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
Nonlinear Behavior: Steady-state

Input Multiplicity

Output Multiplicity (hysteresis)

Van de Vuuse Reactor, Figure M5-2, page 609

Two different input values yield the same output

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
\[
\begin{align*}
\dot{x} &= f(x,u) \\
y &= g(x)
\end{align*}
\]

Integrate model from time step k-1 to k
\[
\hat{x}_k = F_{t_s} \left( \hat{x}_{k-1}, u_{k-1} \right)
\]
\[
\hat{y}_{k|k-1} = g(\hat{x}_k)
\]

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
\[u_k, u_{k+1}, \ldots, u_{k+P-1}\]

Integrate model from time step k to k+P (based on hypothetical control moves)
\[
\begin{align*}
\hat{x}_{k+1} &= F_{t_s} \left( \hat{x}_k, u_k \right) \\
\hat{y}_{k+1|k} &= g(\hat{x}_{k+1}) + d_k \\
to \\
\hat{x}_{k+P} &= F_{t_s} \left( \hat{x}_{k+P-1}, u_{k+P-1} \right) \\
\hat{y}_{k+P|k} &= g(\hat{x}_{k+P}) + d_k
\end{align*}
\]

Evaluate objective function and repeat until optimum is obtained
Exothermic CSTR
Setpoint change to unstable steady-state

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

Additive Disturbance Assumption
Non-Convex Problem

Objective Function
(Decrease in Setpoint)

$M = 1$, different values of $P$

Decrease in Setpoint

Solution depends upon initial guess

Input Multiplicity $\rightarrow$ Multiple Minima

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

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

*Correspondence

Can use linear state-space KF-MPC code!
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)

Drug Infusion Control
Aufderheide & Bequette (2003)
Nonlinear CSTR
First, a Concise Review of Linear MPC

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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

\[ \hat{y}_{k|k} = \hat{y}_{k|k-1} + d_k \]
\[ \hat{y}_{k|k} = y_k \]

“deadbeat” observer

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

\[ \hat{y}_{k+j|k} = \sum_{i=1}^{j} s_i \Delta u_{k-i+j} + \sum_{i=j+1}^{N-1} s_i \Delta u_{k-i+j} + s_N u_{k-N+j} + \hat{d}_{k+j} \]

forced response \[ s_i \Delta u_{k-i+j} \]
free response \[ s_N u_{k-N+j} \]
correction term \[ \hat{d}_{k+j} \]

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

constant additive disturbance

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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)

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State Space Models & State Estimation

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

Assume disturbance propagation

\[ d_{k+1} = d_k \]

Appended state formulation

\[
\begin{bmatrix}
    x_{k+1} \\
    d_{k+1} \\
    x_{k+1}^a \\
    x_k \\
    d_k
\end{bmatrix}
= \begin{bmatrix}
    \Phi & \Gamma^d \\
    0 & I \\
    \Phi^a & \Gamma^d \\
    \Phi^a & \Gamma^a \\
    0 & \Gamma^a
\end{bmatrix}
\begin{bmatrix}
    x_k \\
    d_k \\
    x_k^a \\
    x_k^a \\
    d_k
\end{bmatrix}
+ \begin{bmatrix}
    \Gamma \\
    0
\end{bmatrix} u_k
\]

\[ y_k = \begin{bmatrix}
    C & 0 \\
    C^a & 0
\end{bmatrix}
\begin{bmatrix}
    x_k \\
    d_k
\end{bmatrix}
\]

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State Estimation Problem

\[ d_{k+1} = d_k + w_k \quad \text{Random walk} \]

\[
\begin{bmatrix}
    x_{k+1} \\
    d_{k+1} \\
    x^a_{k+1} \\
    d^a_{k+1}
\end{bmatrix} =
\begin{bmatrix}
    \Phi & I \\
    0 & I
\end{bmatrix}
\begin{bmatrix}
    x_k \\
    d_k \\
    x^a_k \\
    d^a_k
\end{bmatrix} +
\begin{bmatrix}
    \Gamma \\
    0
\end{bmatrix}
\begin{bmatrix}
    u_k \\
    \Gamma^w
\end{bmatrix} w_k
\]

\[ y_k = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix}
    x_k \\
    d_k
\end{bmatrix} + v_k \]

Kalman Filter

\[
\hat{x}_{k|k-1}^a = \Phi^a \hat{x}_{k-1|k-1}^a + \Gamma^a u_{k-1} \quad \text{Prediction}
\]

\[
\hat{x}_{k|k}^a = \hat{x}_{k|k-1}^a + L_k \left( y_k - C^a \hat{x}_{k|k-1}^a \right) \quad \text{Correction}
\]

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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


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Disturbance Models

State or Input Disturbance

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

\[
y_k = \begin{bmatrix}
    C \\
    C^a
\end{bmatrix}
\begin{bmatrix}
    x_k \\
    d_k \\
    x^a_k
\end{bmatrix}
\]

Additive Output Disturbance

\[
\begin{bmatrix}
    x_{k+1} \\
    p_{k+1} \\
    x^a_{k+1}
\end{bmatrix} =
\begin{bmatrix}
    \Phi & 0 \\
    0 & I \\
    \Phi^a & \Gamma^a
\end{bmatrix}
\begin{bmatrix}
    x_k \\
    p_k \\
    x^a_k
\end{bmatrix}
+ \begin{bmatrix}
    \Gamma \\
    0 \\
    \Gamma^a
\end{bmatrix} u_k
\]

\[
y_k = \begin{bmatrix}
    C & G_p
\end{bmatrix}
\begin{bmatrix}
    x_k \\
    p_k \\
    x^a_k
\end{bmatrix}
\]

DMC: \( G_p = I \)

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Disturbance Models

General Input and Output Disturbances

\[
\begin{bmatrix}
  x_{k+1} \\
  d_{k+1} \\
  p_{k+1}
\end{bmatrix} = \begin{bmatrix}
  \Phi & \Gamma^d & 0 \\
  0 & I & 0 \\
  0 & 0 & I
\end{bmatrix} \begin{bmatrix}
  x_k \\
  d_k \\
  p_k
\end{bmatrix} + \begin{bmatrix}
  \Gamma \\
  0 \\
  0
\end{bmatrix} u_k
\]

\[
y_k = \begin{bmatrix}
  C & 0 & G_p
\end{bmatrix} \begin{bmatrix}
  x_k \\
  d_k \\
  p_k
\end{bmatrix}
\]


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State Estimator

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

\[
\begin{bmatrix}
\hat{x}_{k|k} \\
\hat{d}_{k|k} \\
\hat{p}_{k|k}
\end{bmatrix} = 
\begin{bmatrix}
\hat{x}_{k|k-1} \\
\hat{d}_{k|k-1} \\
\hat{p}_{k|k-1}
\end{bmatrix} + 
\begin{bmatrix}
L_x \\
L_d \\
L_p
\end{bmatrix}
\begin{bmatrix}
y_k - C^a \\
\hat{x}_{k|k-1} \\
\hat{d}_{k|k-1} \\
\hat{p}_{k|k-1}
\end{bmatrix}
\]

Deterministic or stochastic observer design

For offset-free performance:

# disturbances = # outputs, and augmented system must be detectable


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Problem: Unmeasured Step Input Disturbance

DMC vs. KF-MPC

DMC: additive output disturbance assumption (bias)

KF-MPC: appended state, estimated step input disturbance

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

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

Additive output disturbance

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

Step input disturbance

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

\[
\begin{bmatrix}
  i x_{k+1} \\
  i d_{k+1}
\end{bmatrix} = \begin{bmatrix}
  \Phi & G_x \\
  0 & I
\end{bmatrix} \begin{bmatrix}
  i x_k \\
  i d_k
\end{bmatrix} + \begin{bmatrix}
  \Gamma \\
  0
\end{bmatrix} u_k
\]
\[
\begin{bmatrix}
  i y_k
\end{bmatrix} = \begin{bmatrix}
  C & G_y
\end{bmatrix} \begin{bmatrix}
  i x_k \\
  i d_k
\end{bmatrix}
\]

Additive output disturbance

\[ G_x = \Gamma^d \]
\[ G_x = 0 \]

Step input

\[ G_y = 0 \]
\[ G_y = I \]

Additive output
Kalman predictor/corrector equations

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

\[
i^y_k = \begin{bmatrix}
  iC \\
  G_y
\end{bmatrix} \begin{bmatrix}
  i^x_k \\
  i^d_k
\end{bmatrix} + v_k
\]

Prediction

\[
i^\hat{x}^a_{k|k-1} = i^\Phi a i^\hat{x}^a_{k-1|k-1} + i^\Gamma a u_{k-1}
\]

Correction

\[
i^\hat{x}^a_{k|k} = i^\hat{x}^a_{k|k-1} + iL(y - iC a i^\hat{x}^a_{k|k-1})
\]

Updated output prediction

\[
i^\hat{y}^a_{k|k} = iC a i^\hat{x}^a_{k|k}
\]

Additive output

\[
iL = \begin{bmatrix}
  0 \\
  I
\end{bmatrix}
\]

Kalman gain

Step input
Weight Calculation

\[ i \varepsilon_k = y_k - i \hat{y}_{k|k} \quad \text{Model residual} \]

\[ i p_k = \frac{\exp(-0.5 i \varepsilon_k^T \Lambda_i \varepsilon_k) i p_{k-1}}{\sum_{j=1}^{n} \exp(-0.5 j \varepsilon_k^T \Lambda_j \varepsilon_k) j p_{k-1}} \quad \text{Bayesian probability,} \]

\[ i p_k \]

\[ i w_k = \begin{cases} 
\frac{i p_k}{\sum_{j=1}^{n} j p_k} & \text{if } i p_k > \delta \\
0 & \text{if } i p_k \leq \delta 
\end{cases} \quad \text{Weight, } i \text{th model} \]
Model Predictive Control

- “Model average” for the output prediction
  \[
  \bar{y}_{k+j|k} = \sum_{i=1}^{n} w_k i \hat{y}_{k+j|k}
  \]

- 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 $V, T, \rho$

$A \rightarrow B \rightarrow C$

$A + A \rightarrow D$

Region with RHP zeros (nonminimum phase behavior)

Connection between IM and RHP zeros:
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

\[
\begin{bmatrix}
    x_{k+1} \\
    d_{k+1} \\
    x_{k+1}^a
\end{bmatrix} =
\begin{bmatrix}
    \Phi & \Gamma^d & x_k \\
    0 & 1 & d_k \\
    \phi^a & \Gamma^a & x_k^a
\end{bmatrix} +
\begin{bmatrix}
    \Gamma \\
    u_k \\
    \Gamma^a
\end{bmatrix} w_k +
\begin{bmatrix}
    0 \\
    \Gamma^w \\
    \Gamma^{w,a}
\end{bmatrix} v_k
\]

\[
y_k =
\begin{bmatrix}
    C & 0 \\
    C^a & x_k^a
\end{bmatrix}
\]

\[
\begin{bmatrix}
    x_{k+1} \\
    d_{k+1} \\
    \Delta d_{k+1} \\
    x_{k+1}^a
\end{bmatrix} =
\begin{bmatrix}
    \Phi & \Gamma^d & x_k \\
    0 & 1 & d_k \\
    0 & 0 & \Delta d_k \\
    \phi^a & \Gamma^a & x_k^a
\end{bmatrix} +
\begin{bmatrix}
    \Gamma \\
    u_k \\
    \Gamma^a \\
    \Gamma^{w,a}
\end{bmatrix} w_k +
\begin{bmatrix}
    0 \\
    0 \\
    1 \\
    \Gamma^w
\end{bmatrix} v_k
\]

\[
y_k =
\begin{bmatrix}
    C & 0 \\
    C^a & x_k^a
\end{bmatrix}
\]

\[
\begin{bmatrix}
    x_{k+1} \\
    d_{k+1} \\
    x_{k+1}^a
\end{bmatrix} =
\begin{bmatrix}
    \Phi & \Gamma^d & x_k \\
    0 & \Phi^w & d_k \\
    \phi^a & \Gamma^a & x_k^a
\end{bmatrix} +
\begin{bmatrix}
    \Gamma \\
    u_k \\
    \Gamma^a
\end{bmatrix} w_k +
\begin{bmatrix}
    0 \\
    \Gamma^w \\
    \Gamma^{w,a}
\end{bmatrix} v_k
\]

\[
y_k =
\begin{bmatrix}
    C & 0 \\
    C^a & d_k
\end{bmatrix}
\]
Ramp Disturbance

DMC vs. KF-MPC (ramp) (Q=100, R=1), ramp disturbance

development variables
Unmeasured Feed Concentration

feed conc, actual & estimated, KF (Q=100,R=1)

time

Caf

deviation variables
Periodic Disturbance

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

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

Results in sin variation in feed concentration

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

Poles on imaginary axis

Appended state form
DMC vs. KF-MPC

DMC vs. KF-MPC (Q=100, R=1), actual plant outputs

deviation variables
Feed Concentration Estimate

feed conc, actual & estimated, KF (Q=100,R=1)  deviation variables

Actual

Estimate

Caf

time
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


**Multiple Model Predictive Control Strategy for Disturbance Rejection***†,‡

Matthew Kuure-Kinsey§ and B. Wayne Bequette*
Primary difference is in the “disturbance bank”
Disturbance Bank Structure

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

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

Measured output

Weights
Presentation Summary

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

- Brian Aufderheide (2002)
- 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 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
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 $r$
- Insulin infusion rate $u$
- Glucose sensor signal $y$

**Feedback**

Hyunjin Lee
Now at Shell Development

Jing Sun

Ruben Rojas
Fulbright Scholar
Venezuela

Fraser Cameron