Multiple Model Predictive Control (MMPC) for Nonlinear Systems and Improved Disturbance Rejection

- Motivation & Tutorial Overview
- Multiple Model Predictive Control
  - Nonlinear Processes
  - Disturbance Rejection
- Summary

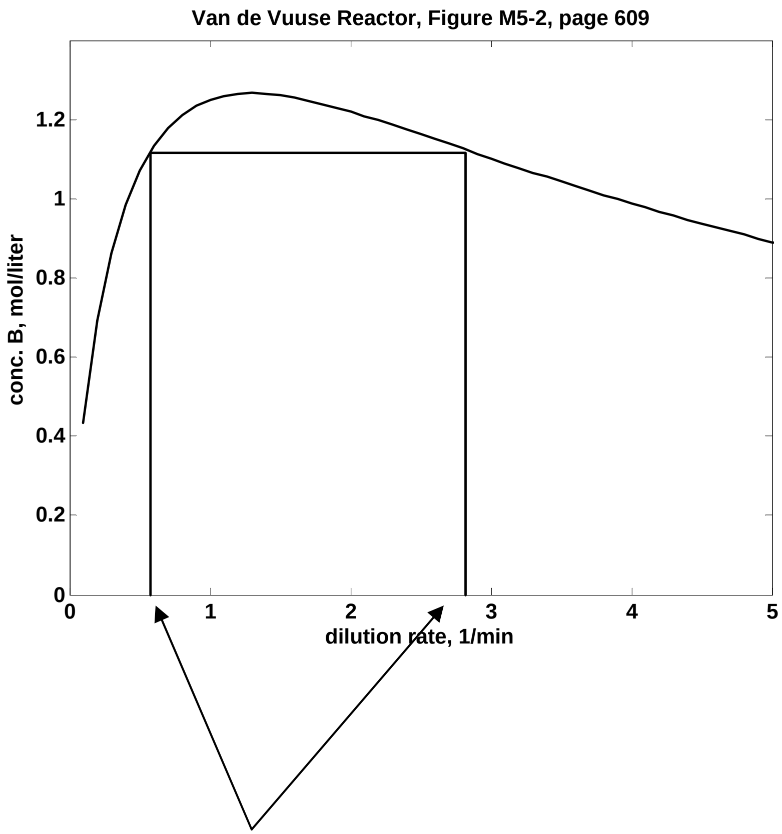
B. Wayne Bequette

PASI 2011 | Process Modeling and Optimization for Energy and Sustainability
July 19-29, 2011, Angra dos Reis, RJ, Brazil

Rensselaer
Chemical and Biological Engineering

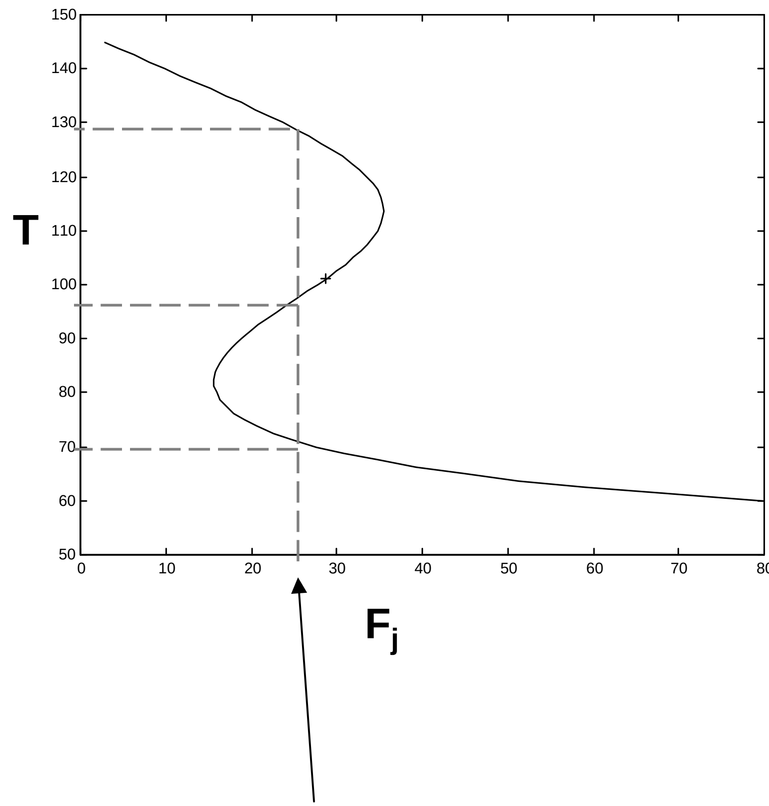
Nonlinear Behavior: Steady-state

Input Multiplicity

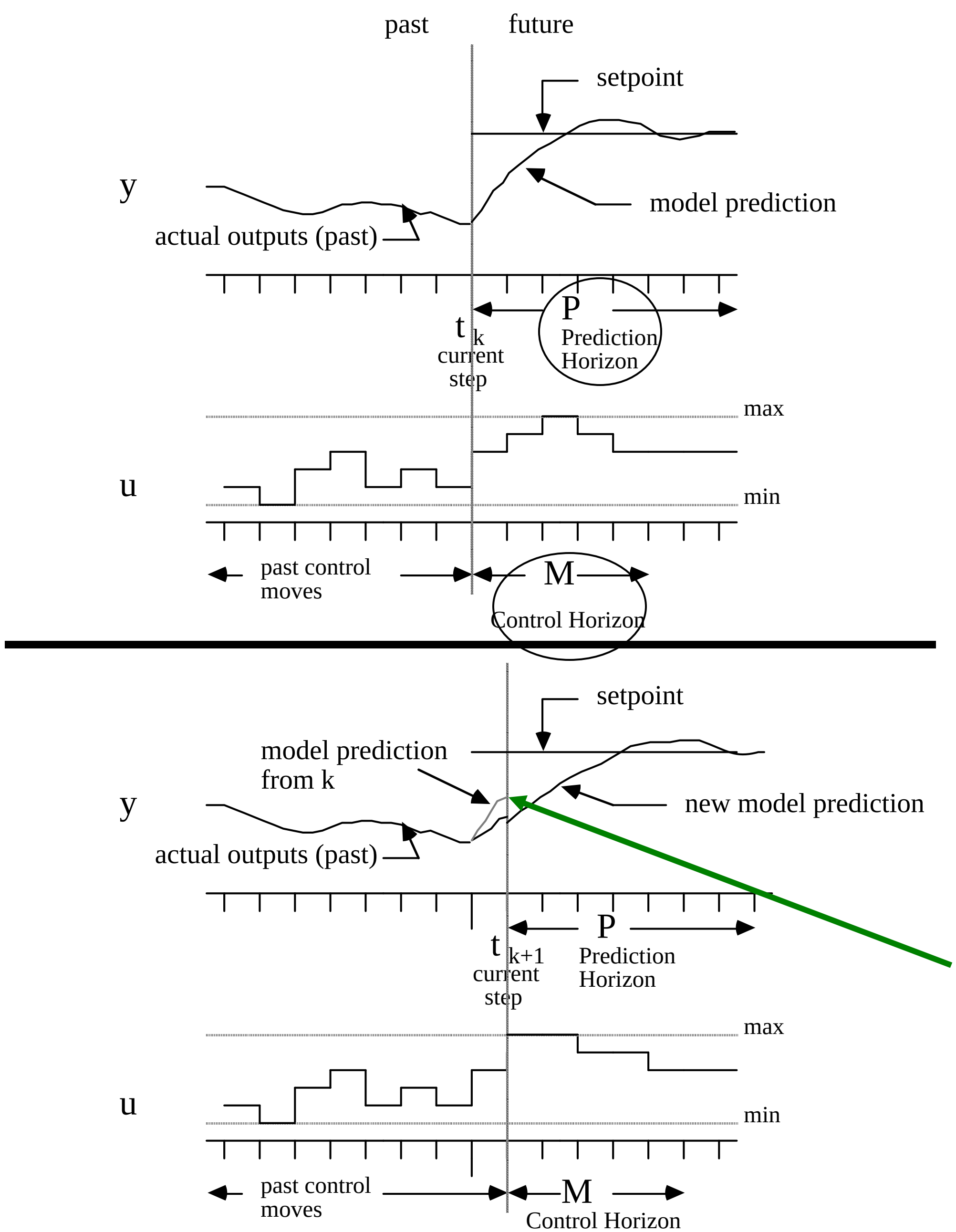


Two different input values
yield the same output

Output Multiplicity (hysteresis)



One input can yield three
different output values



MPC

- Constraints
- Multivariable
- Time-delays

- Objective function?
- Optimization technique?
- Model type?

- Disturbances/mismatch?
  - Current and Future
- Initial cond./state est.?

“hidden slide” provided for additional background

Our Approaches to Nonlinear MPC

- Quadratic Objective Function
- Models
  - Fundamental: numerical integration or collocation
  - Fundamental with linearization at each time step
  - **Multiple model**
  - Artificial neural network
- State Estimates/Initial Conditions
  - Additive output disturbance (e.g. DMC)
  - Estimation horizon (optimization)
  - Extended/appended state Kalman Filter
    - **Importance of stochastic states**

Intuitive Nonlinear Model-based Strategy

Model equations

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

Integrate model from time step k-1 to k

$$\hat{x}_k = F_{t_s}(\hat{x}_{k-1}, u_{k-1})$$
$$\hat{y}_{k|k-1} = g(\hat{x}_k)$$

Obtain plant measurement

$$y_k$$

Calculate model error

(additive output disturbance)

$$d_k = y_k - \hat{y}_{k|k-1}$$

Choose hypothetical set of current and future control moves

$$u_k, u_{k+1}, \cdots, u_{k+P-1}$$

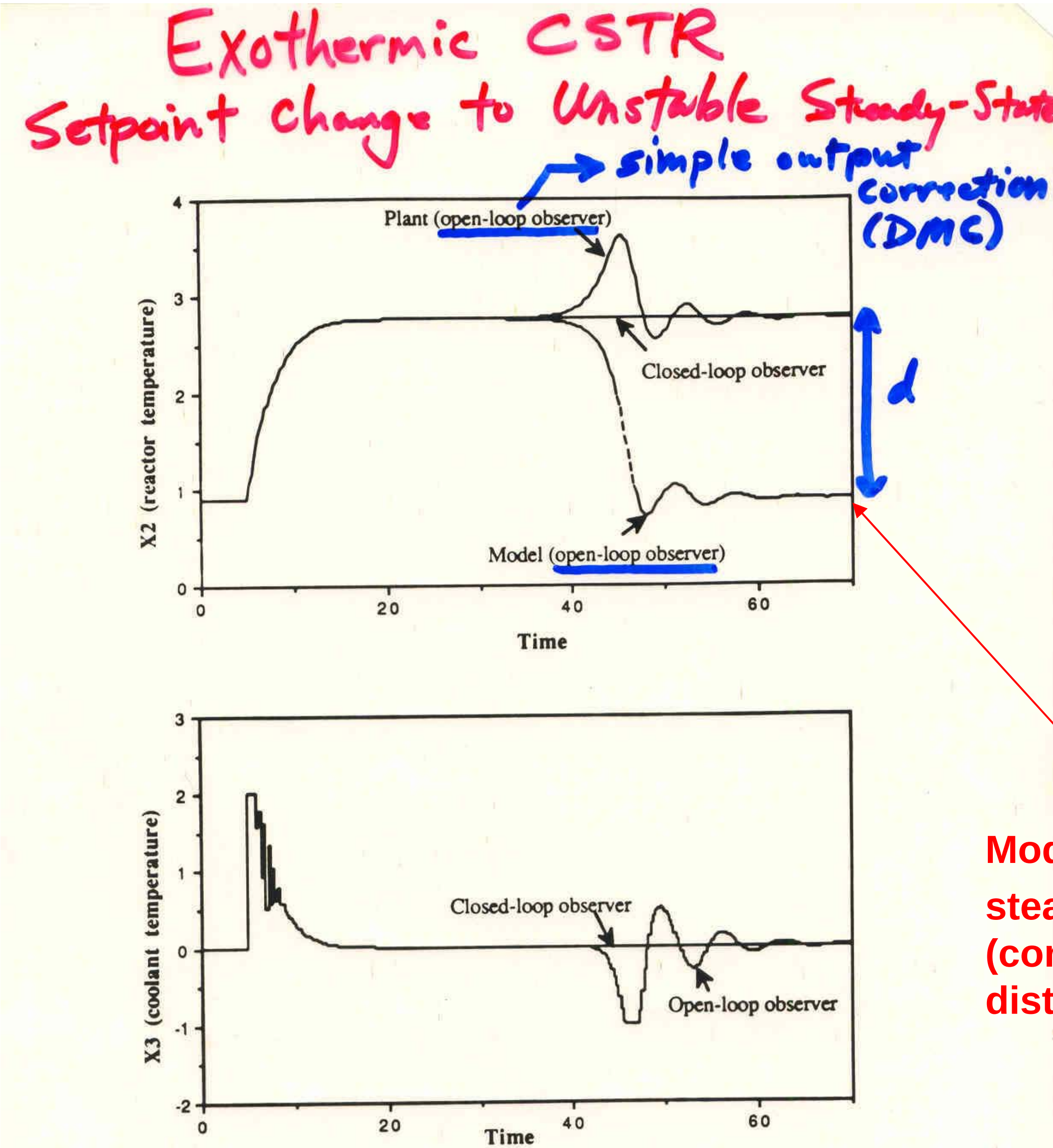
Integrate model from time step k to k+P (based on hypothetical control moves)

$$\hat{x}_{k+1} = F_{t_s}(\hat{x}_k, u_k)$$
$$\hat{y}_{k+1|k} = g(\hat{x}_{k+1}) + d_k$$

to

$$\hat{x}_{k+P} = F_{t_s}(\hat{x}_{k+P-1}, u_{k+P-1})$$
$$\hat{y}_{k+P|k} = g(\hat{x}_{k+P}) + d_k$$

Evaluate objective function and repeat until optimum is obtained

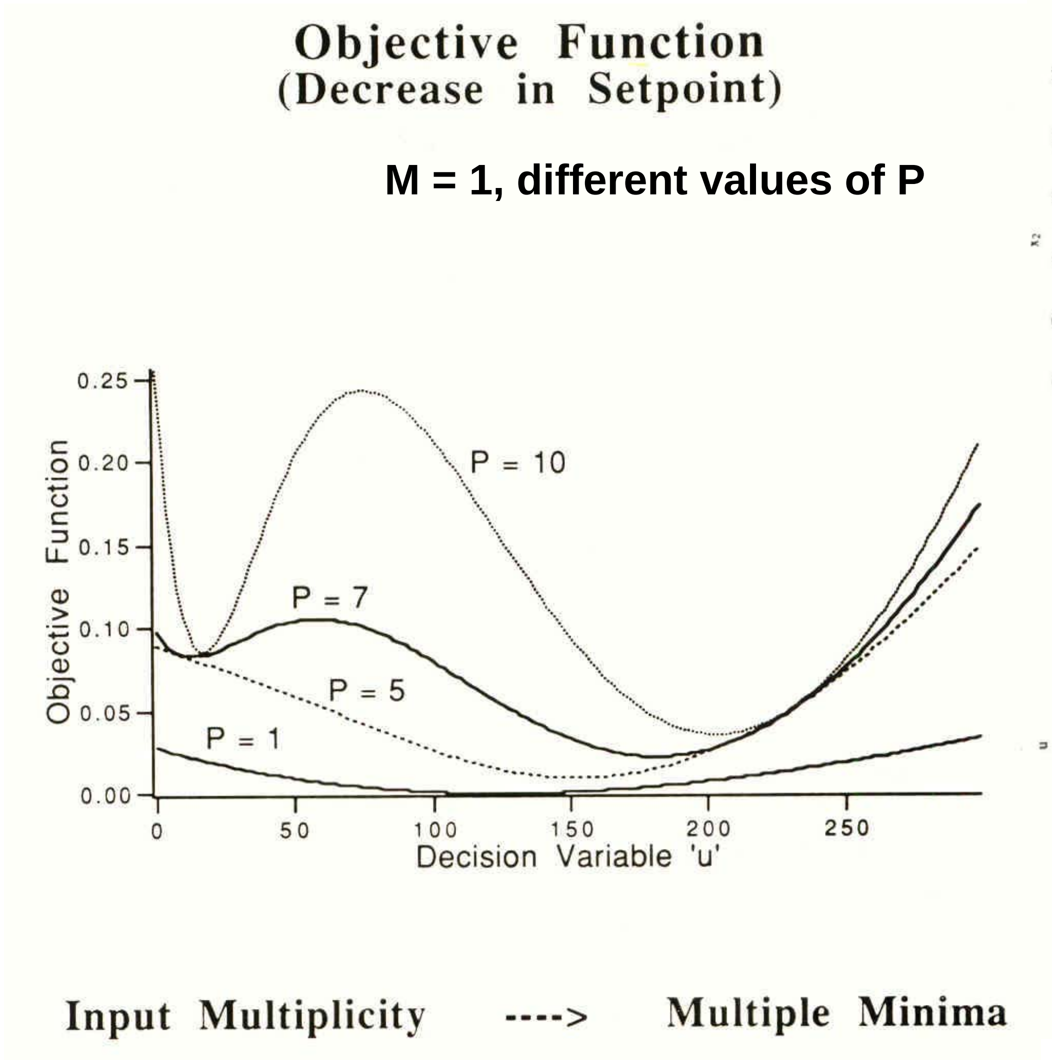


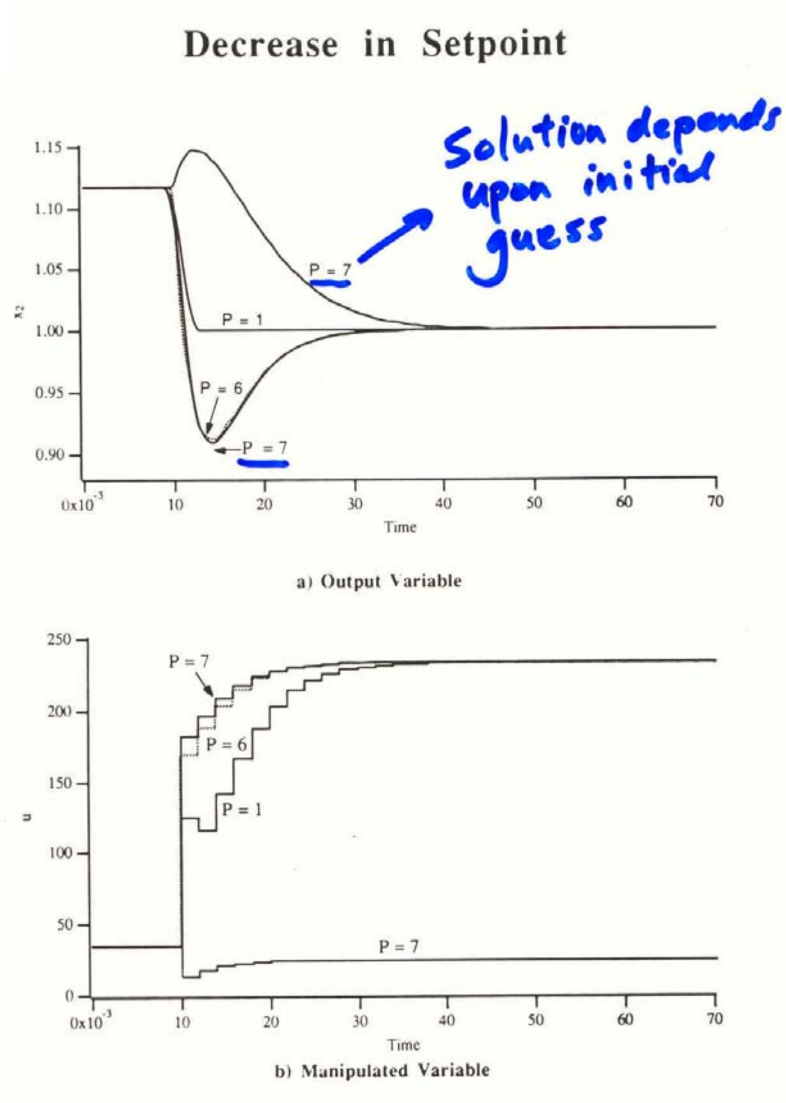
Response to a setpoint change to a open-loop unstable operating point with a perfect model. P = 10, M = 1.

Additive Disturbance Assumption

Model converges to different steady-state than plant (compensated by additive disturbance term)

Non-Convex Problem





Sistu and Bequette, 1992 ACC

EKF-based NMPC (Lee & Ricker, 1994)

- Nonlinear Model, integrate from step k-1 to k
- State Estimation: Extended Kalman Filter
  - Linearized at each time step
  - Find best state estimate at time step k
- Prediction
  - One integration of NL ODEs based on set of control moves (**unforced or "free response"**) from step k to k+P
  - Perturbation (linear) model - effect of changes in control moves (**forced**)
- Optimization
  - QP, since linear model is used

Can use linear state-space KF-MPC code!

1530 *Ind. Eng. Chem. Res.* **1994,** *33,* 1530–1541

Extended Kalman Filter Based Nonlinear Model Predictive Control

Jay H. Lee*

Department of Chemical Engineering, Auburn University, Auburn, Alabama 36849-5127

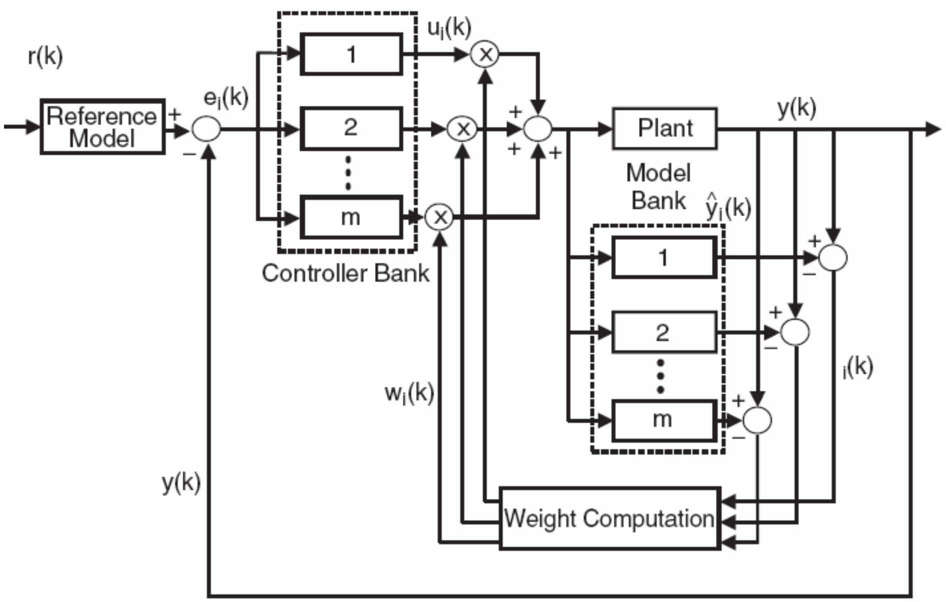
N. Lawrence Ricker

Department of Chemical Engineering, University of Washington, Seattle, Washington 98195

Motivation for Multiple Linear Models

- Development time for fundamental models
  - Difficulty with physiological systems
- Much data required for artificial neural networks
  - Problems with “overfitting” and extrapolation
- At particular operating points, linear models are often a good description
  - How to switch between models?

Multiple Model-based Control



Multiple Model Adaptive Control (MMAC)

Athans et al. (1977) – LQG, Jet aircraft control

Roy, Kaufman - Drug infusion control

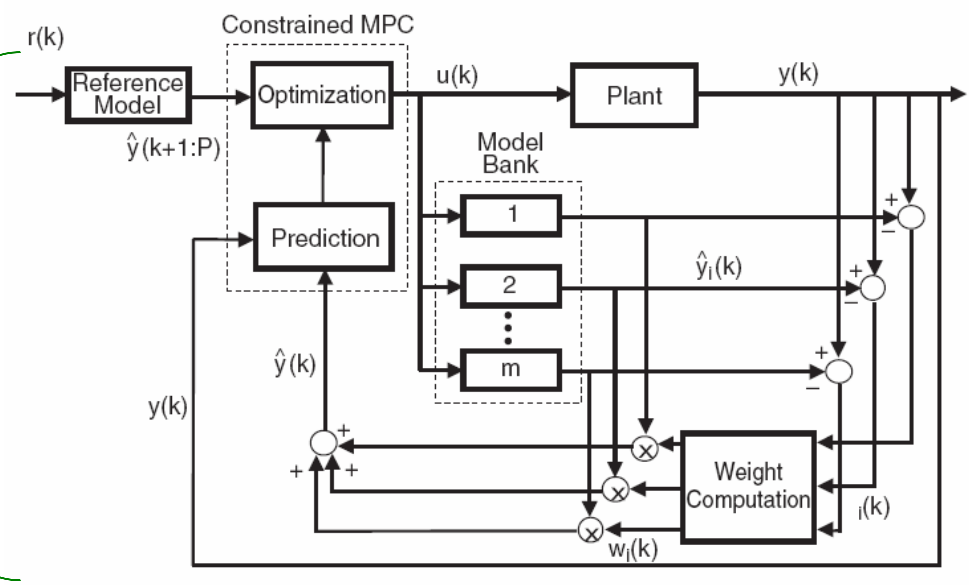
Schott, Bequette (1997) – PI, CSTR

Multiple Model Predictive Control (MMPC)

Rao et al. (2001, 2003)

Drug Infusion Control

Aufderheide & Bequette (2003)
Nonlinear CSTR



First, a Concise Review of Linear MPC

“hidden slide” provided for additional background

Step Response & Additive Output

Correction term → $d_k = y_k - \hat{y}_{k|k-1}$

measured output (y_k) **model predicted output** ($\hat{y}_{k|k-1}$)

The "corrected prediction" is set equal to the measured output

$$\hat{y}_{k|k} = \hat{y}_{k|k-1} + d_k \quad \Longleftrightarrow \quad \hat{y}_{k|k} = y_k$$

"deadbeat" observer

The "corrected prediction" for jth future step is (step response form)

$$\hat{y}_{k+j|k} = \underbrace{\sum_{i=1}^{j} s_i \Delta u_{k-i+j}}_{\text{effect of future control moves}} + \underbrace{\sum_{i=j+1}^{N-1} s_i \Delta u_{k-i+j} + s_N u_{k-N+j}}_{\text{effect of past control moves}} + \underbrace{\hat{d}_{k+j}}_{\text{correction term}}$$

forced response (first sum) — **free response** (remaining terms)

$$\hat{d}_{k+j} = \hat{d}_{k+j-1} = \cdots = d_k = y_k - \hat{y}_{k|k-1}$$

constant additive disturbance

"hidden slide" provided for additional background

Problems with "Classical MPC" (e.g. DMC)

- Finite Step/Impulse Models Limited
  - Many parameters (~50 for each input-output relationship)
  - Limited to open-loop stable processes (there is no corrective feedback to model states)
- Additive Output Disturbance Assumption
  - Poor performance for input step disturbances
  - No explicit measurement noise trade-off

The most common criticism of MPC (Shinskey, 2002)

"hidden slide" provided for additional background

State Space Models & State Estimation

$$x_{k+1} = \Phi x_k + \Gamma u_k + \Gamma^d d_k$$
$$y_k = C x_k$$

For perturbations to manipulated inputs

$$\underbrace{\Gamma^d = \Gamma}$$

Assume disturbance propagation

$$d_{k+1} = d_k$$

Appended state formulation

$$\underbrace{\begin{bmatrix} x_{k+1} \\ d_{k+1} \end{bmatrix}}_{x^a_{k+1}} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d \\ 0 & I \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x^a_k} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \end{bmatrix}}_{\Gamma^a} u_k$$

$$y_k = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x^a_k}$$

"hidden slide" provided for additional background

State Estimation Problem

$$d_{k+1} = d_k + w_k$$ Random walk

$$\underbrace{\begin{bmatrix} x_{k+1} \\ d_{k+1} \end{bmatrix}}_{x_{k+1}^a} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d \\ 0 & I \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x_k^a} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \end{bmatrix}}_{\Gamma^a} u_k + \underbrace{\begin{bmatrix} 0 \\ \Gamma^w \end{bmatrix}}_{\Gamma^{w,a}} w_k \qquad y_k = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x_k^a} + v_k$$

Kalman Filter

$$\hat{x}_{k|k-1}^a = \Phi^a \hat{x}_{k-1|k-1}^a + \Gamma^a u_{k-1}$$ **Prediction**

$$\hat{x}_{k|k}^a = \hat{x}_{k|k-1}^a + L_k \left(y_k - C^a \hat{x}_{k|k-1}^a \right)$$ **Correction**

“hidden slide” provided for additional background

Offset-Free Performance

- Next few slides present conditions for offset-free performance
- Unmeasured disturbances estimated as either state or output disturbances
- State observer techniques can then be used

Ref: Muske & Badgwell, J. Proc. Cont., 12: 617-632 (2002)

“hidden slide” provided for additional background

Disturbance Models

State or Input Disturbance

$$\underbrace{\begin{bmatrix} x_{k+1} \\ d_{k+1} \end{bmatrix}}_{x_{k+1}^a} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d \\ 0 & I \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x_k^a} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \end{bmatrix}}_{\Gamma^a} u_k \qquad y_k = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x_k^a}$$

Additive Output Disturbance

$$\underbrace{\begin{bmatrix} x_{k+1} \\ p_{k+1} \end{bmatrix}}_{x_{k+1}^a} = \underbrace{\begin{bmatrix} \Phi & 0 \\ 0 & I \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} x_k \\ p_k \end{bmatrix}}_{x_k^a} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \end{bmatrix}}_{\Gamma^a} u_k \qquad y_k = \underbrace{\begin{bmatrix} C & G_p \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} x_k \\ p_k \end{bmatrix}}_{x_k^a}$$

DMC: $G_p = I$

“hidden slide” provided for additional background

Disturbance Models

General Input and Output Disturbances

$$\begin{bmatrix} x_{k+1} \\ d_{k+1} \\ p_{k+1} \end{bmatrix} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix}}_{\Phi^a} \begin{bmatrix} x_k \\ d_k \\ p_k \end{bmatrix} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \\ 0 \end{bmatrix}}_{\Gamma^a} u_k \qquad y_k = \underbrace{\begin{bmatrix} C & 0 & G_p \end{bmatrix}}_{C^a} \begin{bmatrix} x_k \\ d_k \\ p_k \end{bmatrix}$$

Ref: Muske & Badgwell, J. Proc. Cont., 12: 617-632 (2002)

“hidden slide” provided for additional background

State Estimator

$$\begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{d}_{k|k-1} \\ \hat{p}_{k|k-1} \end{bmatrix} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix}}_{\Phi^a} \begin{bmatrix} \hat{x}_{k-1:k-1} \\ \hat{d}_{k-1|k-1} \\ \hat{p}_{k-1|k-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \\ 0 \end{bmatrix}}_{\Gamma^a} u_{k-1}$$

$$\begin{bmatrix} \hat{x}_{k|k} \\ \hat{d}_{k|k} \\ \hat{p}_{k|k} \end{bmatrix} = \begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{d}_{k|k-1} \\ \hat{p}_{k|k-1} \end{bmatrix} + \begin{bmatrix} L_x \\ L_d \\ L_p \end{bmatrix} \left(y_k - C^a \begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{d}_{k|k-1} \\ \hat{p}_{k|k-1} \end{bmatrix} \right)$$

Deterministic or stochastic observer design

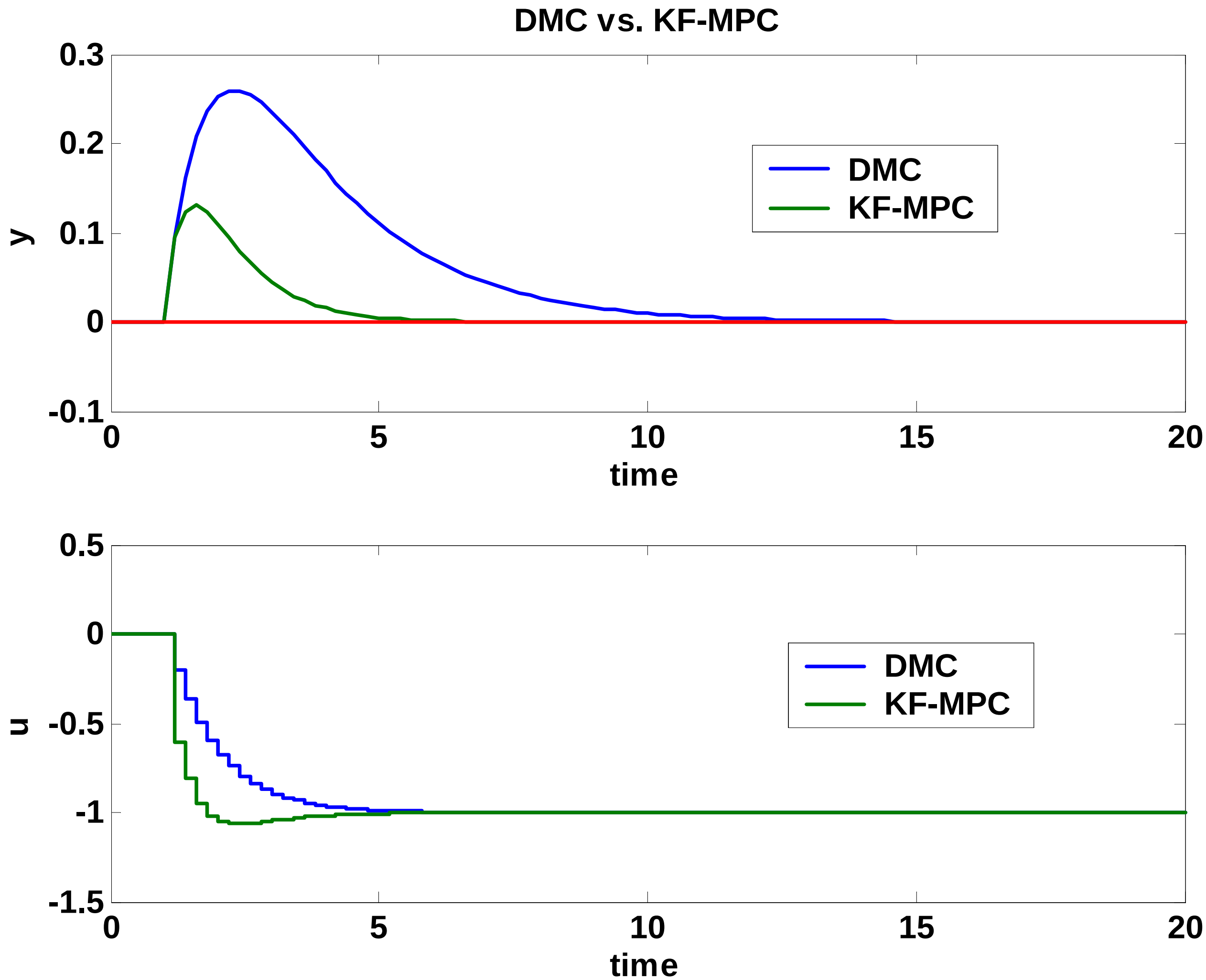
For offset-free performance:

disturbances = # outputs, and augmented system must be detectable

Ref: Muske & Badgwell, J. Proc. Cont., 12: 617-632 (2002)

“hidden slide” provided for additional background

Problem: Unmeasured Step Input Disturbance

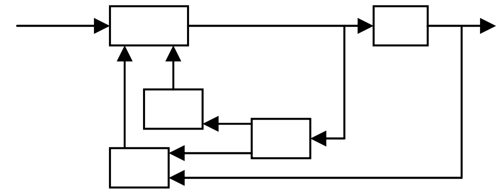


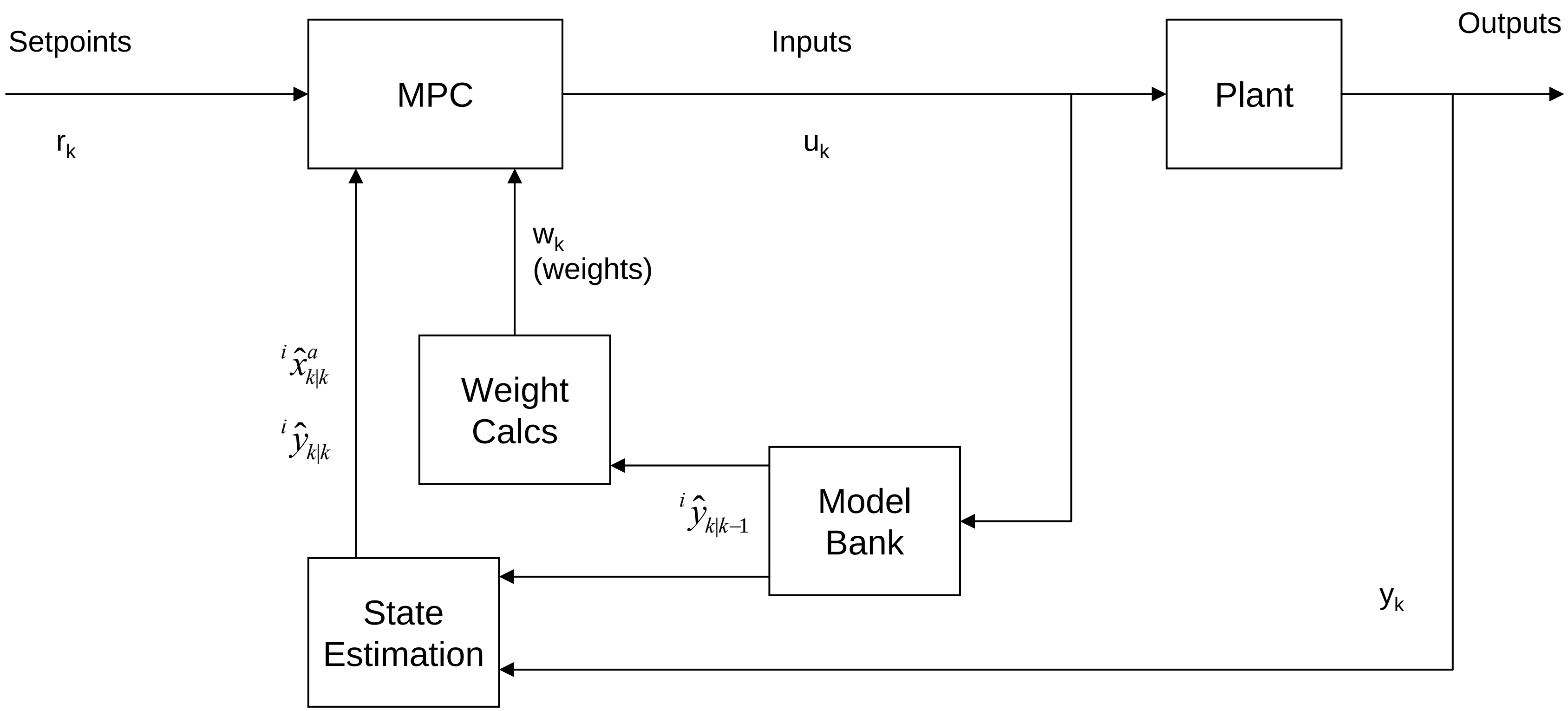
DMC: additive output disturbance assumption (bias)

KF-MPC: appended state, estimated step input disturbance

“hidden slide” provided for additional background

Structure of MMPC



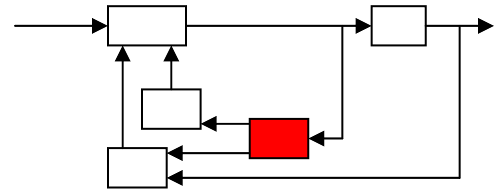


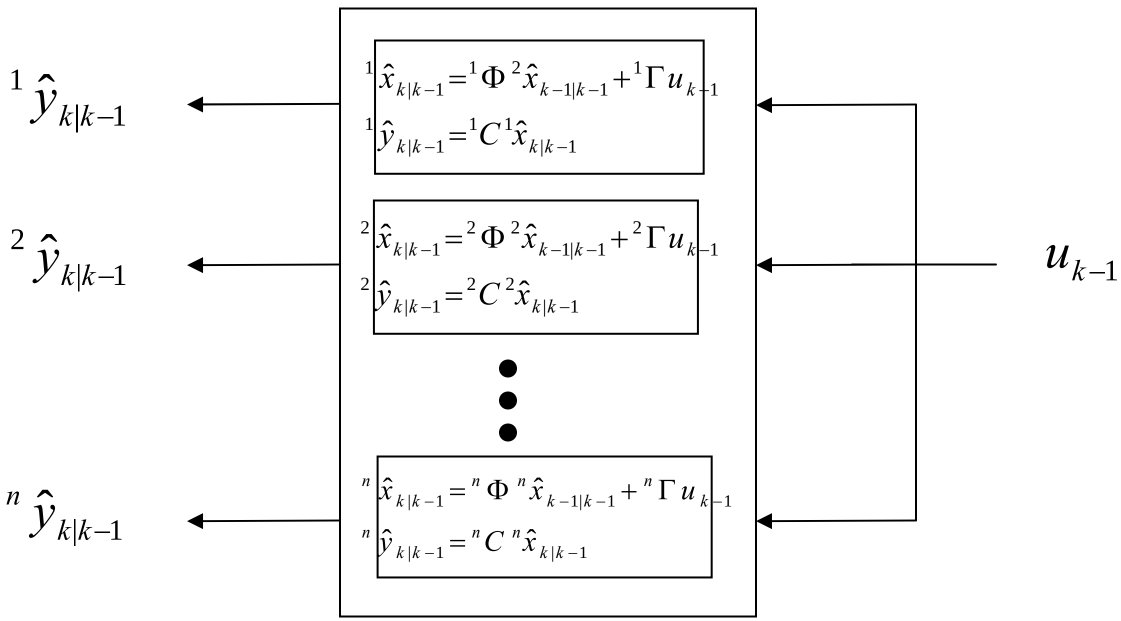
Multiple Model Predictive Control of Nonlinear Systems

Matthew Kuure-Kinsey† and B. Wayne Bequette‡

Int. Workshop on Assessment and Future Directions of NMPC
Pavia, Italy, September 5-9, 2008

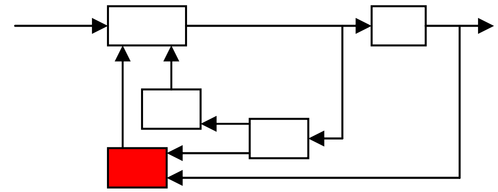
Model Bank Details





- Each of the n linear models represents the system at a specified operating condition
- A model predicted output is calculated for each model using the current manipulated input

State Estimation



- Need a way to account for model uncertainty and mismatch.

$$ {}^{i}x_{k+1} = {}^{i}\Phi\, {}^{i}x_k + {}^{i}\Gamma u_k $$
$$ {}^{i}y_k = {}^{i}C\, {}^{i}x_k $$

Additive output disturbance

$$ {}^{i}x_{k+1} = {}^{i}\Phi\, {}^{i}x_k + {}^{i}\Gamma u_k $$
$$ {}^{i}d_{k+1} = {}^{i}d_k $$
$$ {}^{i}y_k = {}^{i}C\, {}^{i}x_k + {}^{i}d_k $$

Step input disturbance

$$ {}^{i}x_{k+1} = {}^{i}\Phi\, {}^{i}x_k + {}^{i}\Gamma u_k + {}^{i}\Gamma^{d}\, {}^{i}d_k $$
$$ {}^{i}d_{k+1} = {}^{i}d_k $$
$$ {}^{i}y_k = {}^{i}C\, {}^{i}x_k $$

$$ \begin{bmatrix} {}^{i}x_{k+1} \\ {}^{i}d_{k+1} \end{bmatrix} = \begin{bmatrix} {}^{i}\Phi & G_x \\ 0 & I \end{bmatrix} \begin{bmatrix} {}^{i}x_k \\ {}^{i}d_k \end{bmatrix} + \begin{bmatrix} {}^{i}\Gamma \\ 0 \end{bmatrix} u_k $$

$$ {}^{i}y_k = \begin{bmatrix} {}^{i}C & G_y \end{bmatrix} \begin{bmatrix} {}^{i}x_k \\ {}^{i}d_k \end{bmatrix} $$

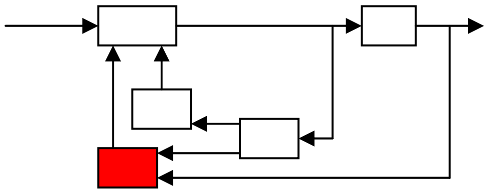
$G_x = {}^{i}\Gamma^{d}$ **Step input**

$G_x = 0$ **Additive output**

$G_y = 0$ **Step input**

$G_y = I$ **Additive output**

State Estimation



- Kalman predictor/corrector equations

$$\begin{bmatrix} {}^i x_{k+1} \\ {}^i d_{k+1} \end{bmatrix} = \begin{bmatrix} {}^i\Phi & G_x \\ 0 & I \end{bmatrix} \begin{bmatrix} {}^i x_k \\ {}^i d_k \end{bmatrix} + \begin{bmatrix} {}^i\Gamma \\ 0 \end{bmatrix} u_k + \begin{bmatrix} 0 \\ {}^i\Gamma^w \end{bmatrix} {}^i w_k$$

$${}^i y_k = \begin{bmatrix} {}^i C & G_y \end{bmatrix} \begin{bmatrix} {}^i x_k \\ {}^i d_k \end{bmatrix} + v_k$$

$${}^i x^a_{k+1} = {}^i\Phi^{a\,i}\hat{x}^a_k + {}^i\Gamma^a u_k + {}^i\Gamma^{1,w\,i} w_k$$

$${}^i y_k = {}^i C^{a\,i} x^a_k + v_k$$

$${}^i\hat{x}^a_{k|k-1} = {}^i\Phi^{a\,i}\hat{x}^a_{k-1|k-1} + {}^i\Gamma^a u_{k-1}$$ Prediction

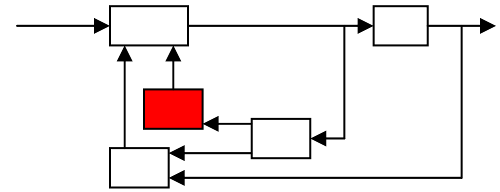
$${}^i\hat{x}^a_{k|k} = {}^i\hat{x}^a_{k|k-1} + {}^i L\left(y - {}^i C^{a\,i}\hat{x}^a_{k|k-1}\right)$$ Correction

$${}^i\hat{y}_{k|k} = {}^i C^{a\,i}\hat{x}^a_{k|k}$$ Updated output prediction

$${}^i L = \begin{bmatrix} 0 \\ I \end{bmatrix}$$ **Additive output**

$${}^i L = Kalman\ gain$$ **Step input**

Weight Calculation



$${}^{i}\varepsilon_k = y_k - {}^{i}\hat{y}_{k|k}$$

Model residual

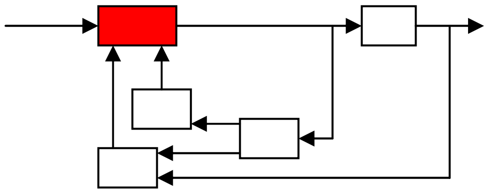
$${}^{i}p_k = \frac{\exp\left(-0.5\ {}^{i}\varepsilon_k^T\ {}^{i}\Lambda\ {}^{i}\varepsilon_k\right)\ {}^{i}p_{k-1}}{\sum_{j=1}^{n} \exp\left(-0.5\ {}^{j}\varepsilon_k^T\ {}^{i}\Lambda\ {}^{j}\varepsilon_k\right)\ {}^{j}p_{k-1}}$$

Bayesian probability, i^{th} model

$${}^{i}w_k = \begin{cases} \dfrac{{}^{i}p_k}{\sum_{j=1}^{n} {}^{j}p_k} & {}^{i}p_k > \delta \\ 0 & {}^{i}p_k \le \delta \end{cases}$$

Weight, i^{th} model

Model Predictive Control



- "Model average" for the output prediction

$$\bar{y}_{k+j|k} = \sum_{i=1}^{n} {}^{i}w_k \; {}^{i}\hat{y}_{k+j|k}$$

- Quadratic objective function

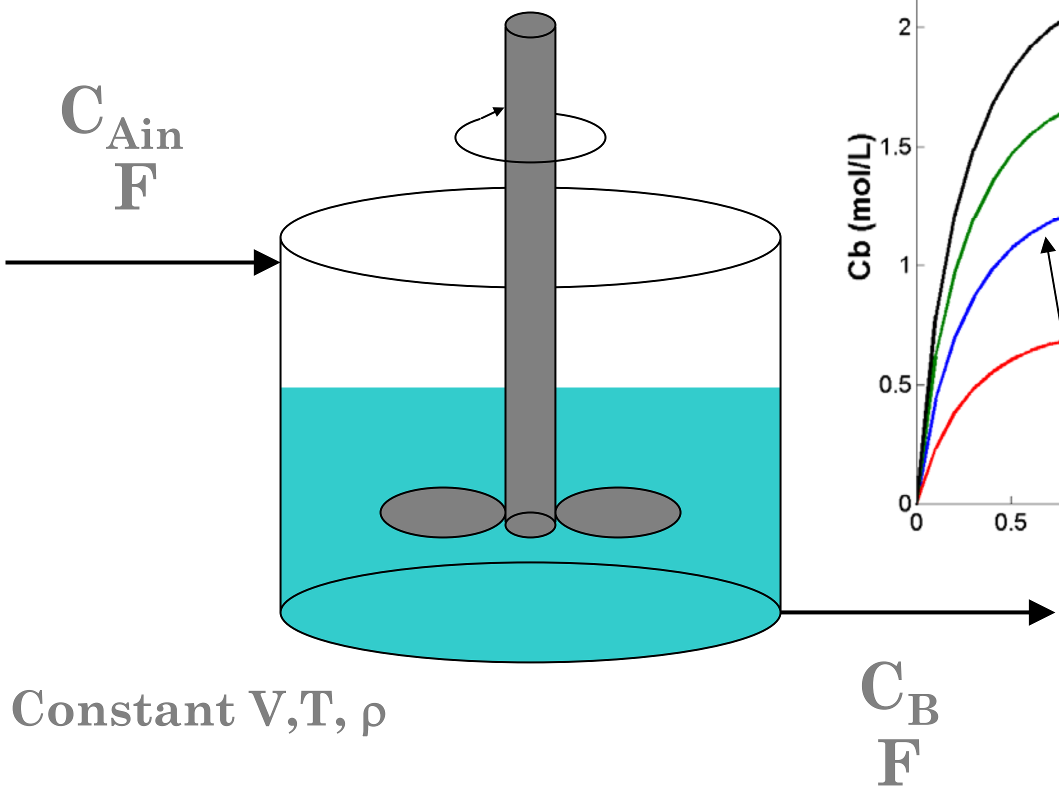
$$\min \Phi = \left(R - \bar{Y}\right)^T W_y \left(R - \bar{Y}\right) + \Delta U^T W_u \Delta U$$

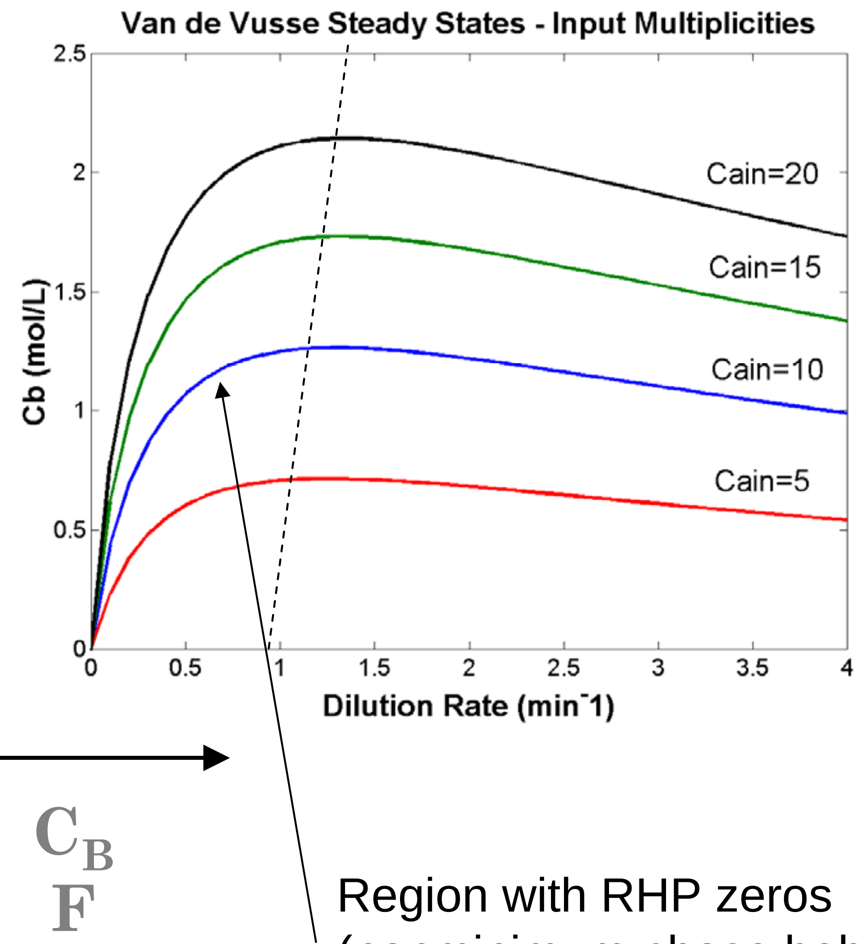
Analytical Solution

- Constraints on inputs and outputs

Quadratic Program (QP)

Van de vuuse isothermal reactor





Constant V,T, ρ

$A \rightarrow B \rightarrow C$

$A + A \rightarrow D$

Region with RHP zeros
(nonminimum phase behavior)

Connection between IM and RHP zeros:

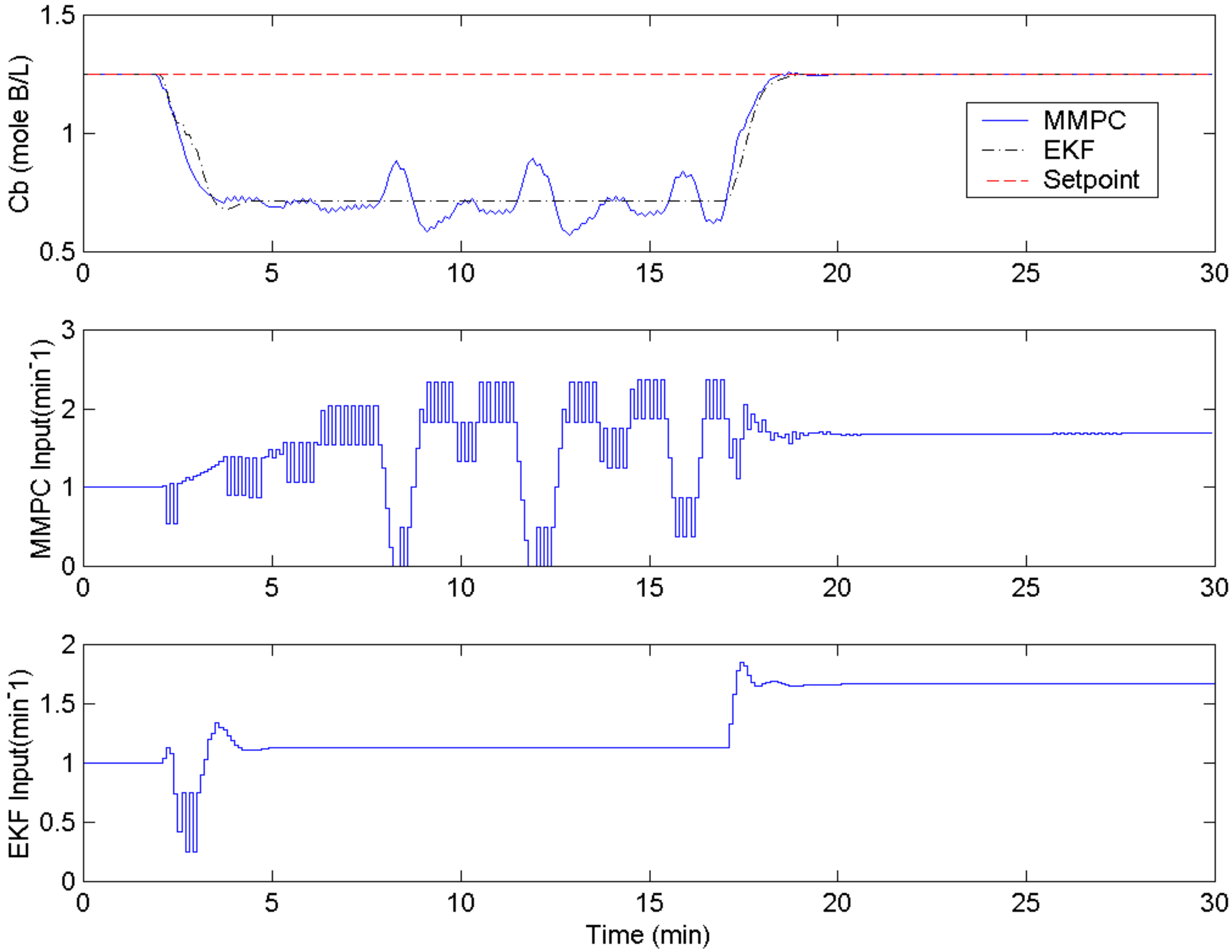
Sistu & Bequette, *Chem. Eng. Sci.* (1996)

Feed Concentration Disturbance

C_B (y)

MMPC (u)

EKF-based NL-MPC (u)



Disturbances & Propagation Into Future

- Output step
  - Generally poor assumption for chemical processes
- Input step
  - Improved performance for many processes
- Input ramp
  - Motivated by experience with diabetes problems
- Pulse
  - Duties performed infrequently (shift change, etc.)
- Periodic
  - Poorly tuned upstream controllers, diurnal variations

Step, Ramp, Generic

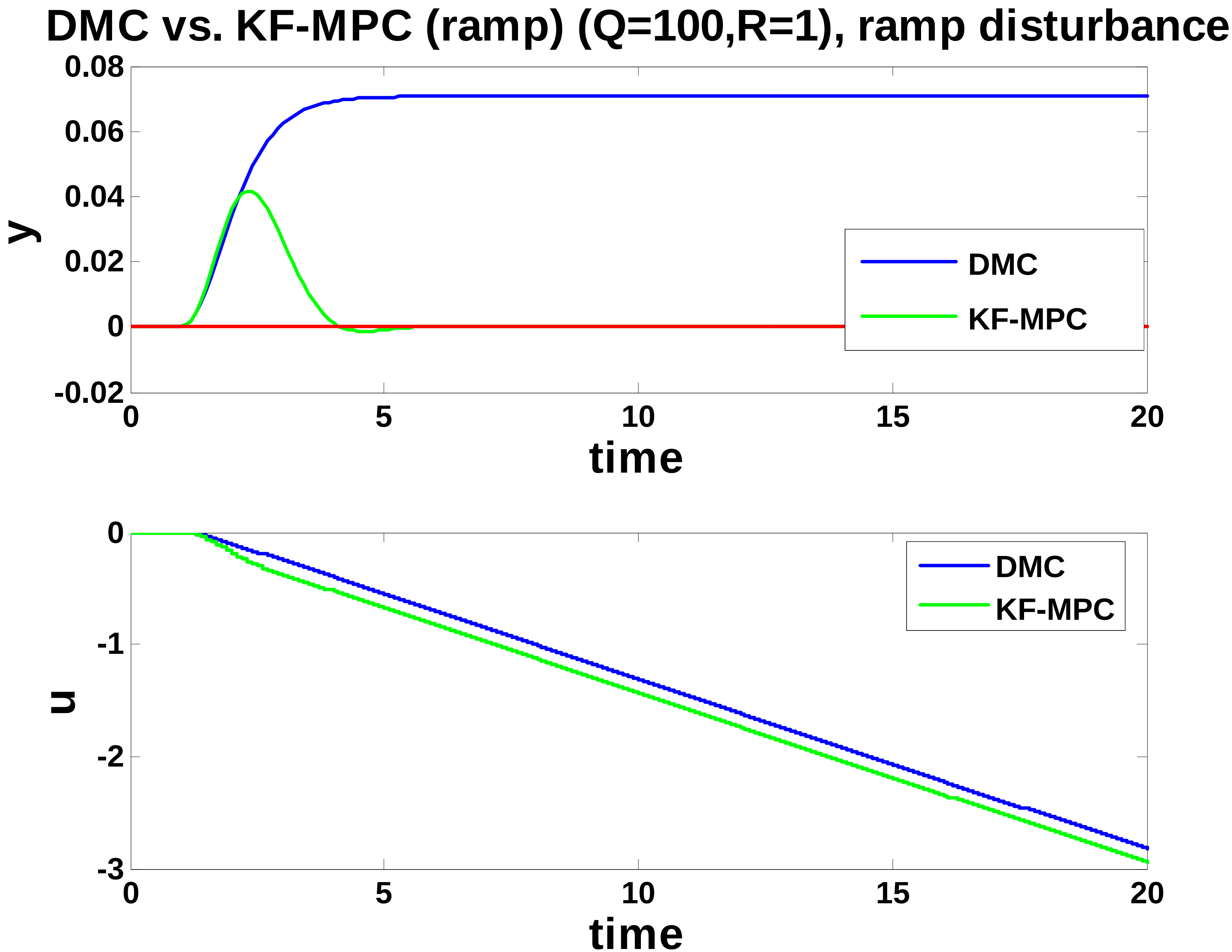
$$\underbrace{\begin{bmatrix} x_{k+1} \\ d_{k+1} \end{bmatrix}}_{x^a_{k+1}} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d \\ 0 & 1 \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x^a_k} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \end{bmatrix}}_{\Gamma^a} u_k + \underbrace{\begin{bmatrix} 0 \\ \Gamma^w \end{bmatrix}}_{\Gamma^{w,a}} w_k \qquad y_k = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x^a_k} + v_k$$

$$\underbrace{\begin{bmatrix} x_{k+1} \\ \begin{bmatrix} d_{k+1} \\ \Delta d_{k+1} \end{bmatrix} \end{bmatrix}}_{x^a_{k+1}} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d \\ \begin{bmatrix} 0 \\ 0 \end{bmatrix} & \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} x_k \\ \begin{bmatrix} d_k \\ \Delta d_k \end{bmatrix} \end{bmatrix}}_{x^a_k} + \underbrace{\begin{bmatrix} \Gamma \\ \begin{bmatrix} 0 \\ 0 \end{bmatrix} \end{bmatrix}}_{\Gamma^a} u_k + \underbrace{\begin{bmatrix} 0 \\ \begin{bmatrix} 0 \\ 1 \end{bmatrix} \end{bmatrix}}_{\Gamma^{w,a}} w_k \qquad y_k = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} x_k \\ \begin{bmatrix} d_k \\ \Delta d_k \end{bmatrix} \end{bmatrix}}_{x^a_k} + v_k$$

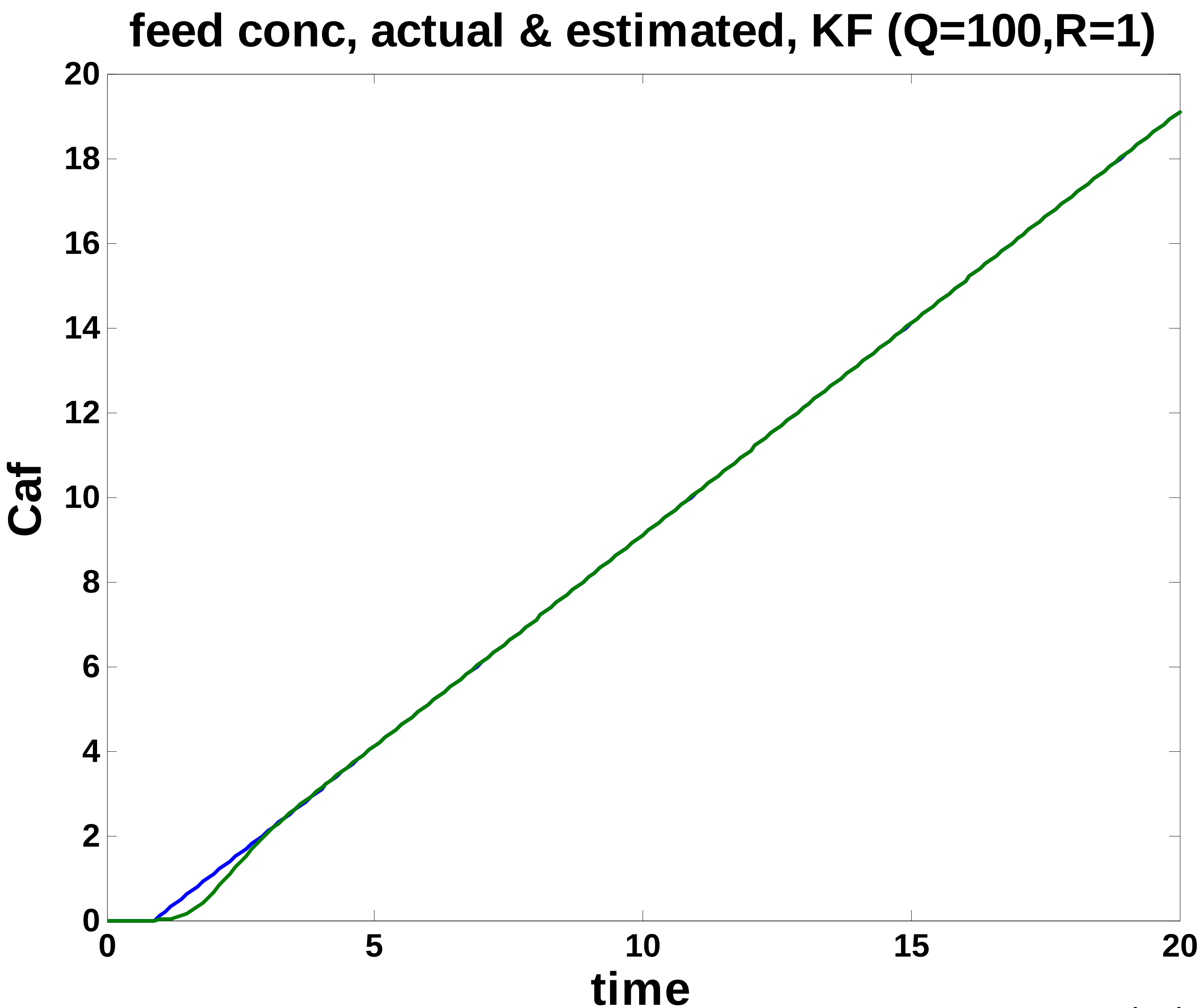
$$\underbrace{\begin{bmatrix} x_{k+1} \\ d_{k+1} \end{bmatrix}}_{x^a_{k+1}} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d \\ 0 & \Phi^w \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x^a_k} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \end{bmatrix}}_{\Gamma^a} u_k + \underbrace{\begin{bmatrix} 0 \\ \Gamma^w \end{bmatrix}}_{\Gamma^{w,a}} w_k \qquad y_k = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} x_k \\ d_k \end{bmatrix}}_{x^a_k} + v_k$$

Ramp Disturbance

deviation variables



Unmeasured Feed Concentration



deviation variables

Periodic Disturbance

$$\begin{bmatrix} \dot{C}_A \\ \dot{C}_B \end{bmatrix} = \begin{bmatrix} -2.4048 & 0 \\ 0.8333 & -2.2381 \end{bmatrix} \begin{bmatrix} C_A \\ C_B \end{bmatrix} + \begin{bmatrix} 7 & 0.5714 \\ -1.117 & 0 \end{bmatrix} \begin{bmatrix} F/V \\ C_{Af} \end{bmatrix}$$

$$\begin{bmatrix} \dot{C}_{Af} \\ \ddot{C}_{Af} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\omega^2 & 0 \end{bmatrix} \begin{bmatrix} C_{Af} \\ \dot{C}_{Af} \end{bmatrix} + \begin{bmatrix} 0 \\ d \end{bmatrix}$$

Poles on imaginary axis

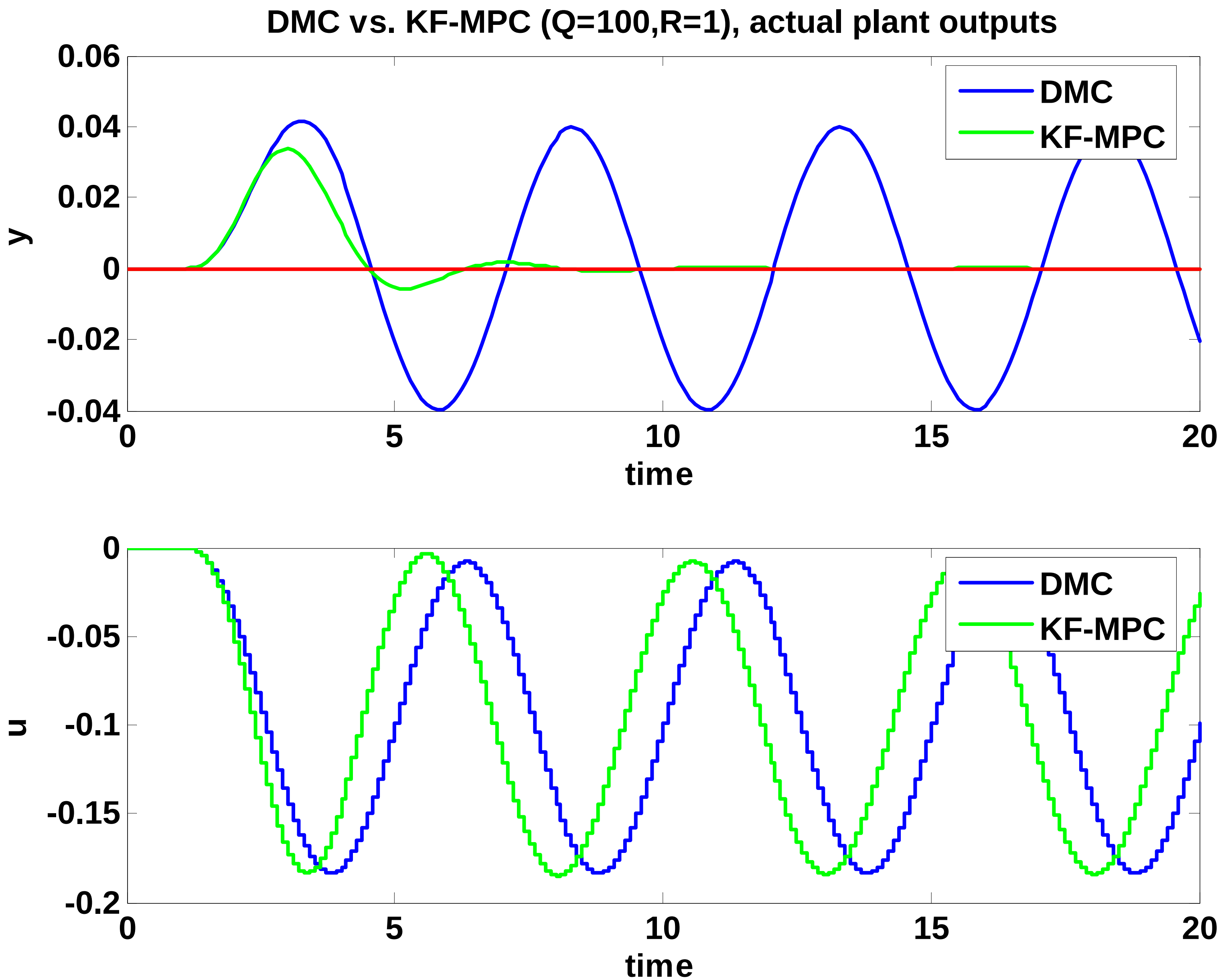
Results in sin variation in feed concentration

$$\begin{bmatrix} \dot{C}_A \\ \dot{C}_B \\ \dot{C}_{Af} \\ \ddot{C}_{Af} \end{bmatrix} = \begin{bmatrix} -2.4048 & 0 & 0.5714 & 0 \\ 0.8333 & -2.2381 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -\omega^2 & 0 \end{bmatrix} \begin{bmatrix} C_A \\ C_B \\ C_{Af} \\ \dot{C}_{Af} \end{bmatrix} + \begin{bmatrix} 7 & 0 \\ -1.117 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} F/V \\ d \end{bmatrix}$$

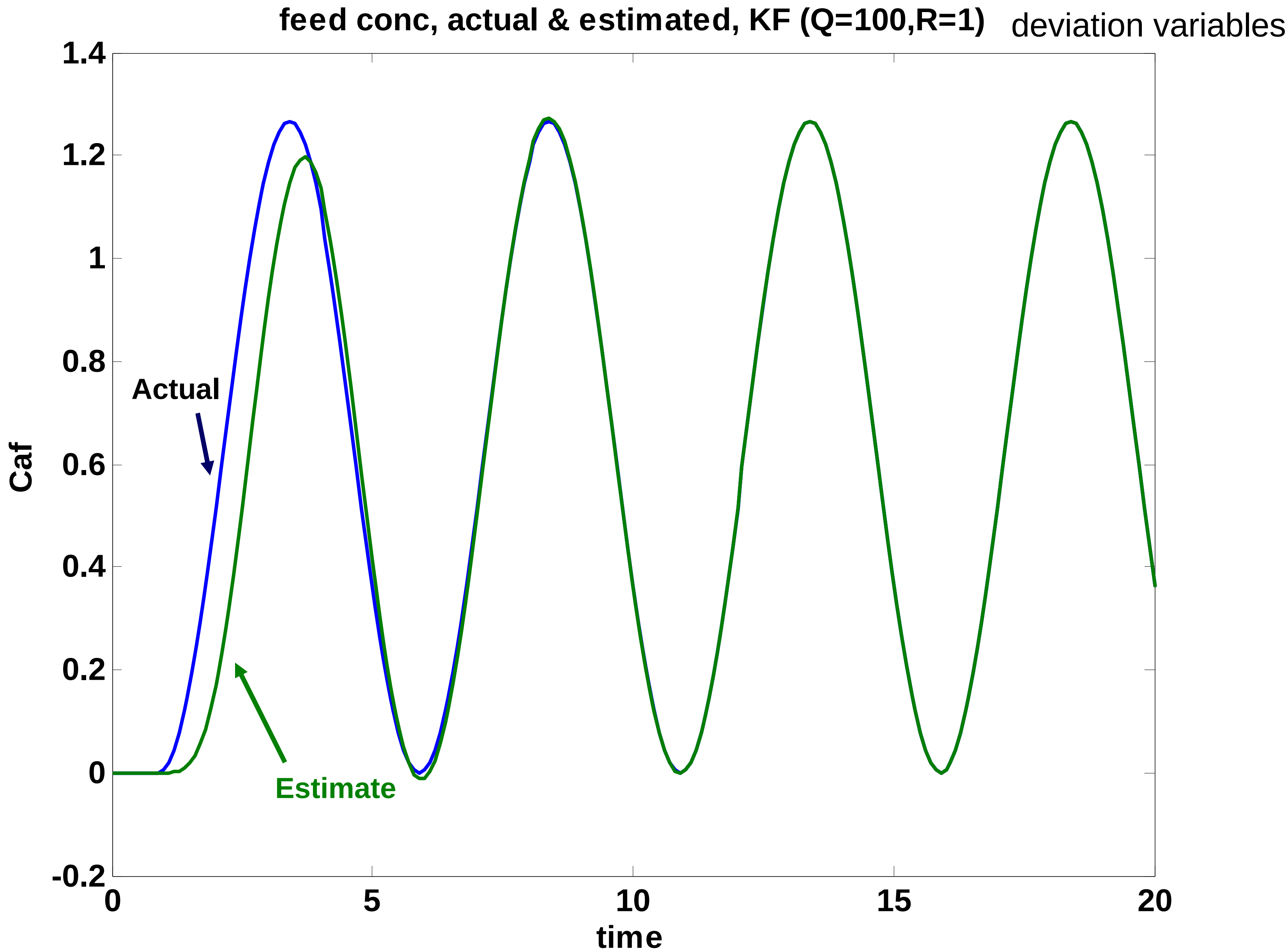
Appended state form

DMC vs. KF-MPC

deviation variables



Feed Concentration Estimate



Numerous Potential Disturbances

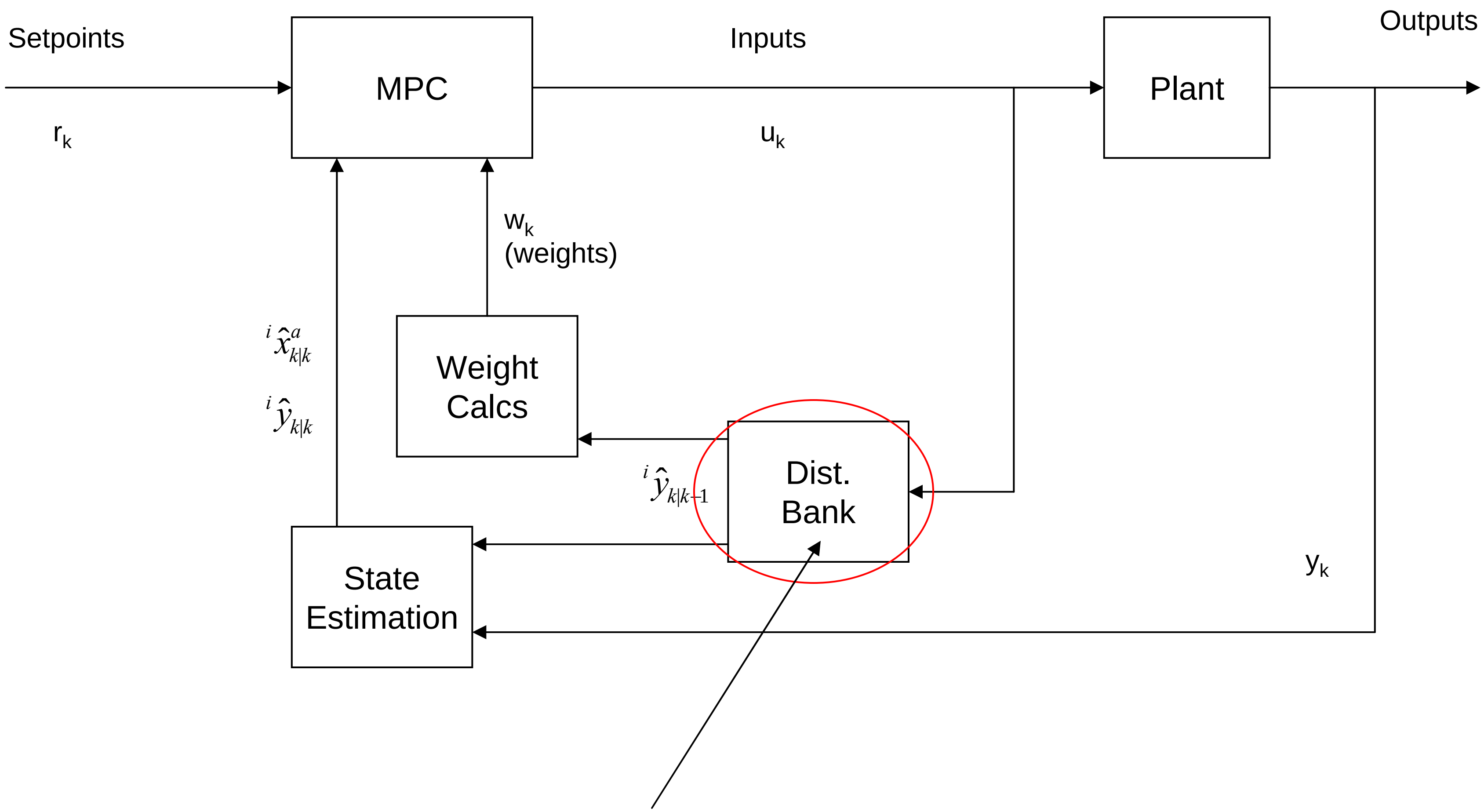
- Current Practice
  - Choose most important disturbance(s) to estimate & reject (number of disturbances = number of measurements)
- Model Bank
  - Each model associated with a different type of disturbance
  - Weighting/Blending or Switching between models

Ind. Eng. Chem. Res. **2010**, *49*, 7983–7989

Multiple Model Predictive Control Strategy for Disturbance Rejection[†,‡]

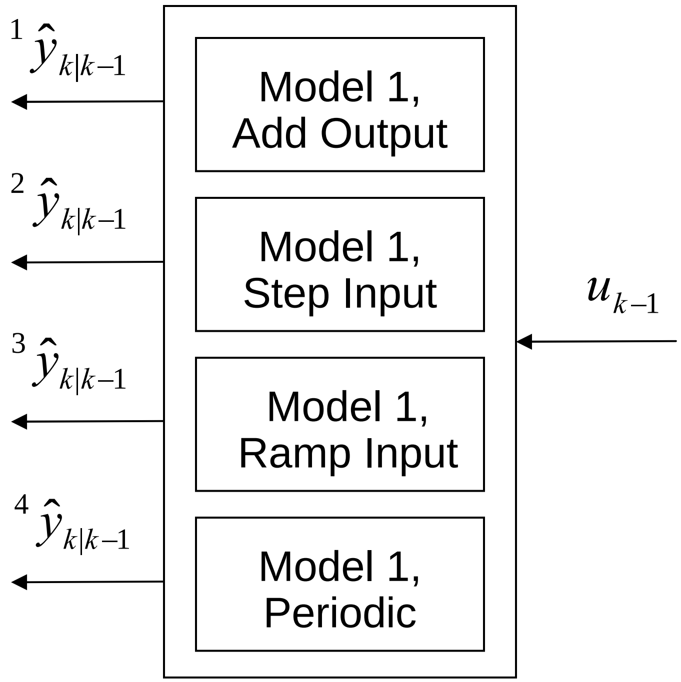
Matthew Kuure-Kinsey[§] **and B. Wayne Bequette***

Disturbance Estimation - Framework



Primary difference is in the “disturbance bank”

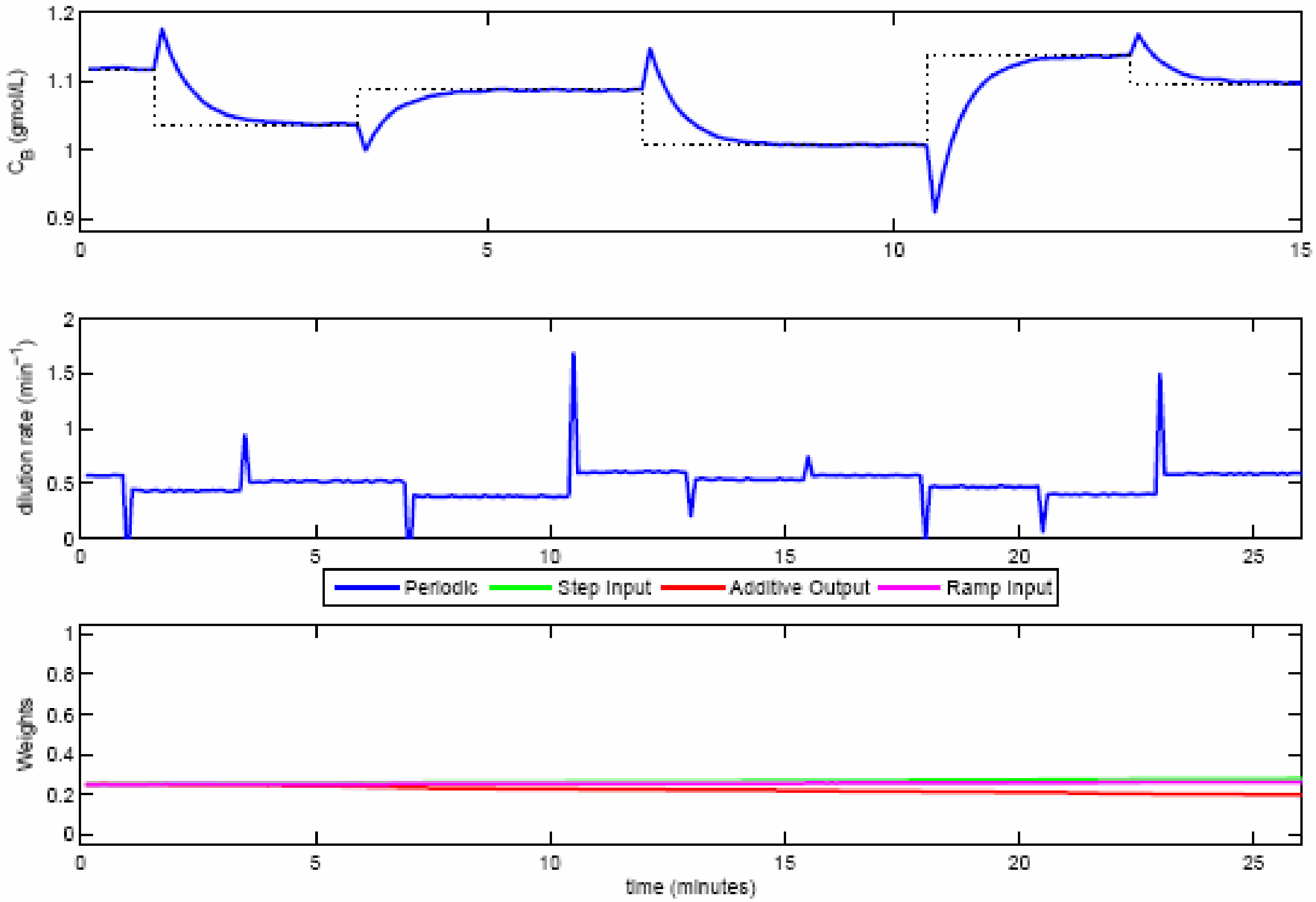
Disturbance Bank Structure



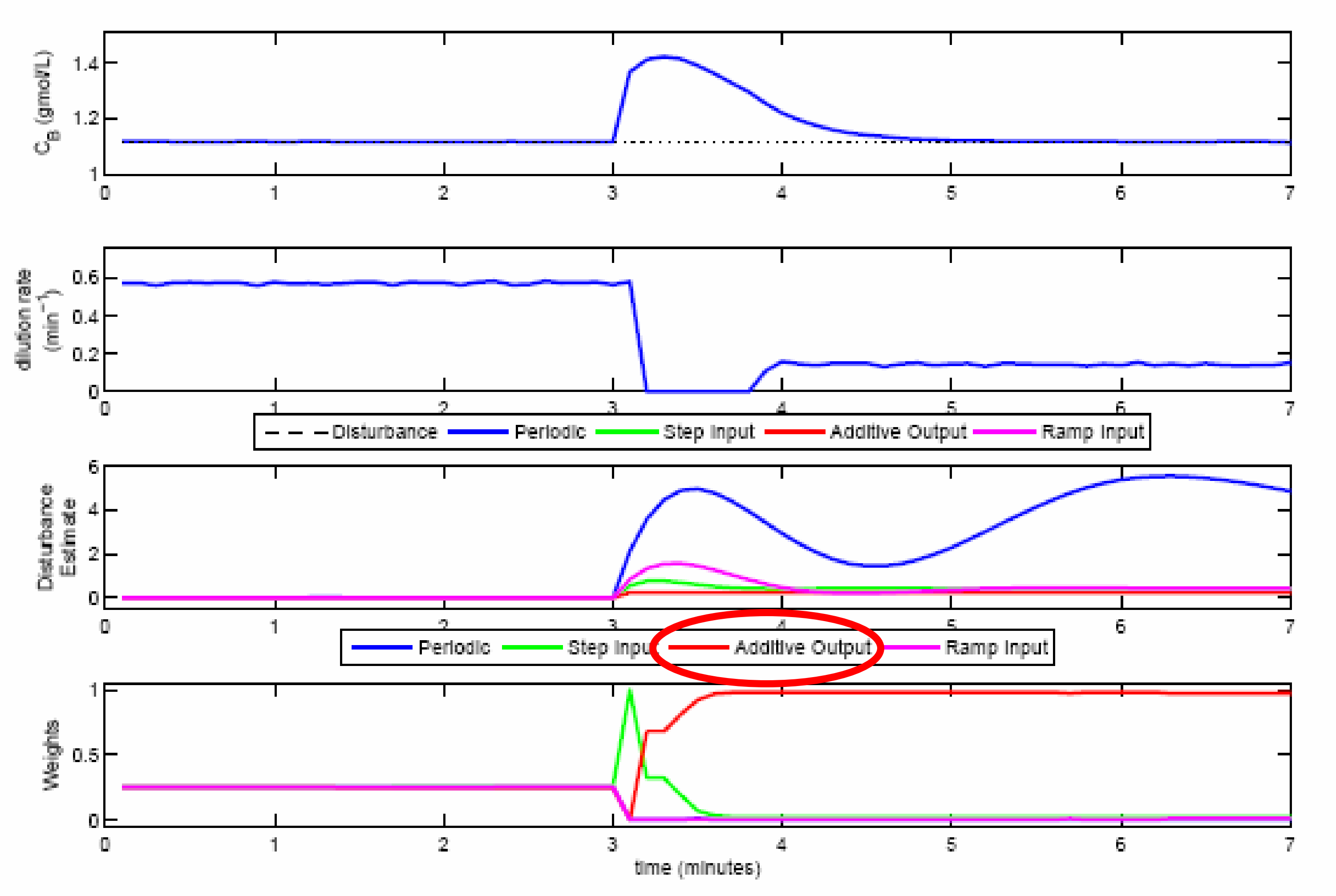
$$\underbrace{\begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{d}_{k|k-1} \end{bmatrix}}_{\hat{x}^a_{k+1|k}} = \underbrace{\begin{bmatrix} \Phi & \Gamma^d \\ 0 & \Phi^w \end{bmatrix}}_{\Phi^a} \underbrace{\begin{bmatrix} \hat{x}_{k-1|k-1} \\ \hat{d}_{k-1|k-1} \end{bmatrix}}_{\hat{x}^a_{k-1|k-1}} + \underbrace{\begin{bmatrix} \Gamma \\ 0 \end{bmatrix}}_{\Gamma^a} u_{k-1}$$

$$\hat{y}_{k|k-1} = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C^a} \underbrace{\begin{bmatrix} \hat{x}_{k-1|k} \\ \hat{d}_{k-1|k} \end{bmatrix}}_{x^a_{k|k-1}}$$

Setpoint Tracking (No Disturbances)



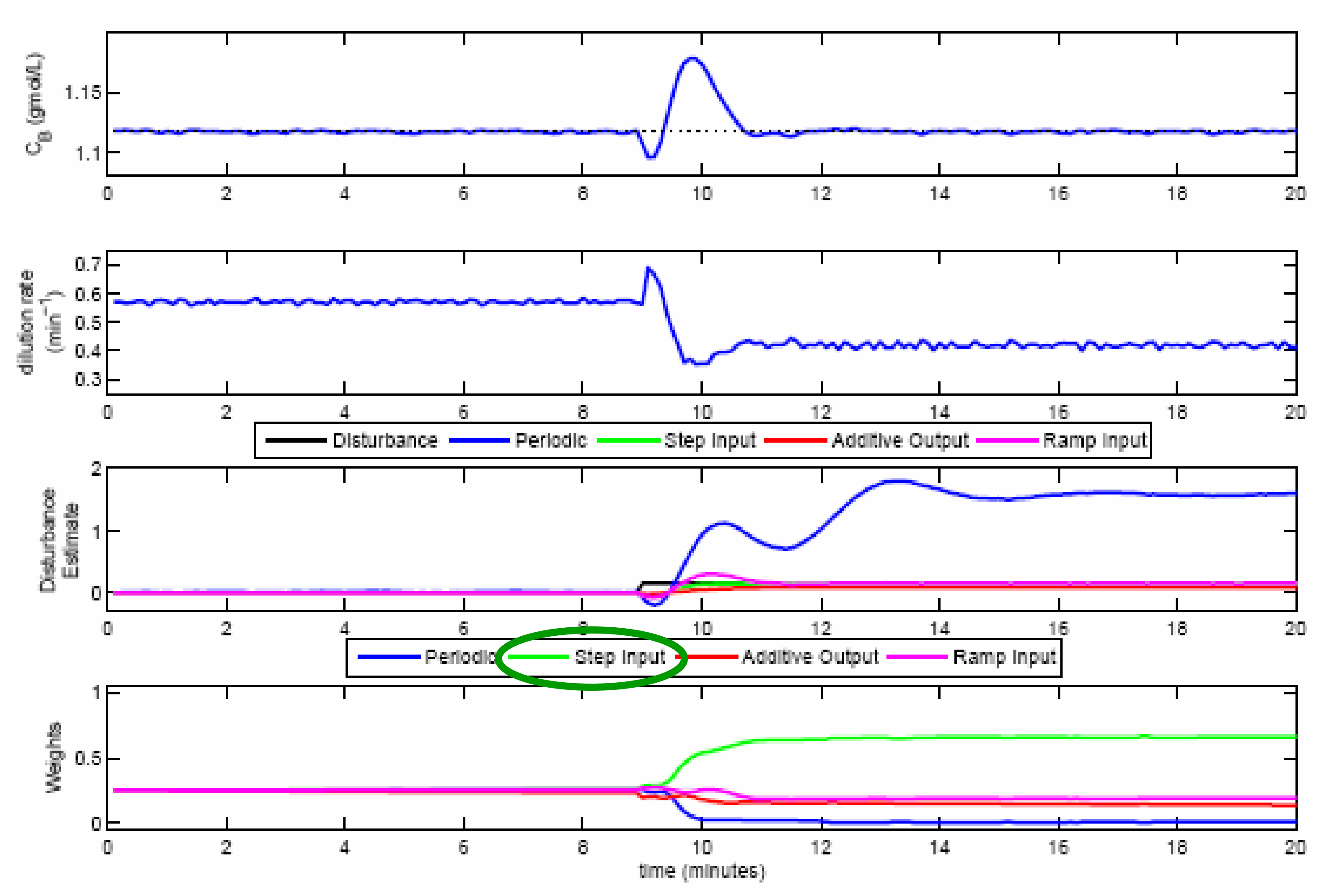
Additive Output Disturbance



Measured output

Weights

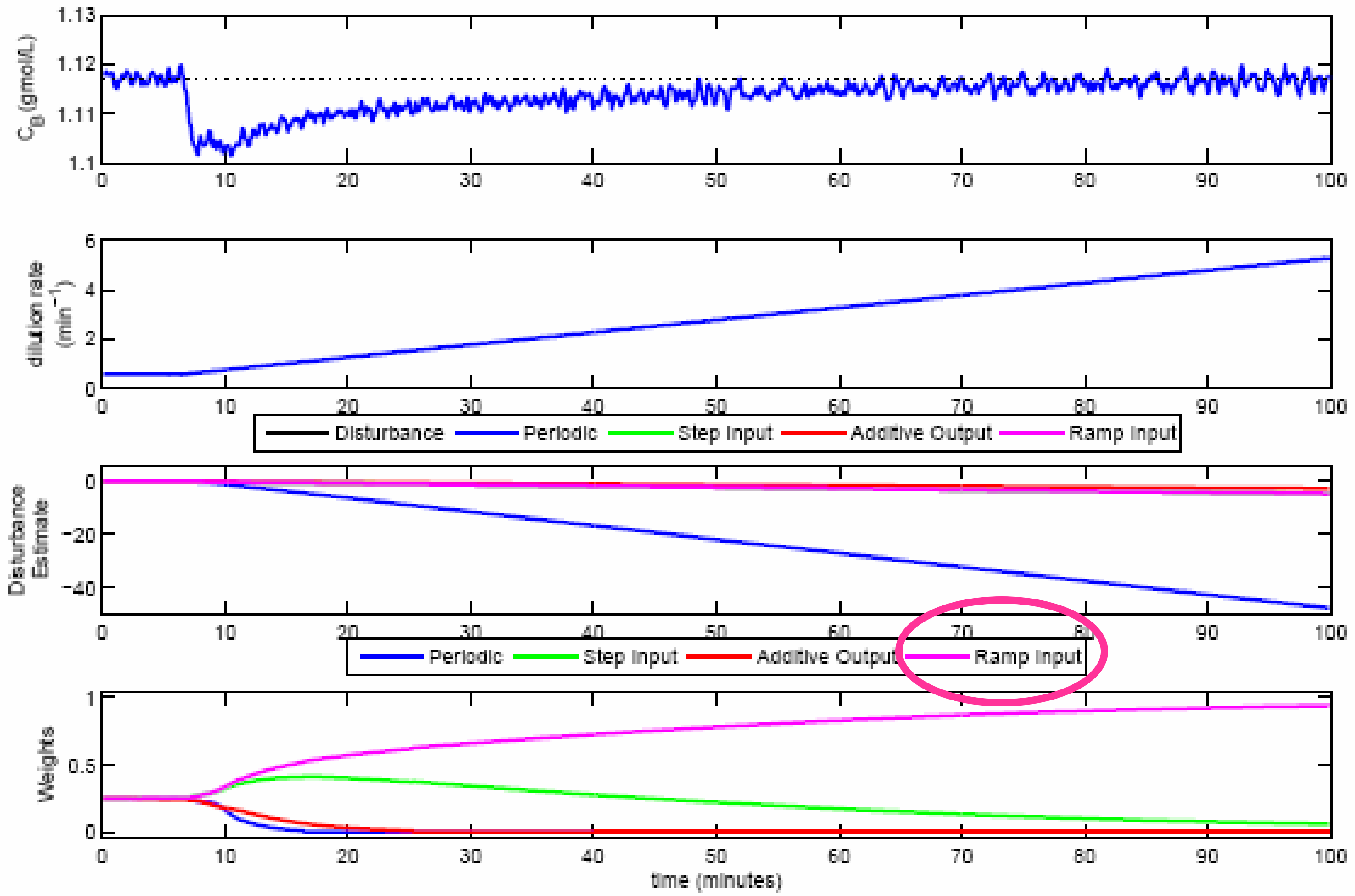
Step Input Disturbance



Measured output

Weights

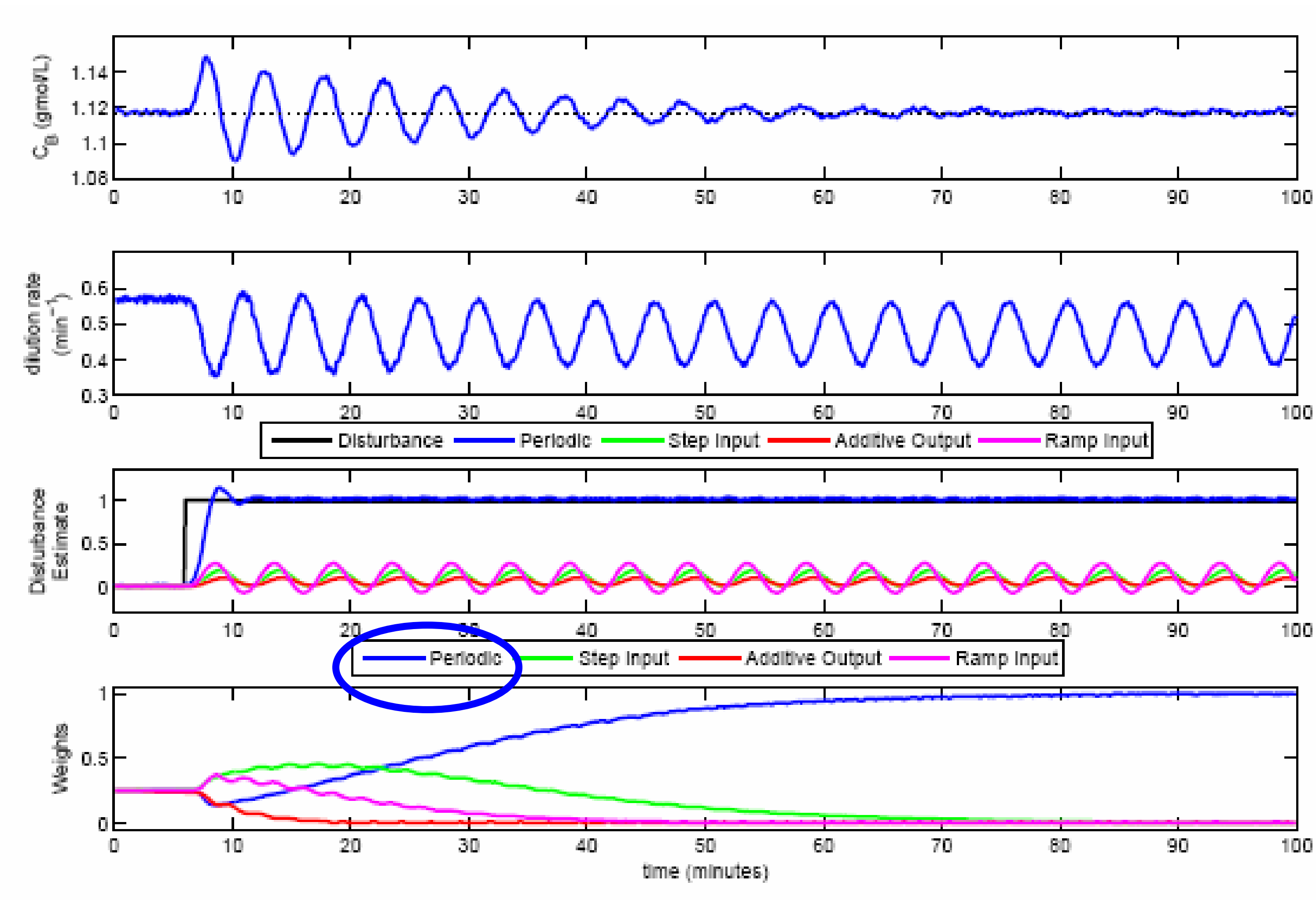
Ramp Input Disturbance



Measured output

Weights

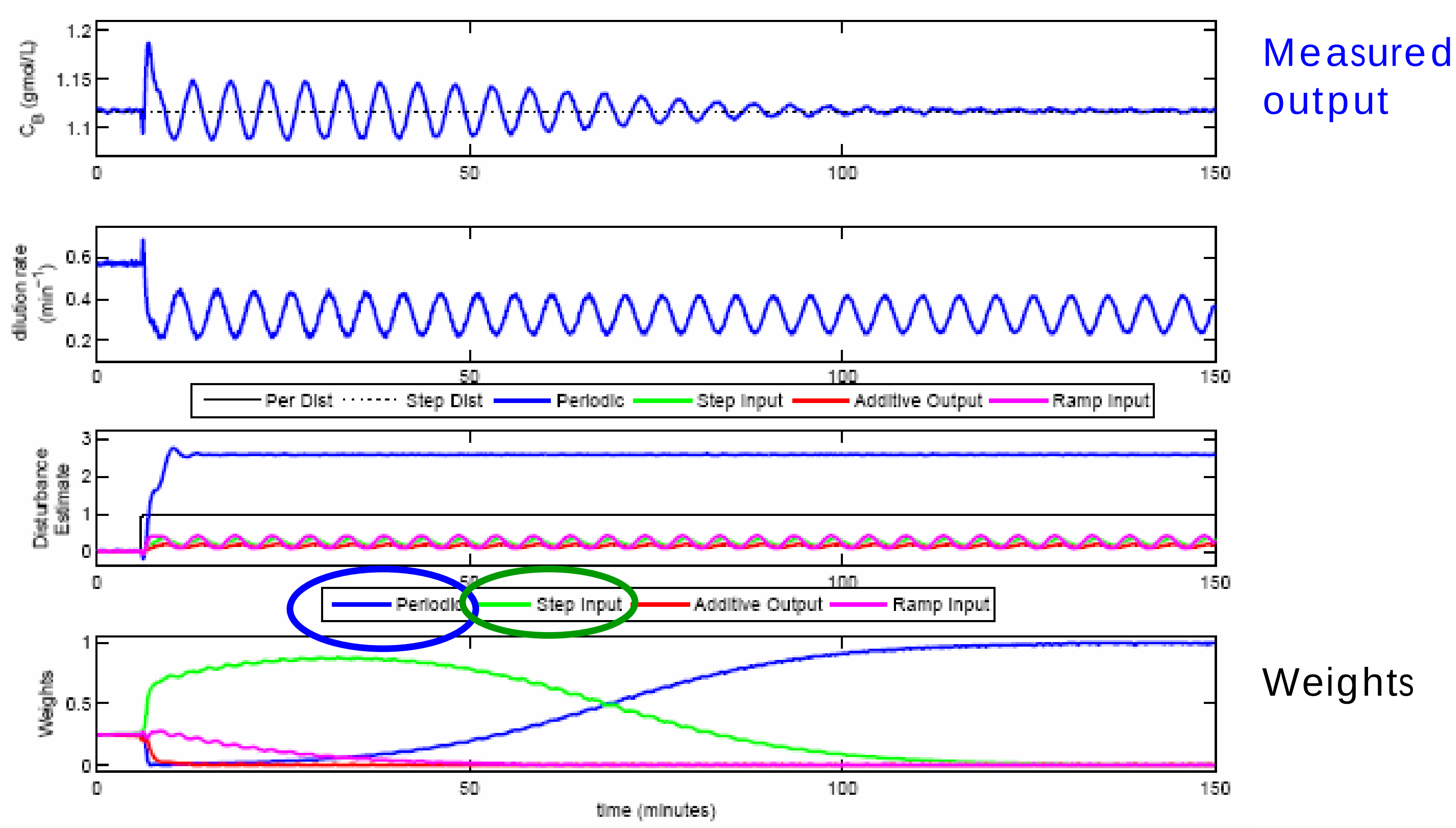
Periodic Input Disturbance



Measured output

Weights

Step + Periodic Input Disturbances



Presentation Summary

- Nonlinear Model Predictive Control
  - Limitations to DMC formulation
  - State estimation-based approaches
  - Multiple linear model-based approaches
  - Formulation for different disturbances

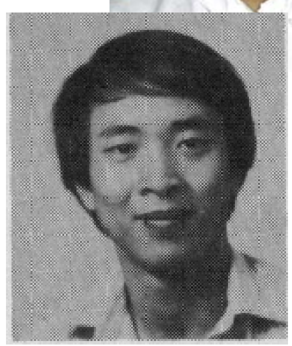
Acknowledgments

- Matthew Kuure-Kinsey (2008)

- Brian Aufderheide (2002)

- Ramesh Rao (2000)
  – ASPENTECH

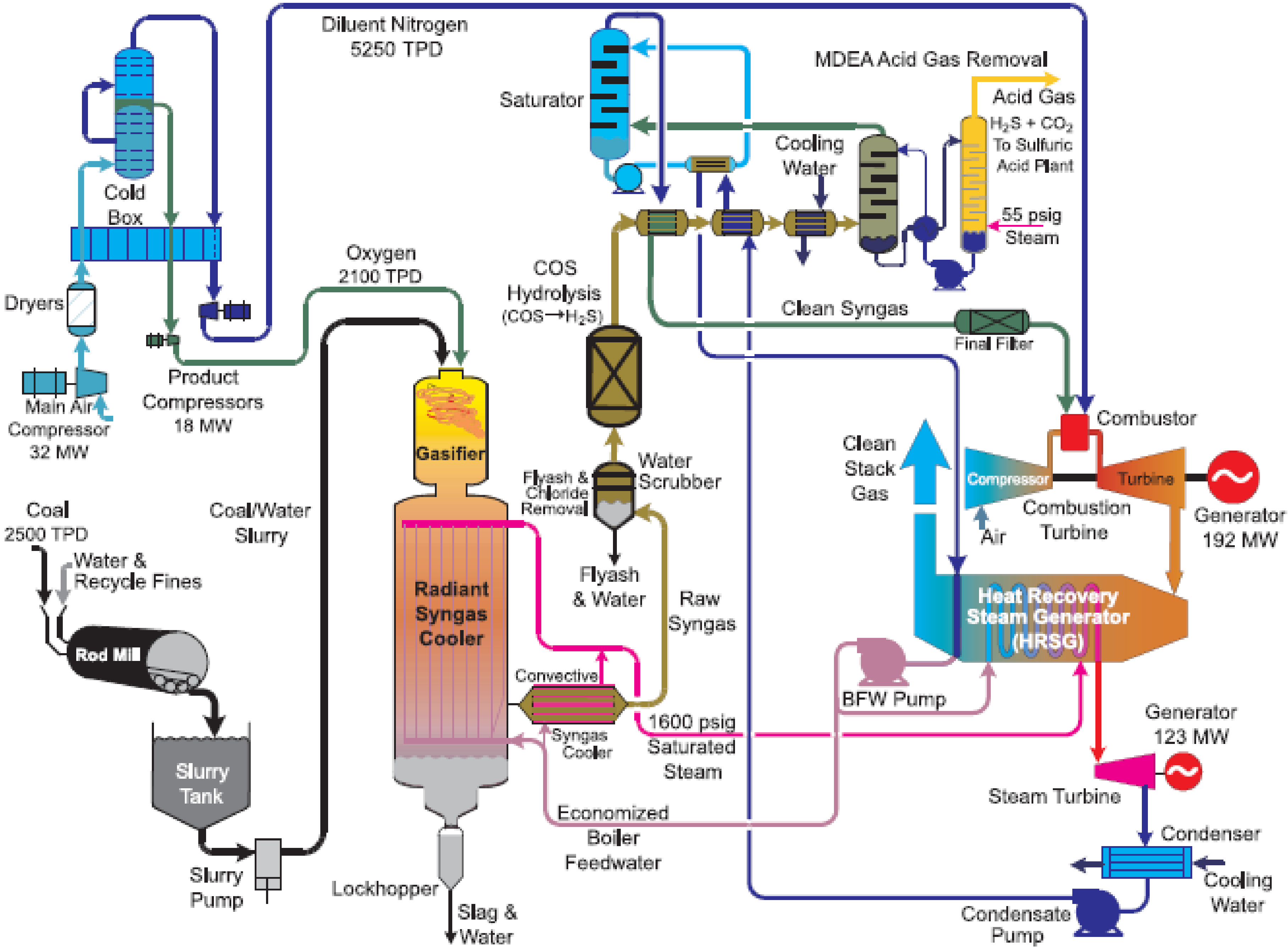
- Clem Yu (1992)
  – Baxter



Current Applications of MPC

- Integrated Gasification Combined Cycle (IGCC) Power Plants
  - Carbon Capture case
- Fuel Cell Systems
  - Smart Grid
- Closed-loop Artificial Pancreas for Type 1 Diabetes

IGCC



Diluent Nitrogen
5250 TPD
Saturator
MDEA Acid Gas Removal
Acid Gas
$H_2S + CO_2$
To Sulfuric
Acid Plant
Cooling
Water
55 psig
Steam
Cold
Box
Dryers
Oxygen
2100 TPD
COS
Hydrolysis
($COS \rightarrow H_2S$)
Clean Syngas
Final Filter
Main Air
Compressor
32 MW
Product
Compressors
18 MW
Gasifier
Combustor
Clean
Stack
Gas
Compressor
Turbine
Generator
192 MW
Air
Combustion
Turbine
Water
Scrubber
Flyash &
Chloride
Removal
Flyash
& Water
Raw
Syngas
Coal
2500 TPD
Coal/Water
Slurry
Water &
Recycle Fines
Rod Mill
Radiant
Syngas
Cooler
Heat Recovery
Steam Generator
(HRSG)
BFW Pump
Convective
Syngas
Cooler
1600 psig
Saturated
Steam
Generator
123 MW
Steam Turbine
Slurry
Tank
Economized
Boiler
Feedwater
Condenser
Cooling
Water
Slurry
Pump
Lockhopper
Slag &
Water
Condensate
Pump

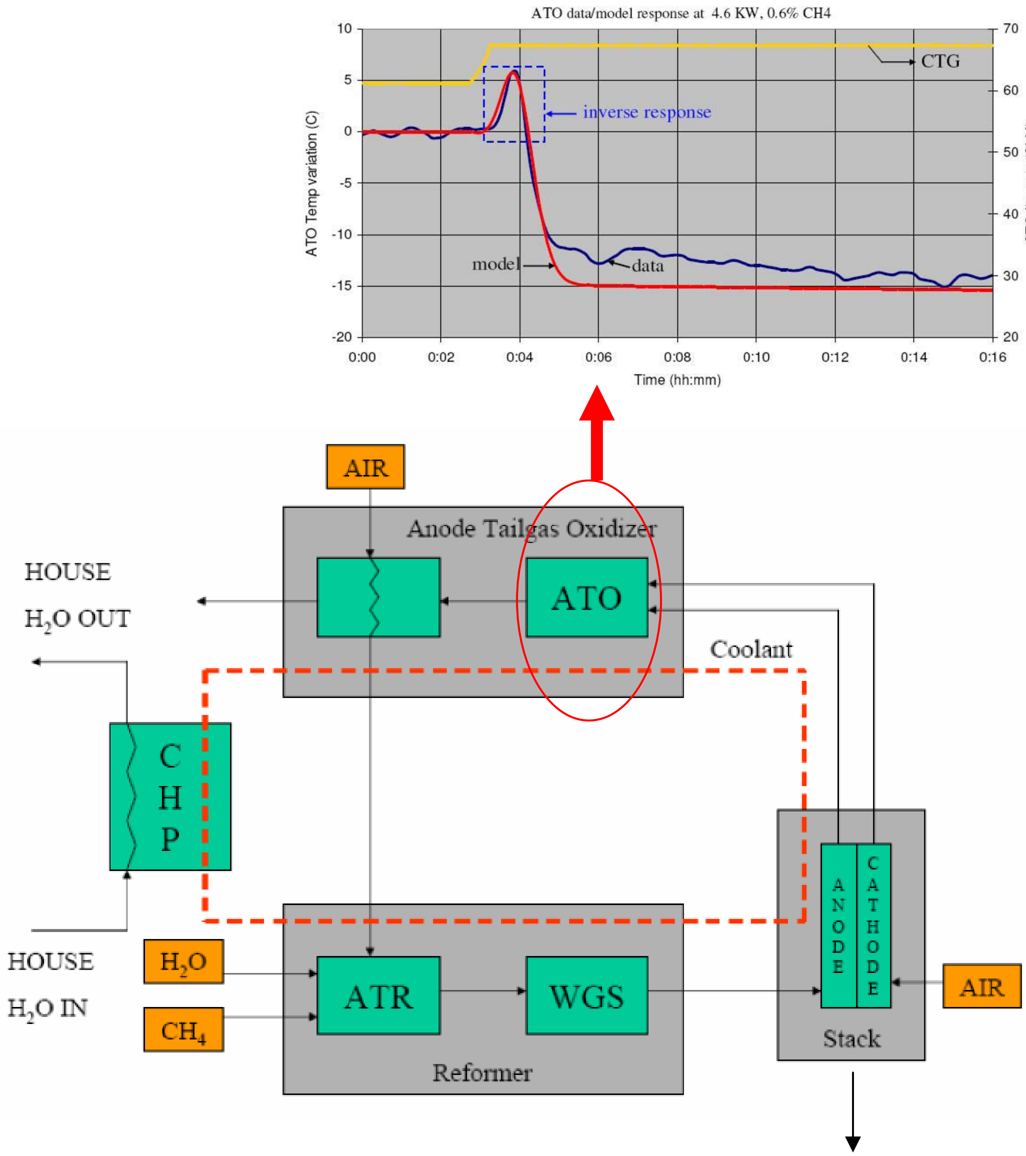
IGCC Summary

- IGCC Power Plant is a complex system to simulate
  - Significant reworking of steady-state flowsheet required adding plant details and dynamic behavior
  - 300 Units & 450 Streams
  - 80,000 equations solved – dynamic simulations
- Linear MPC is a powerful tool to control complex plants
  - Hierarchical Control Structure Design
  - Load Following / Disturbance Rejection
  - Centralized Approach is better suited for following load-demand
  - Negative effect on controllability and robustness w/ increasing level of interactions
- Limitations of this research
  - Simplifying assumptions on some units
  - Proprietary equipment details/ lack of validation data
  - Workaround for software bugs/limitations

Priyadarshi Mahapatra
Ph.D., 2010; NETL

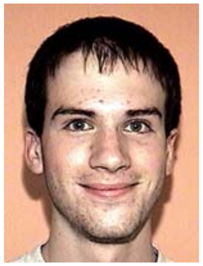
Fuel Cell Systems

- Combined heat & power
- Nonlinear dynamics & control
- Stack condition monitoring
- Real-time optimization
- Nature-inspired membrane and catalyst design (Marc-Olivier Coppens)




Matthew Kuure-Kinsey (Dec '08)
Judy O'Rourke (Dec 2008)

Jeff Marquis
(w/Coppens)



Matt Titus

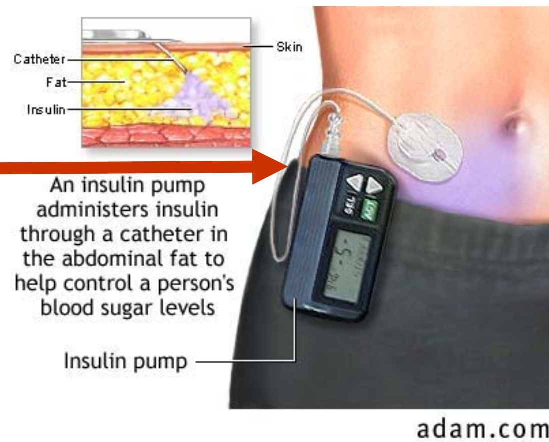
Closed-loop Artificial Pancreas

Meal knowledge: **Feedforward**

Glucose setpoint **r**

Controller

u Insulin infusion rate

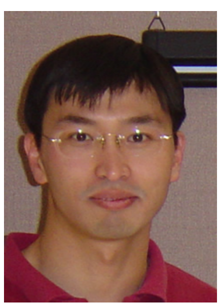


pump subject

Sensor

y

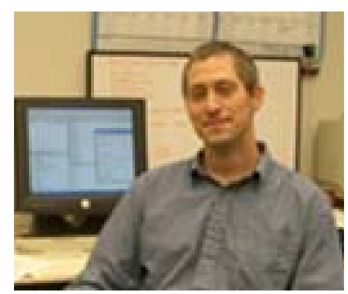
Feedback Glucose sensor signal



Hyunjin Lee
Now at Shell Development

Jing Sun

Ruben Rojas
Fulbright Scholar
Venezuela



Fraser Cameron