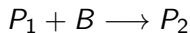
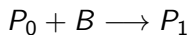
$$L(x, u) = \ell(x, u) - \ell(x_s, u_s) + \lambda(x) - \lambda(f(x, u))$$

- MPC also shown to outperform optimal periodic control
- Angeli, Amrit, and Rawlings (2010)

# Nonlinear chemical reactor example



# Nonlinear chemical reactor example



Species mass balances:

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

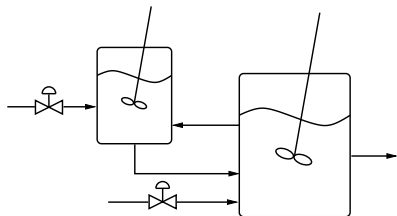
$$\dot{x}_2 = u_2 - x_2 - \sigma_1 x_1 x_2 - \sigma_2 x_2 x_3$$

$$\dot{x}_3 = -x_3 + \sigma_1 x_1 x_2 - \sigma_2 x_2 x_3$$

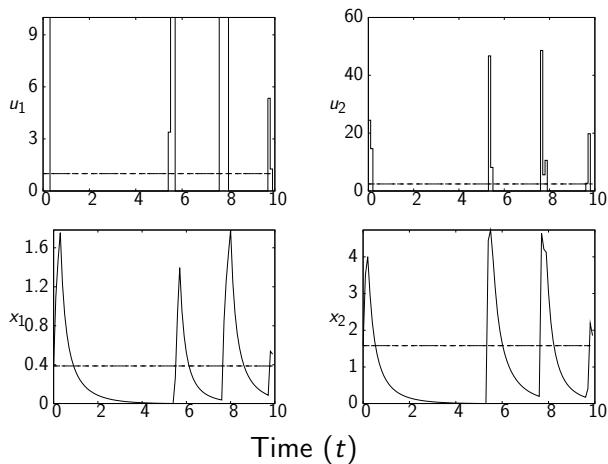
$$\dot{x}_4 = -x_4 + \sigma_2 x_2 x_3$$

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

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



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# What do David Mayne and James Bond have in common?



Besides their dashing good looks . . . both turned 80 this year!

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*SIR SEAN CONNERY told last night how he was "thrilled" that he had reached 80 - and promised that there was life in the old Bond yet.*

[www.dailyrecord.co.uk](http://www.dailyrecord.co.uk)

Aug 25 2010 Exclusive interview by Rick Fulton

## Selected results from David Mayne's research

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- Differential dynamic programming. Active participant in the control revolution of the 1960s. Jacobson and Mayne (1970)
- Particle filtering. First proponent of sampling as a way to address nonlinear estimation problems. Handschin and Mayne (1969)
- Stability of MPC. Helped unify the disparate stability results on receding horizon control and model predictive control. Papers and plenary lectures identifying the “ingredients” for closed-loop stability of MPC. Michalska and Mayne (1993); Mayne, Rawlings, Rao, and Sokaert (2000)

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- Suboptimal MPC. How to ease the requirements for online solution of nonconvex optimizations so that the approach can be implemented in practice. Scokaert, Mayne, and Rawlings (1999)

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- Robust, tube-based MPC. When receding horizon is insufficient and why feedback is required. Mayne (1995); Langson, Chrysochoos, Raković, and Mayne (2004); Raković, Kerrigan, Kouramas, and Mayne (2005); Mayne, Seron, and Raković (2005)

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- Nonlinear moving horizon state estimation. Established the ingredients for stable nonlinear estimation. Rao, Rawlings, and Mayne (2003)

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– *Winston Churchill*

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*Writing a book is an adventure. To begin with it is a toy, then amusement, then it becomes a mistress, then it becomes a master,*

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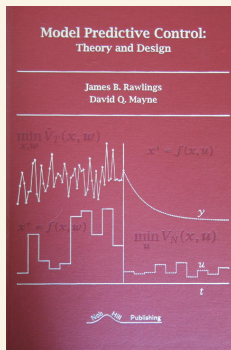
*Writing a book is an adventure. To begin with it is a toy, then amusement, then it becomes a mistress, then it becomes a master, and then it becomes a tyrant,*

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*Writing a book is an adventure. To begin with it is a toy, then amusement, then it becomes a mistress, then it becomes a master, and then it becomes a tyrant, and the last phase is that just as you are about to become reconciled to your servitude, you kill the monster and strew him about to the public.*

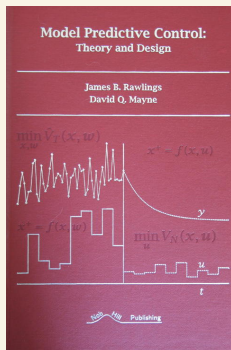
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# Book writing with David



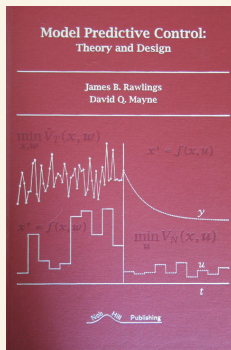
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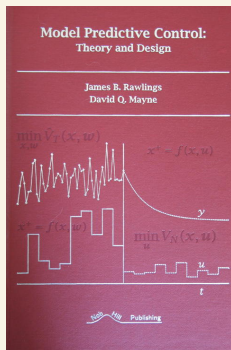
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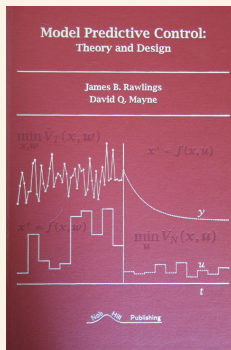
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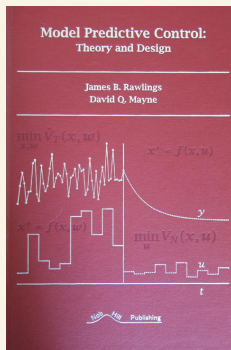
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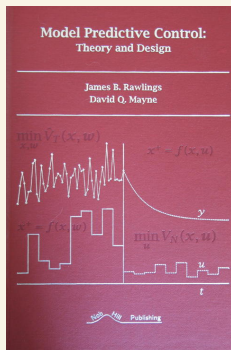
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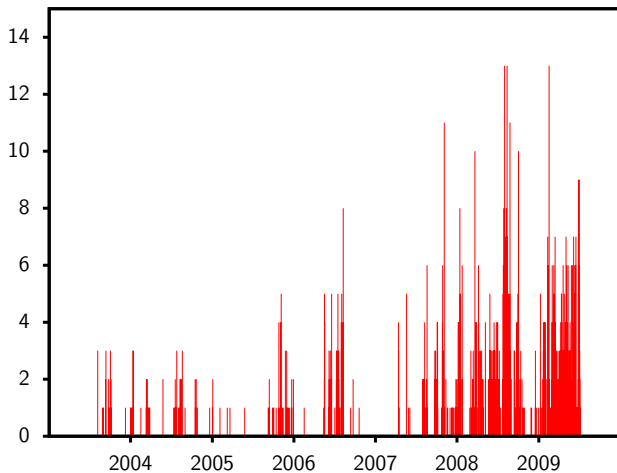


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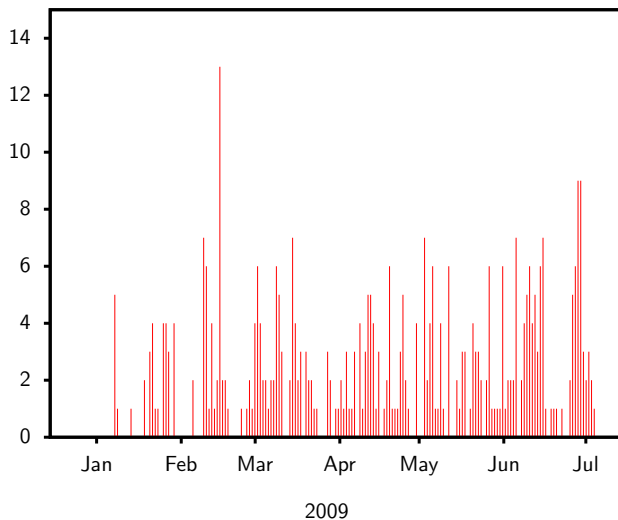
Version	Date	Comment
1	2003 July 19	First version of book sources entered into version control

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1	2003 July 19	First version of book sources entered into version control
1182	2009 July 3	First printing completed

# When are authors working on their books?



# The last six months!



## Personal observations about David

- High standards

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- High standards
- Dedication to the discipline

## Personal observations about David

- High standards
- Dedication to the discipline
- Love of the craft

## Personal observations about David

- High standards
- Dedication to the discipline
- Love of the craft
- Generosity to colleagues

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