

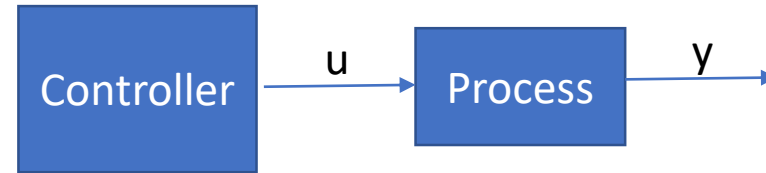
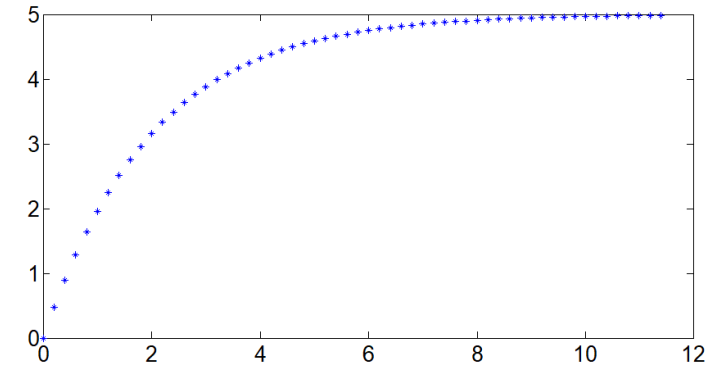
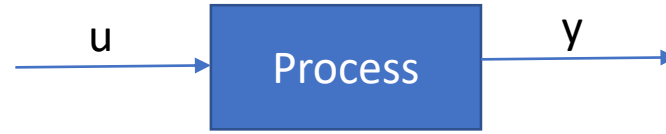
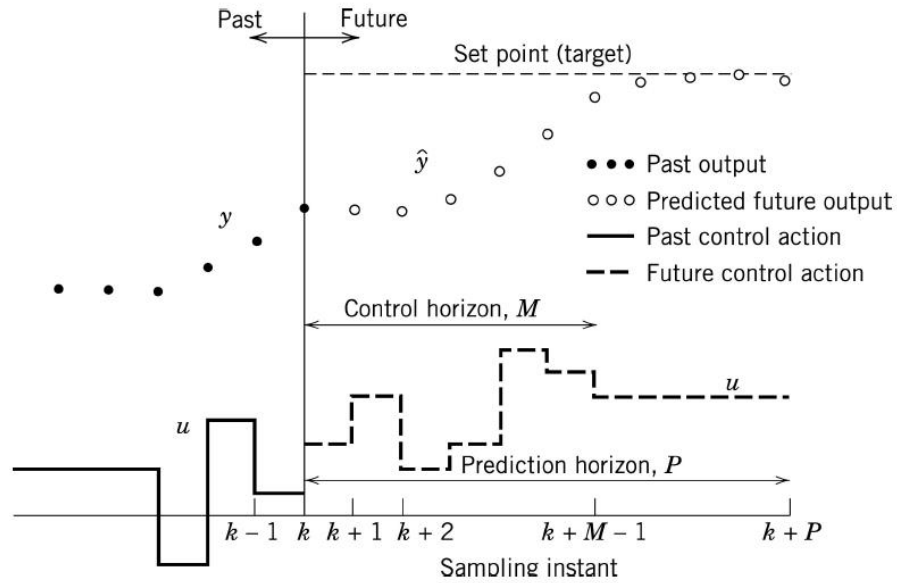
# Modern Control Theory

Model Predict Control - MPC – Lecture 4

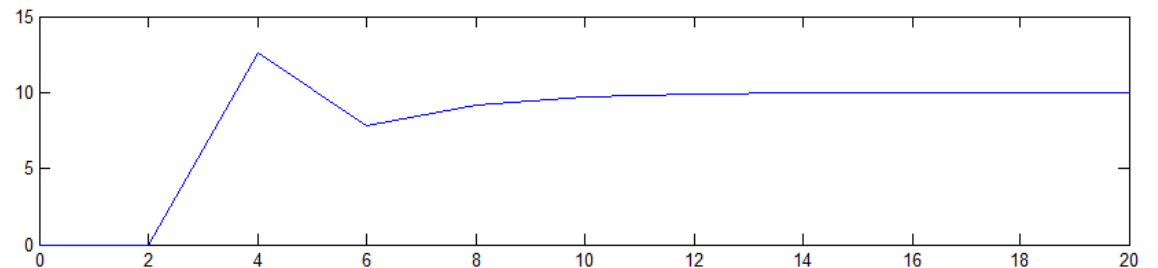
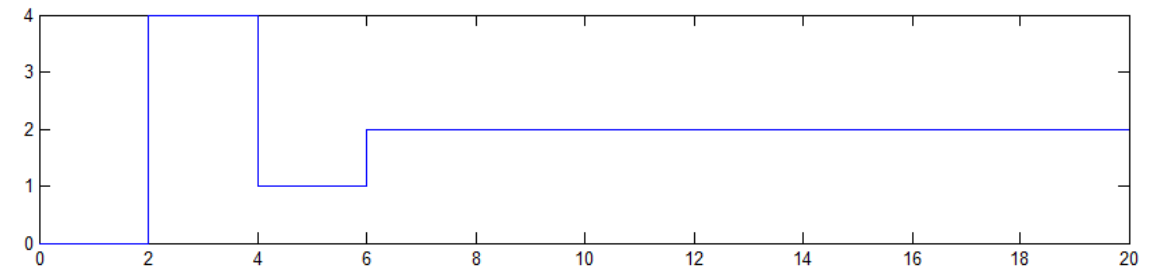
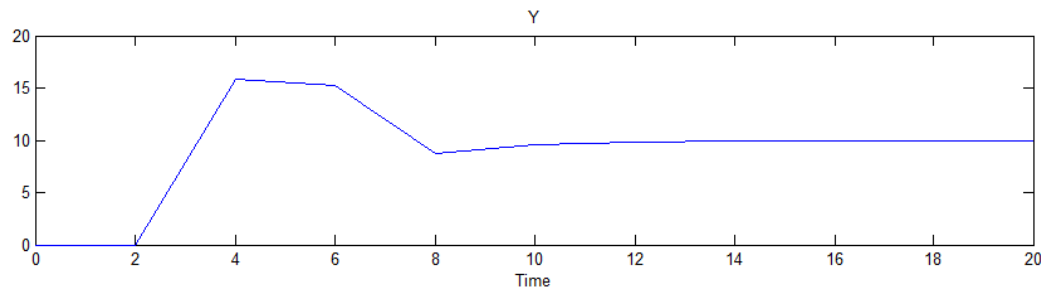
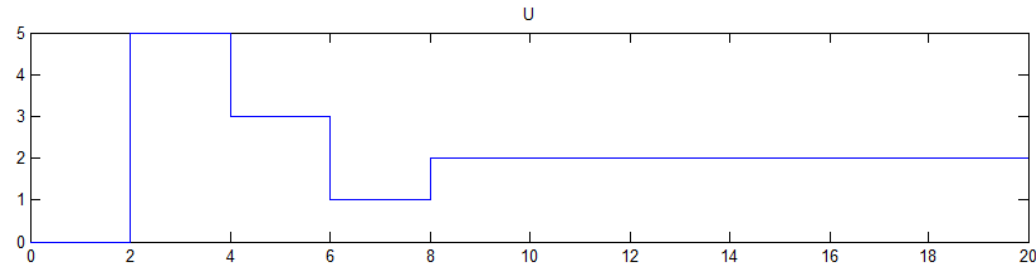
Dynamic Prediction Models

# Why have multiple control moves?

- Example  $5/(2s+1)$

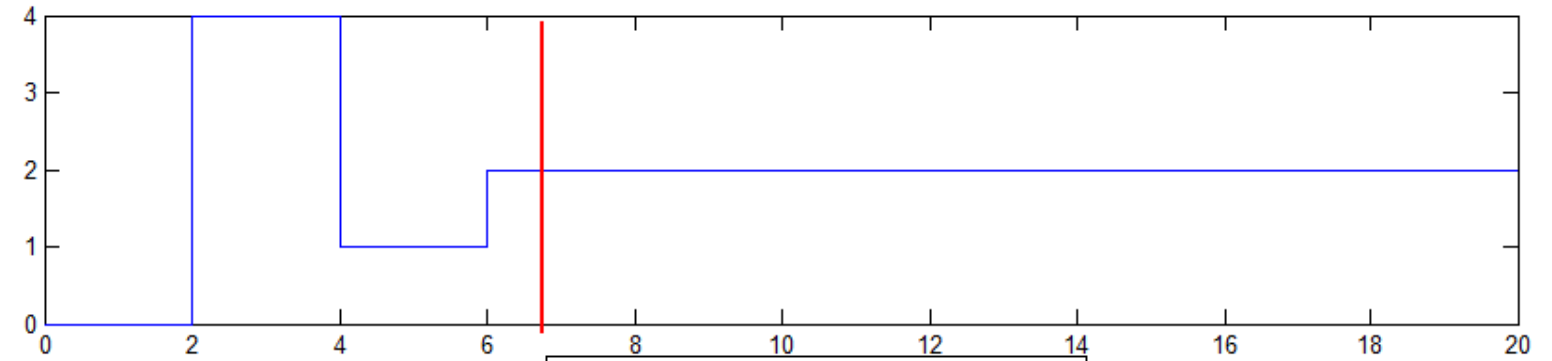
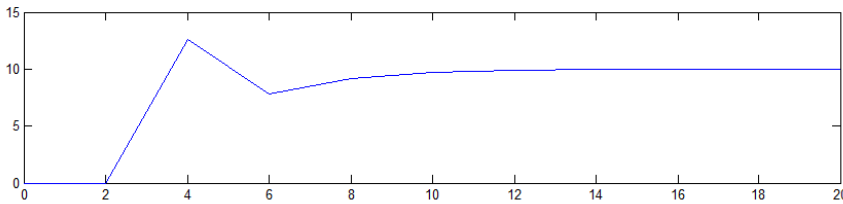
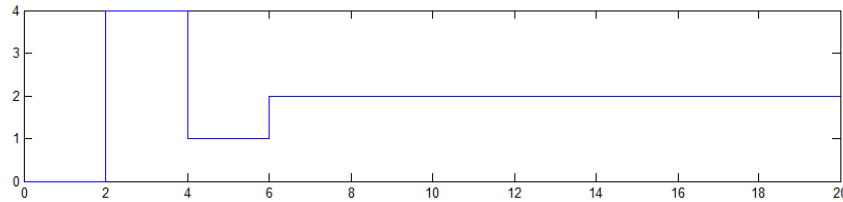


$y \rightarrow 10$ , what should be  $u$ ?  
 $u = 2$

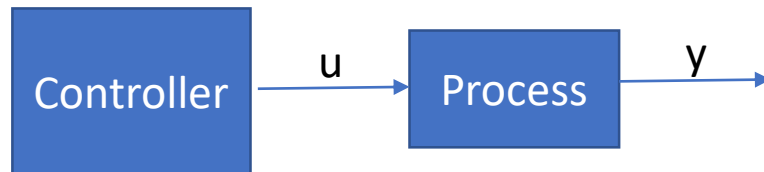
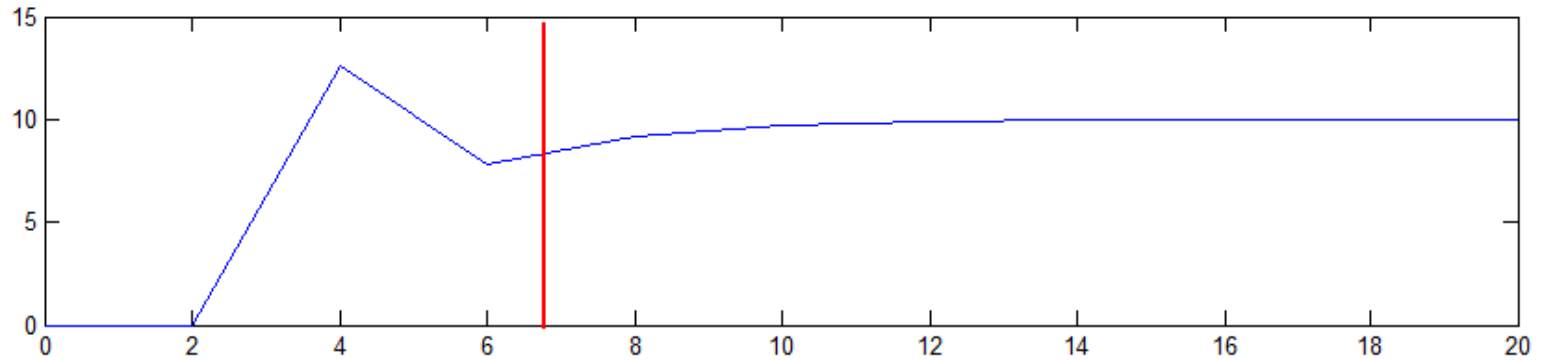


# Does controller need to make control move all the time?

- Example  $5/(2s+1)$



@t=6.8  $u = 2$ ,  $y = 8$



$y \rightarrow 10$

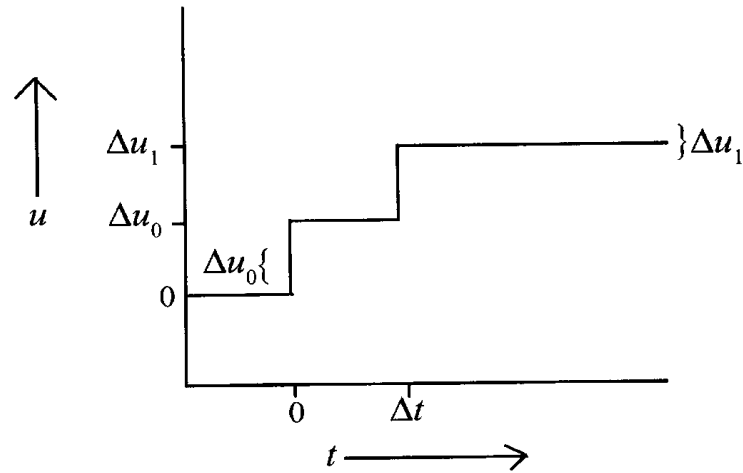
What should controller do?

NO ACTION REQUIRED as it will reach to its Target

# Free response and forced response

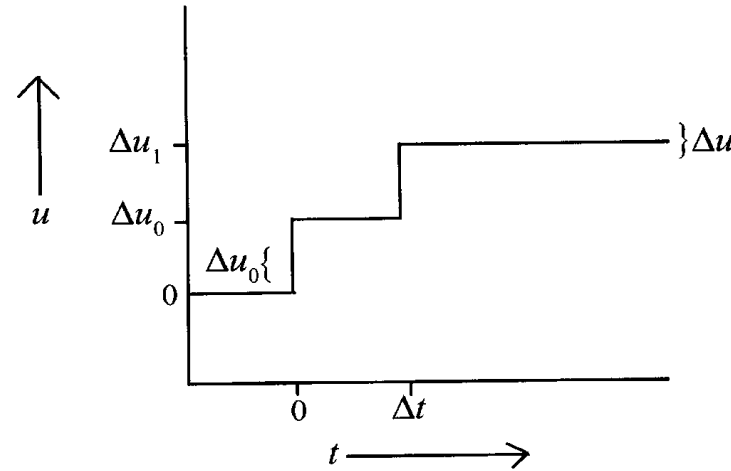
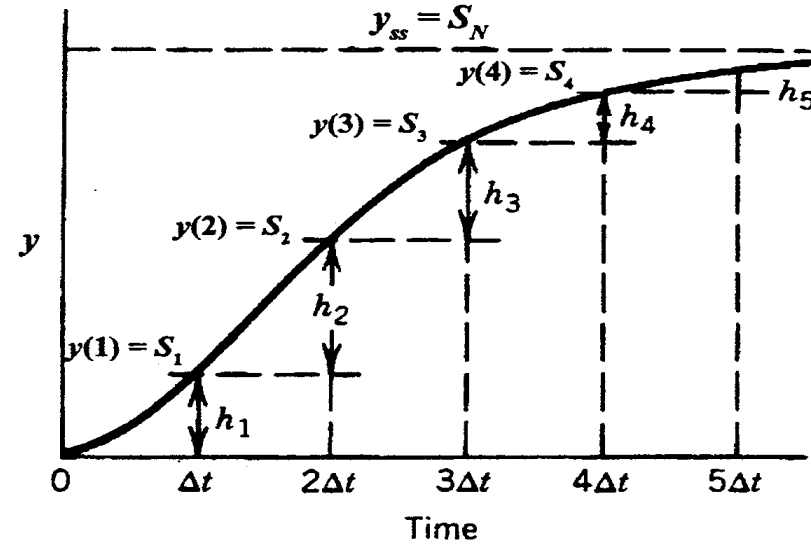
- Free response –
  - Check if the system with current input can reach to the set-point or
  - Find out how close it can take it to the set-point or objective
- Forced response –
  - Don't make any control action if the system can reach to the set-point or
  - Compute control actions that can take it to the set-point or objective over and above the free response.

# Multi move as breaking of multiple staggered step inputs



# Step response predictions (1/2)

From the Principle of Superposition for linear systems:



$$\begin{aligned}
 y_1 &= y_0 + S_1 \Delta u_0 \\
 y_2 &= y_0 + S_2 \Delta u_0 + S_1 \Delta u_1 \\
 y_3 &= y_0 + S_3 \Delta u_0 + S_2 \Delta u_1 \\
 &\vdots \\
 &\vdots \\
 y_N &= y_0 + S_N \Delta u_0 + S_{N-1} \Delta u_1
 \end{aligned}$$

The step response model of a stable SISO process

$$y(k+1) = \sum_{i=1}^N h_i u(k-i+1) = \sum_{i=1}^N (S_i - S_{i-1}) u(k-i+1)$$

$$\Rightarrow y(k+1) = \sum_{i=1}^{N-1} S_i \Delta u(k-i+1) + S_N u(k-N+1)$$

$S_i$  = the  $i$ -th step response coefficient

$N$  = an integer (the **model horizon**)

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

# Step response prediction (2/2)

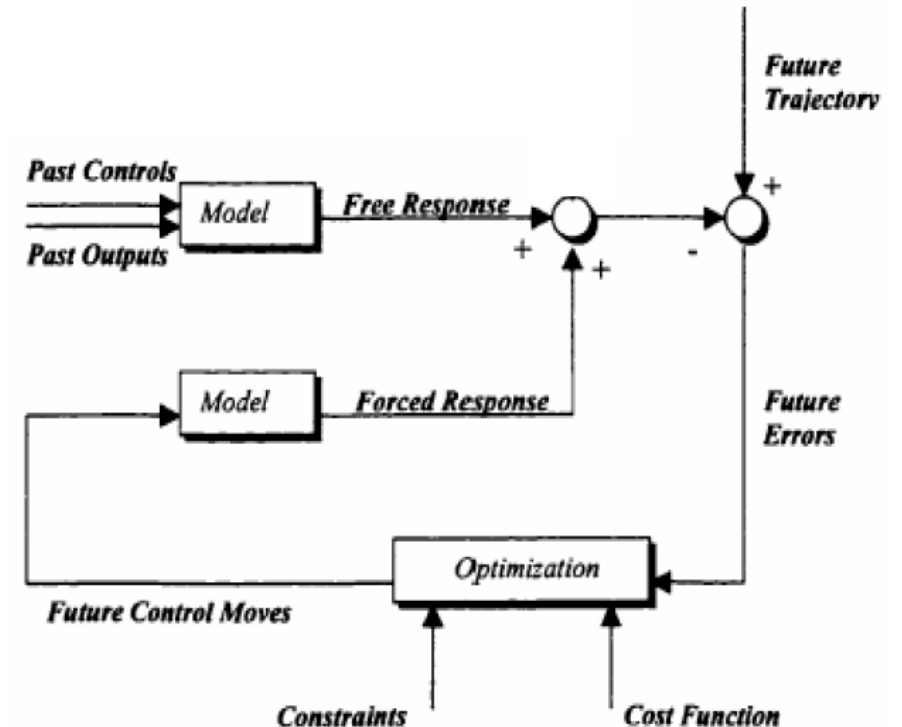
$j^{\text{th}}$  step ahead prediction

$$\hat{y}(k+j) = \underbrace{\sum_{i=1}^j S_i \Delta u(k+j-i)}_{\text{Effects of current and future control actions}} + \underbrace{\sum_{i=j+1}^{N-1} S_i \Delta u(k+j-i) + S_N u(k+j-N)}_{\text{Effects of past control actions}}$$

What happens when  $u(k-i) = u(k-1)$  for all  $i > 0$

Predicted FREE response

$$\hat{y}^o(k+j) = \sum_{i=j+1}^{N-1} S_i \Delta u(k+j-i) + S_N u(k+j-N)$$



# Example – simple predictive receding horizon controller

- Find a predictive control law with single receding horizon move, such that  $\hat{y}(k+J) = y_{sp}$

$j^{\text{th}}$  step ahead prediction

$$\hat{y}(k+j) = \underbrace{\sum_{i=1}^j S_i \Delta u(k+j-i)}_{\text{Forced response}} + \underbrace{\hat{y}^o(k+j)}_{\text{Free response}}$$

Given

$j = J, \hat{y}(k+J) = y_{sp}$

$\Delta u(k+i) = 0$  for  $i > 0$ , i.e.  $\Delta u(k+1) = \Delta u(k+2) \dots = \Delta u(k+J-1) = 0$



$$\hat{y}(k+J) = S_J \Delta u(k) + \hat{y}^o(k+J)$$



$$y_{sp} = S_J \Delta u(k) + \hat{y}^o(k+J)$$



$$\Delta u(k) = \frac{y_{sp} - \hat{y}^o(k+J)}{S_J}$$

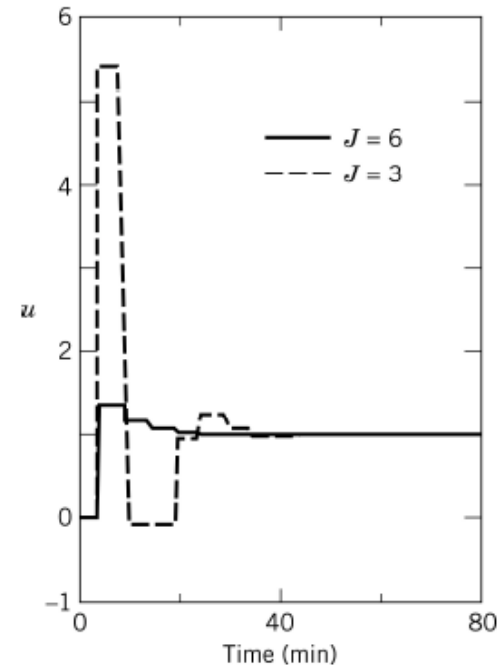
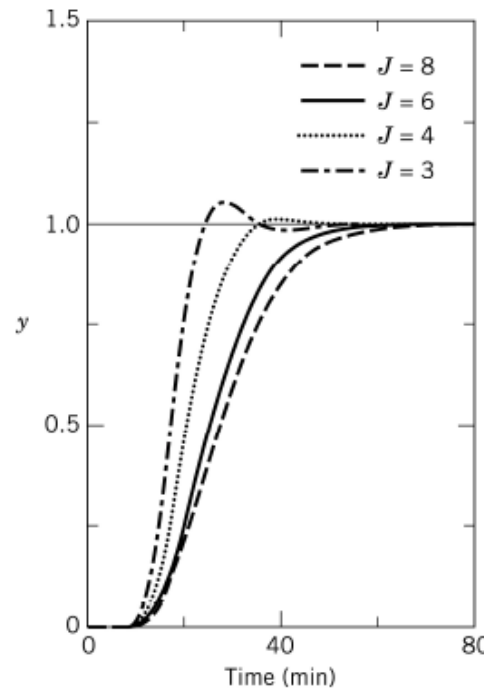
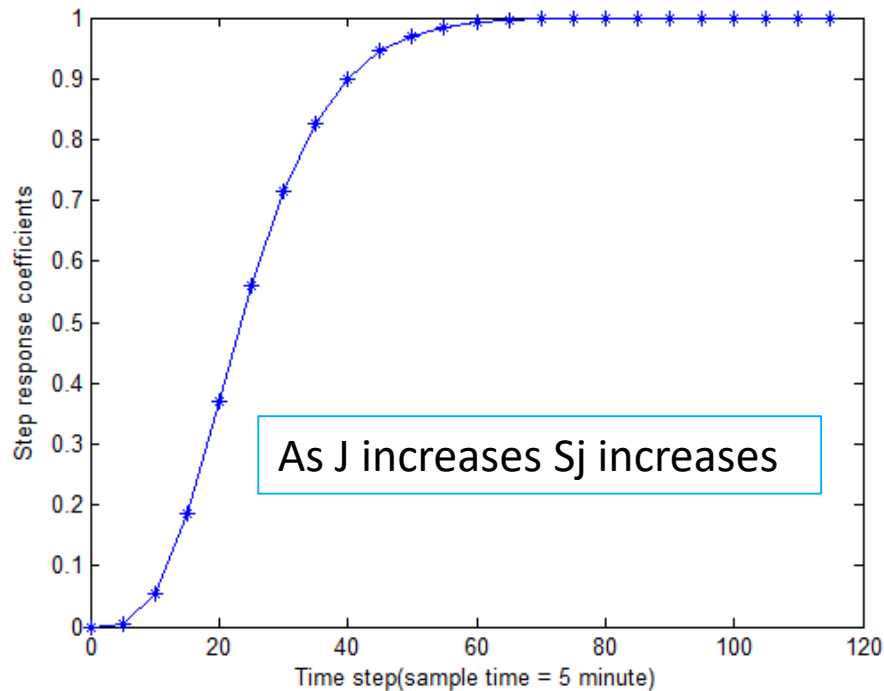
SISO system with prediction-based control law using simple step response coefficients

What are the pitfalls in this?



# Example – simple predictive receding horizon controller

$$\frac{Y(s)}{U(s)} = \frac{1}{(5s + 1)^5} \quad \begin{array}{l} J = 3, 4, 6, 8 \\ \Delta t = 5 \text{ mins} \end{array}$$



$$\Delta u(k) = \frac{y_{sp} - \hat{y}^o(k + J)}{S_J}$$

The move required tend to be smaller as J increases

As J decreases,  $y$  becomes aggressive

# Multi input Multi output prediction models - step response (1/2)

$$\hat{y}(k+1) = \underbrace{S_1 \Delta u(k)}_{\text{Effect of current}} + \underbrace{\sum_{i=2}^{N-1} S_i \Delta u(k-i+1)}_{\text{Effect of past control actions}} + S_N u(k-N+1)$$

$$\hat{y}(k+2) = \underbrace{S_1 \Delta u(k+1)}_{\text{Effect of future control action}} + \underbrace{S_2 \Delta u(k)}_{\text{Effect of current control action}} + \underbrace{\sum_{i=3}^{N-1} S_i \Delta u(k-i+2)}_{\text{Effect of past control actions}} + S_N u(k-N+2)$$

$$\hat{y}(k+j) = \underbrace{\sum_{i=1}^j S_i \Delta u(k+j-i)}_{\text{Forced response}} + \underbrace{\hat{y}^o(k+j)}_{\text{Free response}}$$

$$\begin{bmatrix} \hat{y}(k+1) \\ \hat{y}(k+2) \\ \vdots \\ \hat{y}(k+j) \end{bmatrix} = \begin{bmatrix} S_1 & 0 & \dots & 0 \\ S_2 & S_1 & 0 & \vdots \\ \vdots & \vdots & \ddots & 0 \\ S_j & S_{j-1} & \dots & S_1 \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+j-1) \end{bmatrix} + \begin{bmatrix} \hat{y}^o(k+1) \\ \hat{y}^o(k+2) \\ \vdots \\ \hat{y}^o(k+j) \end{bmatrix}$$

$$\hat{\mathbf{Y}}(k+1) = S \Delta \mathbf{U}(k) + \hat{\mathbf{Y}}^o(k+1)$$

# Multi input Multi output prediction models - step response (2/2)

Principle of superposition: Example 2 inputs and 2 outputs

$$\hat{y}_1(k+1) = \sum_{i=1}^{N-1} S_{11,i} \Delta u_1(k-i+1) + S_{11,N} u_1(k-N+1) \\ + \sum_{i=1}^{N-1} S_{12,i} \Delta u_2(k-i+1) + S_{12,N} u_2(k-N+1)$$

$$\hat{y}_2(k+1) = \sum_{i=1}^{N-1} S_{21,i} \Delta u_1(k-i+1) + S_{21,N} u_1(k-N+1) \\ + \sum_{i=1}^{N-1} S_{22,i} \Delta u_2(k-i+1) + S_{22,N} u_2(k-N+1)$$

P step ahead predictions for M future control moves

'r' inputs  $\dot{\mathbf{u}} = [u_1 \quad u_2 \quad \cdots \quad u_r]^T$

'm' outputs  $\mathbf{y} = [y_1 \quad y_2 \quad \cdots \quad y_m]^T$

$$\hat{\mathbf{Y}}(k+1) \triangleq \begin{bmatrix} \hat{y}(k+1) \\ \hat{y}(k+2) \\ \vdots \\ \hat{y}(k+P) \end{bmatrix}_{mP \times 1} \quad \hat{\mathbf{Y}}^o(k+1) \triangleq \begin{bmatrix} \hat{y}^o(k+1) \\ \hat{y}^o(k+2) \\ \vdots \\ \hat{y}^o(k+P) \end{bmatrix}_{mP \times 1} \quad \Delta \mathbf{U}(k) \triangleq \begin{bmatrix} \Delta \mathbf{u}(k) \\ \Delta \mathbf{u}(k+1) \\ \vdots \\ \Delta \mathbf{u}(k+M-1) \end{bmatrix}_{rM \times 1}$$

$$\hat{\mathbf{Y}}(k+1) = \mathbf{S} \Delta \mathbf{U}(k) + \hat{\mathbf{Y}}^o(k+1)$$

Forced  
response

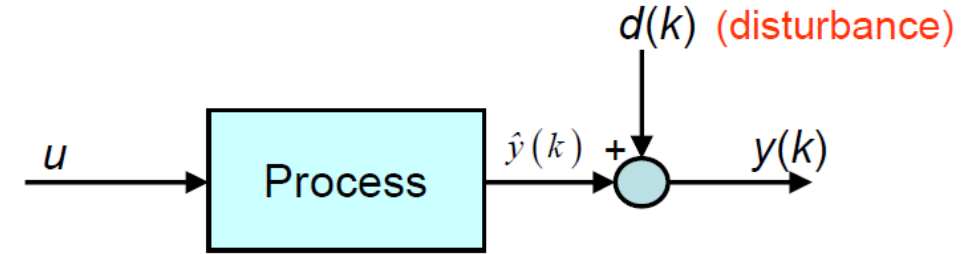
Free  
response

$$\mathbf{S} \triangleq \begin{bmatrix} \mathbf{S}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{S}_2 & \mathbf{S}_1 & \mathbf{0} & \vdots \\ \vdots & \vdots & \ddots & \mathbf{0} \\ \mathbf{S}_M & \mathbf{S}_{M-1} & \cdots & \mathbf{S}_1 \\ \mathbf{S}_{M+1} & \mathbf{S}_M & \cdots & \mathbf{S}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{S}_P & \mathbf{S}_{P-1} & \cdots & \mathbf{S}_{P-M+1} \end{bmatrix} \quad \mathbf{S}_i \triangleq \begin{bmatrix} S_{11,i} & S_{12,i} & \cdots & S_{1r,i} \\ S_{21,i} & \cdots & \cdots & S_{2r,i} \\ \vdots & \vdots & \vdots & \vdots \\ S_{m1,i} & \cdots & \cdots & S_{mr,i} \end{bmatrix}$$

# Correcting for model prediction errors – output feedback

When can predictions drift away actual?

- Inaccurate model
- Unmeasured disturbances



How do we correct the model predictions?  
Output feedback based on the latest measurement

$$\tilde{y}(k+j) \triangleq \hat{y}(k+j) + \underbrace{\left[ y(k) - \hat{y}(k) \right]}_{\substack{\text{Bias term or} \\ \text{correction term or} \\ \text{Estimated disturbance}}}$$

MIMO Model prediction with bias correction

$$\text{'r' inputs} \quad \dot{\mathbf{u}} = [u_1 \quad u_2 \quad \cdots \quad u_r]^T$$

$$\text{'m' outputs} \quad \mathbf{y} = [y_1 \quad y_2 \quad \cdots \quad y_m]^T$$

$$\tilde{\mathbf{Y}}(k+1) = \mathbf{S}\Delta\mathbf{U}(k) + \hat{\mathbf{Y}}^o(k+1) + \mathbf{\Phi}[\mathbf{y}(k) - \hat{\mathbf{y}}(k)]$$

$\mathbf{\Phi}$  is matrix of '1' with dimension  $m_P \times m$

# Nomenclature

- CVs, MVs, and DVs