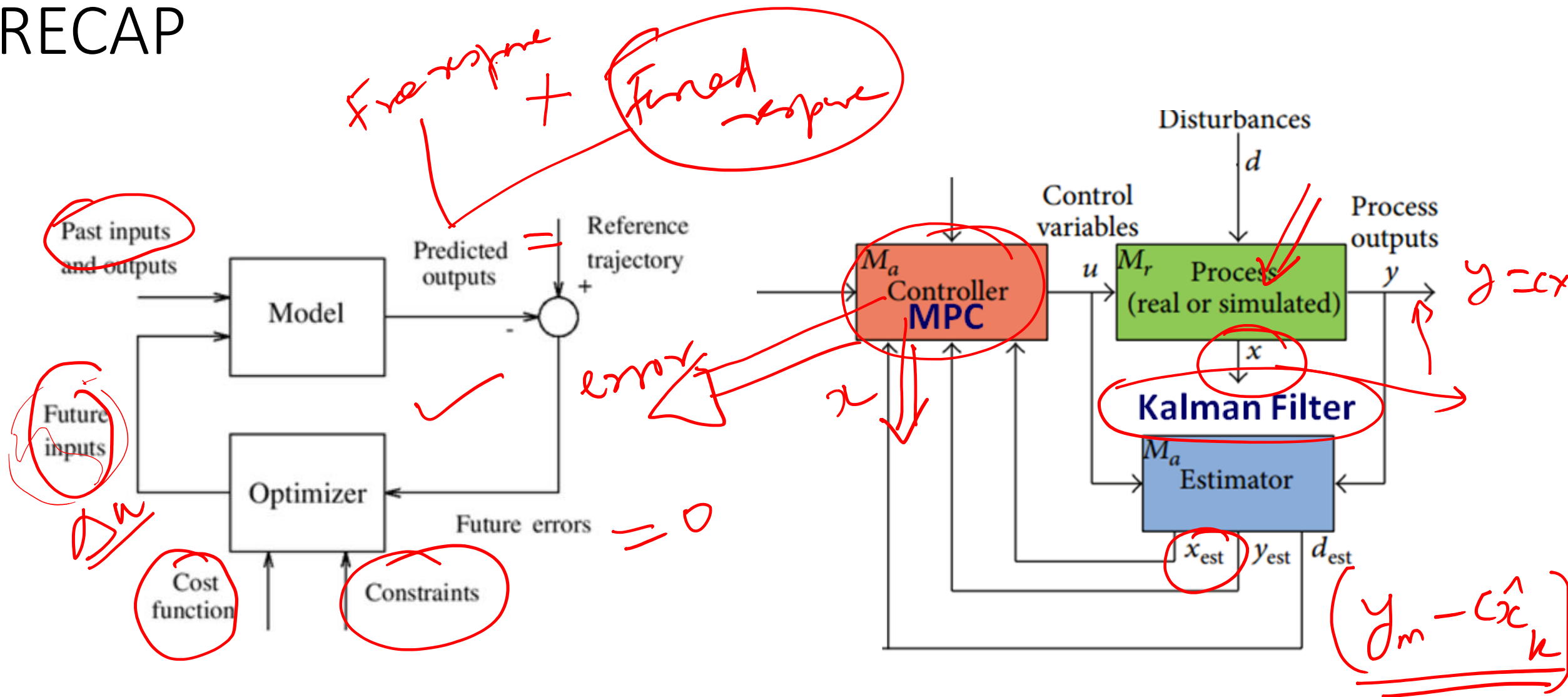


# Modern Control Theory

Model Predict Control - MPC – Lecture 8

Unconstrained Control move calculation

# RECAP



$M_a$ : assumed model used in simulations  
 $M_r$ : real model used in simulations

# Prediction using State space models (6/6)

System representation

$$\begin{aligned} x_m(k+1) &= A_m x_m(k) + B_m u(k) \\ y(k) &= C_m x_m(k) \end{aligned}$$

*SS*

System in incremental form

$$x(k+1) = Ax(k) + B\Delta u(k)$$

$$y(k+1) = Cx(k)$$

$$x(k) = \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix}$$

$$A = \begin{bmatrix} A_m & 0_m^T \\ C_m A_m & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix}$$

$$C = \begin{bmatrix} 0_m & 1 \end{bmatrix}$$

$$D = 0$$

*estimated state* *Causal system*

Output Prediction equation

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

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

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

$$F = \begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ \vdots \\ CA^{N_p} \end{bmatrix}$$

$N_p \times 1$

$$\Phi =$$

$N_p \times N_c$

$$\Phi = \begin{bmatrix} CB & 0 & \dots & 0 \\ CAB & CB & 0 & \dots & 0 \\ CA^2B & CAB & CB & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ CA^{N_p-1}B & CA^{N_p-2}B & CA^{N_p-3}B & \dots & CA^{N_p-N_c}B \end{bmatrix}$$

*Free response* *Forced resp*

# 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

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

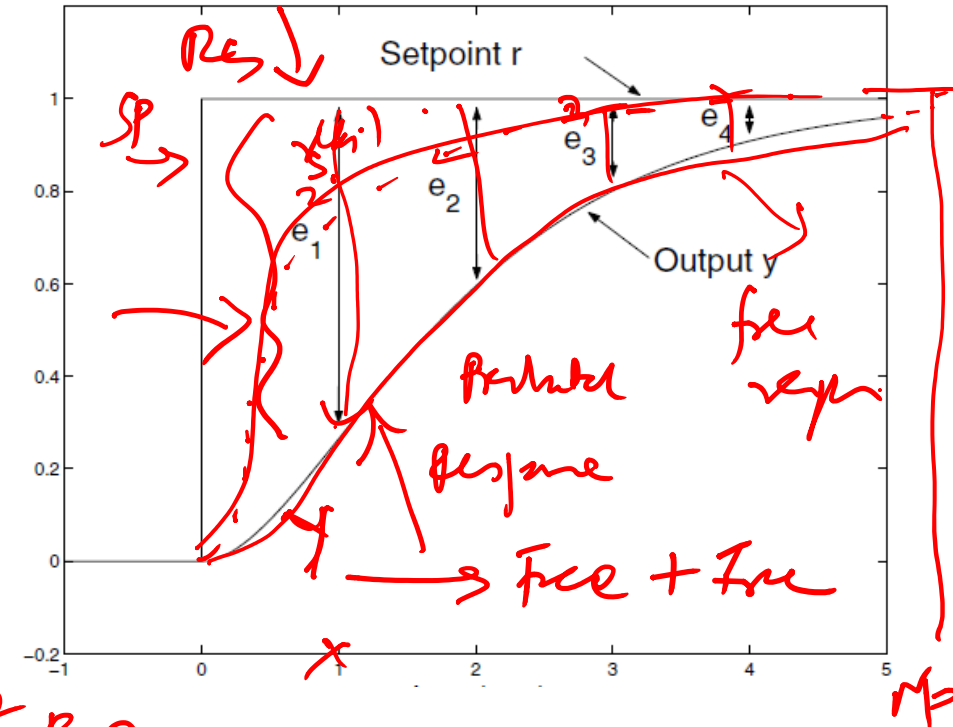
**For SISO system:**

**Y = Np step prediction for output (Np x 1)**

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

$\Delta u = N_c$  future control moves ( $N_c \times 1$ )

**R is scalar – penalty on control move**



# Unconstrained solution – SISO (1/2)

Objective function

$$J = (R_s - Y)^t (R_s - Y) + \Delta U^t R \Delta U \quad (1)$$

The  $\Delta U$  that minimized  $J$  can be obtained from the solution of

$$\frac{\partial J}{\partial \Delta U} = 0$$

$\neq 0$   
 $\Delta x_k = A \Delta x_{k-1} + B \Delta u_k$   
 $\Delta x_{k+1} = A \Delta x_k + B \Delta u_{k+1}$   
 CB  
 LAB CB  
 ...

Substitute

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

In (1)

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

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

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

# Unconstrained solution – SISO (2/2)

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

Now

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

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

(Hessian matrix)

Solving for  $\Delta U$  we get

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

$$u_{ki} = u_{(ki-1)} + \Delta u_{ki}$$

(first value in  $\Delta U$ )

## 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

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

# Example problem

- Double integrator system

*stop vs open*

$$x_m(k+1) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x_m(k) + \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} u(k)$$

*force*

$$y(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} x_m(k).$$

*Bm → DC gain*

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

Matrices to compute:

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

$$F = \begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ \vdots \\ CA^{N_p} \end{bmatrix} \quad \Phi = \begin{bmatrix} CB & 0 & 0 & \dots & 0 \\ CAB & CB & 0 & \dots & 0 \\ CA^2 B & CAB & CB & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{N_p-1} B & CA^{N_p-2} B & CA^{N_p-3} B & \dots & CA^{N_p-N_c} B \end{bmatrix}$$

$N_p \times 1$

$N_p \times N_c$

$$A = \begin{bmatrix} A_m & 0_m^T \\ C_m A_m & 1 \end{bmatrix} \quad B = \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix} \quad C = \begin{bmatrix} 0_m & 1 \end{bmatrix}$$

$$x(k) = \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix}$$

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