

Modern Control Theory

Model Predict Control - MPC – Lecture 9

Unconstrained Control move calculation - MIMO

Prediction using State space models (6/6)

System
representation

$$\begin{aligned} \mathbf{x}_m(k+1) &= \mathbf{A}_m \mathbf{x}_m(k) + \mathbf{B}_m \mathbf{u}(k) \\ y(k) &= \mathbf{C}_m \mathbf{x}_m(k) \end{aligned}$$



System in
incremental form

$$\mathbf{x}(k+1) = \mathbf{A} \mathbf{x}(k) + \mathbf{B} \Delta \mathbf{u}(k)$$

$$y(k+1) = \mathbf{C} \mathbf{x}(k)$$

$$\mathbf{x}(k) = \begin{bmatrix} \Delta \mathbf{x}_m(k) \\ y(k) \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} \mathbf{A}_m & \mathbf{0}_m^T \\ \mathbf{C}_m \mathbf{A}_m & 1 \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} \mathbf{B}_m \\ \mathbf{C}_m \mathbf{B}_m \end{bmatrix} \quad \mathbf{C} = \begin{bmatrix} \mathbf{0}_m & 1 \end{bmatrix}$$

Output Prediction
equation

$$\mathbf{Y} = \begin{bmatrix} y(k_i+1) | k_i \\ y(k_i+2) | k_i \\ y(k_i+3) | k_i \\ \vdots \\ y(k_i+N_p) | k_i \end{bmatrix}$$

$$\Delta \mathbf{U} = \begin{bmatrix} \Delta u(k_i) \\ \Delta u(k_i+1) \\ \Delta u(k_i+2) \\ \vdots \\ \Delta u(k_i+N_c-1) \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{F} \hat{\mathbf{x}}(k_i) + \Phi \Delta \mathbf{U}$$

$$\mathbf{F} = \begin{bmatrix} \mathbf{C} \mathbf{A} \\ \mathbf{C} \mathbf{A}^2 \\ \mathbf{C} \mathbf{A}^3 \\ \vdots \\ \mathbf{C} \mathbf{A}^{N_p} \end{bmatrix}$$

$N_p \times 1$

$$\Phi = \begin{bmatrix} \mathbf{C} \mathbf{B} & 0 & 0 & \dots & 0 \\ \mathbf{C} \mathbf{A} \mathbf{B} & \mathbf{C} \mathbf{B} & 0 & \dots & 0 \\ \mathbf{C} \mathbf{A}^2 \mathbf{B} & \mathbf{C} \mathbf{A} \mathbf{B} & \mathbf{C} \mathbf{B} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{C} \mathbf{A}^{N_p-1} \mathbf{B} & \mathbf{C} \mathbf{A}^{N_p-2} \mathbf{B} & \mathbf{C} \mathbf{A}^{N_p-3} \mathbf{B} & \dots & \mathbf{C} \mathbf{A}^{N_p-N_c} \mathbf{B} \end{bmatrix}$$

$N_p \times N_c$

Unconstrained solution – SISO (2/2)

$$J = (R_s - Y)^T (R_s - Y) + \Delta U^T \bar{R} \Delta U$$

$$J = (R_s - F \hat{x}(k_i))^T (R_s - F \hat{x}(k_i)) - 2 \Delta U^T \Phi^T (R_s - F \hat{x}(k_i)) + \Delta U^T (\Phi^T \Phi + R) \Delta U$$

Now
$$\frac{\partial J}{\partial \Delta U} = -2 \Phi^T (R_s - F \hat{x}(k_i)) + 2 (\Phi^T \Phi + R) \Delta U = 0$$

$$(\Phi^T \Phi + R) \Delta U = \Phi^T (R_s - F \hat{x}(k_i))$$

Solving for ΔU we get

$$\Delta U = (\Phi^T \Phi + R)^{-1} \Phi^T (R_s - F \hat{x}(k_i))$$

$$u_{ki} = u_{(ki-1)} + \Delta u_{ki} \text{ (first value in } \Delta U \text{)}$$

$$\Delta U(k_i) = \begin{bmatrix} 1 & 0 & \dots & 0 \end{bmatrix} (\Phi^T \Phi + \bar{R})^{-1} (\Phi^T \bar{R}_s r(k_i) - \Phi^T F \hat{x}(k_i))$$

- **Implementation steps ONLINE**

1. Obtain the current measurements of states,
2. Estimate the states using Kalman filter
3. Compute the optimal finite horizon control sequence $(u_k, u_{k+1}, \dots, u_M)$
4. Implement first move u_k
5. Repeat from Step 1

Prediction using State space models - MIMO

m inputs, q outputs and n1 states

For good control $q \leq m$

$$x_m(k+1) = A_m x_m(k) + B_m u(k) + B_d \omega(k)$$

$w(k)$ is integrated white noise

$$y(k) = C_m x_m(k),$$

$$\omega(k) - \omega(k-1) = \epsilon(k)$$

A_m is $n1 \times n1$ B_m is $n1 \times m$ B_d is $n1 \times m$ C_m is $q \times n1$

u is $m \times 1$ y is $q \times 1$

$$\Delta x_m(k) = x_m(k) - x_m(k-1) \quad \begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} A_m & o_m^T \\ C_m A_m & I_{q \times q} \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix} \Delta u(k) + \begin{bmatrix} B_d \\ C_m B_d \end{bmatrix} \epsilon(k)$$

$$\Delta u(k) = u(k) - u(k-1)$$

$$\Delta y(k+1) = y(k+1) - y(k)$$

$$y(k) = \begin{bmatrix} o_m & I_{q \times q} \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix}$$

Incremental form

$$x(k+1) = Ax(k) + B\Delta u(k) + B_\epsilon \epsilon(k) \quad y(k) = Cx(k)$$

Augmented
'q' Integrators

$$\rho(\lambda) = \det \begin{bmatrix} \lambda I - A_m & o_m^T \\ -C_m A_m & (\lambda - 1) I_{q \times q} \end{bmatrix} = (\lambda - 1)^q \det(\lambda I - A_m) = 0$$

Prediction using State space models - MIMO

System
representation

$$\begin{aligned} \mathbf{x}_m(k+1) &= \mathbf{A}_m \mathbf{x}_m(k) + \mathbf{B}_m \mathbf{u}(k) \\ y(k) &= \mathbf{C}_m \mathbf{x}_m(k) \end{aligned}$$

System in
incremental form

$$\mathbf{x}(k+1) = \mathbf{A} \mathbf{x}(k) + \mathbf{B} \Delta \mathbf{u}(k)$$

$$y(k+1) = \mathbf{C} \mathbf{x}(k)$$

Output Prediction equation
 $q \times N_p \times 1$

$$\mathbf{Y} = \begin{bmatrix} y(k_i+1) | k_i \\ y(k_i+2) | k_i \\ y(k_i+3) | k_i \\ \vdots \\ y(k_i+N_p) | k_i \end{bmatrix}$$

Output Prediction equation
 $m \times N_c \times 1$

$$\Delta \mathbf{U} = \begin{bmatrix} \Delta u(k_i) \\ \Delta u(k_i+1) \\ \Delta u(k_i+2) \\ \vdots \\ \Delta u(k_i+N_c-1) \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{F} \hat{\mathbf{x}}(k_i) + \mathbf{\Phi} \Delta \mathbf{U}$$

$$\mathbf{F} = \begin{bmatrix} \mathbf{C} \mathbf{A} \\ \mathbf{C} \mathbf{A}^2 \\ \mathbf{C} \mathbf{A}^3 \\ \vdots \\ \mathbf{C} \mathbf{A}^{N_p} \end{bmatrix}$$

$(q \times N_p \times (n+q))$

$$\mathbf{\Phi} = \begin{bmatrix} \mathbf{C} \mathbf{B} & 0 & 0 & \dots & 0 \\ \mathbf{C} \mathbf{A} \mathbf{B} & \mathbf{C} \mathbf{B} & 0 & \dots & 0 \\ \mathbf{C} \mathbf{A}^2 \mathbf{B} & \mathbf{C} \mathbf{A} \mathbf{B} & \mathbf{C} \mathbf{B} & \dots & 0 \\ \vdots & & & & \\ \mathbf{C} \mathbf{A}^{N_p-1} \mathbf{B} & \mathbf{C} \mathbf{A}^{N_p-2} \mathbf{B} & \mathbf{C} \mathbf{A}^{N_p-3} \mathbf{B} & \dots & \mathbf{C} \mathbf{A}^{N_p-N_c} \mathbf{B} \end{bmatrix}$$

$(q \times N_p \times m \times N_c)$

Cost function

- Minimize the error between set-point and predicted response at all steps
 - This leads faster response
- Minimize the control that minimized the error between set-point and predicted response at all steps

This leads trade off between faster response and use of input energy/

constraints on rate of change of input

$$J = (R_s - Y)^T (R_s - Y) + \Delta U^T \bar{R} \Delta U$$

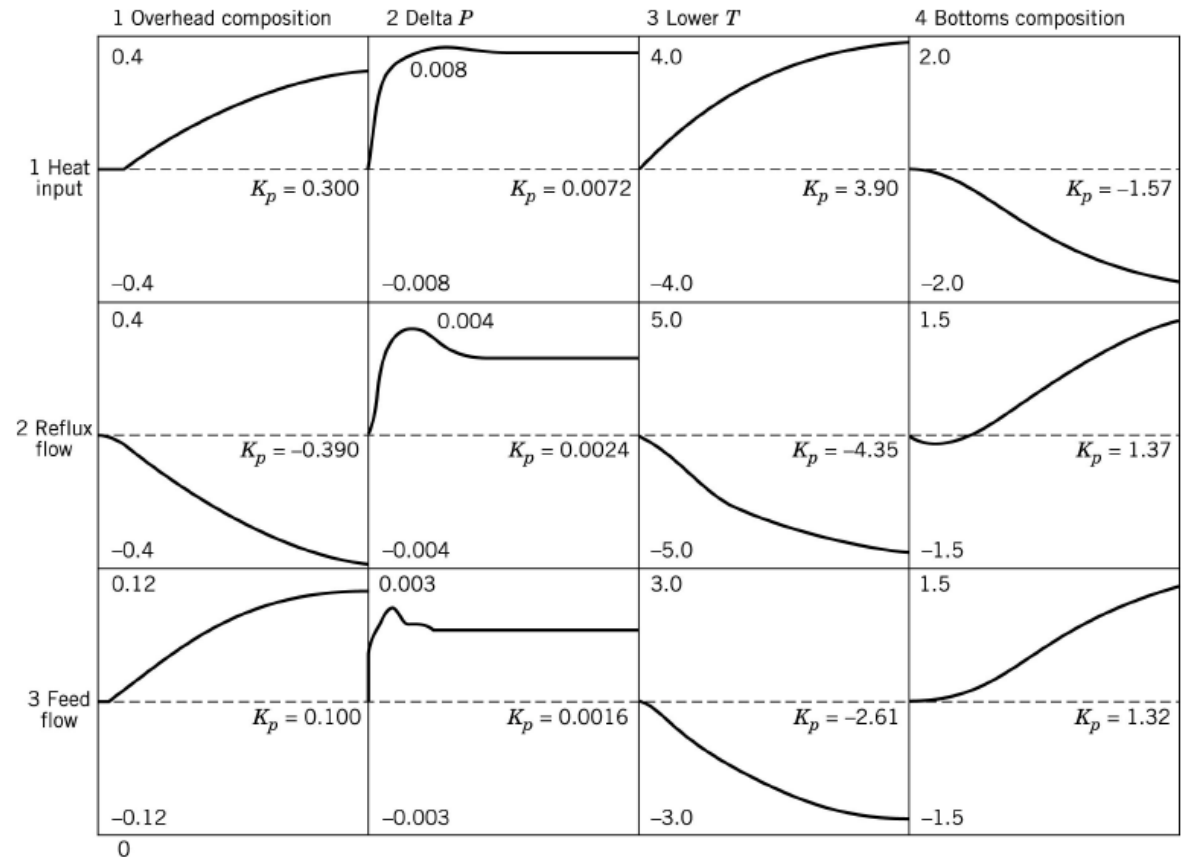
For MIMO system:

Y = step prediction for output ($q \times N_p \times 1$)

Rs = Set-point trajectory into the future ($q \times N_p \times 1$)

Δu = N_c future control moves ($m \times N_c \times 1$)

R – penalty on control move ($m \times N_c \times m \times N_c$)



Unconstrained solution – MIMO

$$J = (R_s - F \hat{x}(k_i))^T (R_s - F \hat{x}(k_i)) - 2 \Delta U^T \Phi^T (R_s - F \hat{x}(k_i)) + \Delta U^T (\Phi^T \Phi + R) \Delta U$$

Now
$$\frac{\partial J}{\partial \Delta U} = -2 \Phi^T (R_s - F \hat{x}(k_i)) + 2 (\Phi^T \Phi + R) \Delta U = 0$$

$$(\Phi^T \Phi + R) \Delta U = \Phi^T (R_s - F \hat{x}(k_i))$$

Solving for ΔU we get

$$\Delta U = (\Phi^T \Phi + R)^{-1} \Phi^T (R_s - F \hat{x}(k_i))$$

$$u_{k_i} = u_{(k_i-1)} + \Delta u_{k_i} \text{ (first } m \text{ value in } \Delta U)$$

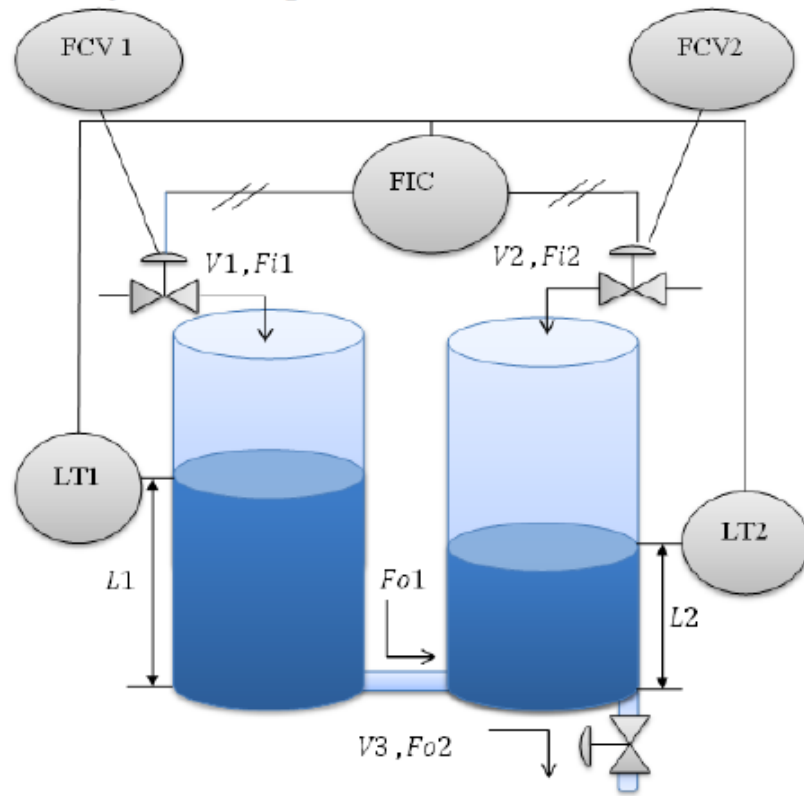
$$\Delta u(k_i) = \overbrace{\begin{bmatrix} I_m & o_m & \dots & o_m \end{bmatrix}}^{N_c} (\Phi^T \Phi + \bar{R})^{-1} (\Phi^T \bar{R}_s r(k_i) - \Phi^T F x(k_i))$$

- **Implementation steps ONLINE**

1. Obtain the current measurements of states,
2. Estimate the states using Kalman filter
3. Compute the optimal finite horizon control sequence $(u_k, u_{k+1}, \dots, u_M)$
4. Implement first move u_k for each of the inputs
5. Repeat from Step 1

Example problem

Level control of coupled tanks



$$A1. \frac{dL1}{dt} = Fi1 - Fo1$$

$$Fo1 = \alpha1. \sqrt{L1 - L2}$$

$$A2. \frac{dL2}{dt} = Fi2 - Fo2 + Fo1$$

$$Fo2 = \alpha2. \sqrt{L2}$$

Linearize around some operating point (h1.h2), we get

$$x = \begin{pmatrix} h1 \\ h2 \end{pmatrix} \quad u = \begin{pmatrix} fi1 \\ fi2 \end{pmatrix}$$

$$y = \begin{pmatrix} h1 \\ h2 \end{pmatrix}$$

$$A_m = \begin{pmatrix} -\frac{\alpha1}{2.A1} \cdot \frac{1}{\sqrt{(L1-L2)}} & \frac{\alpha1}{2.A1} \cdot \frac{1}{\sqrt{(L1-L2)}} \\ \frac{\alpha1}{2.A2} \cdot \frac{1}{\sqrt{(L1-L2)}} & \frac{-1}{2.A2} \cdot \left(\frac{\alpha1}{\sqrt{(L1-L2)}} + \frac{\alpha2}{\sqrt{L2}} \right) \end{pmatrix}$$

$$B_m = \begin{pmatrix} \frac{1}{A1} & 0 \\ 0 & \frac{1}{A2} \end{pmatrix}$$

$$C_m = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$$D_m = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

Matrices to compute:

$$\Phi, F, \Phi^T \Phi, \Phi^T R_s, \Phi^T F$$

$$\Delta U = (\Phi^T \Phi + R)^{-1} \Phi^T (R_s - F \hat{x}(k_i))$$

Demo

Linearize around
L1 = 4m, L2 = 3.5m $A_m = \begin{pmatrix} -7.923 & 7.923 \\ 9.781 & -12.97 \end{pmatrix}$ $B_m = \begin{pmatrix} 5.093 & 0 \\ 0 & 6.288 \end{pmatrix}$ $C_m = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

- Sampling time = 0.05 secs, discretize
- $N_p = 10$, $N_c = 3$