

# Predictive control

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# Outline

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- I Introduction
- II Linear optimal prediction
- III One step ahead predictive control

## Some mathematical définitions

$$t = kT_e \quad \longrightarrow \quad x(t) \triangleq x(kT_e)$$
$$t - i = (k - i)T_e$$

*Shift operator*

$$q^{-i}x(t) = x(t - i)$$

$$P(q^{-1}) = p_0 + p_1q^{-1} + p_2q^{-2} \dots + p_nq^{-n}$$

$$P(q^{-1})x(t) = p_0x(t) + p_1x(t - 1) + p_2x(t - 2) + \dots + p_nx(t - n)$$

*Derivation*

$$\frac{\partial P(q^{-1})x(t)}{\partial x(t-i)} = p_i$$

# Class of systems

$$\left\{ \begin{array}{ll} A(q^{-1})y(t) = q^{-d-1}B(q^{-1})u(t)+v(t) & \text{Model of the system} \\ D(q^{-1})v(t) = C(q^{-1})\gamma(t) & \text{Disturbance model} \end{array} \right.$$

↓ Z transform

$$Y(z^{-1}) = \frac{z^{-d-1}B(z^{-1})}{A(z^{-1})}U(z^{-1}) + \frac{1}{A(z^{-1})}V(z^{-1})$$

$$V(z^{-1}) = \frac{C(z^{-1})}{D(z^{-1})} \quad \rightarrow \quad \text{Disturbance Former Filter}$$

# Class of systems

$$A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2} + \dots + a_{n_a} q^{-n_a}$$

$$B(q^{-1}) = b_0 + b_1 q^{-1} + b_2 q^{-2} + \dots + b_{n_b} q^{-n_b}$$

$$C(q^{-1}) = c_0 + c_1 q^{-1} + c_2 q^{-2} + \dots + c_{n_c} q^{-n_c}$$

$$D(q^{-1}) = 1 + d_1 q^{-1} + d_2 q^{-2} + \dots + d_{n_d} q^{-n_d}$$

## *Disturbance Former Filter*

*Step*

$$D(q^{-1}) = 1 - q^{-1}$$

*Ramp*

$$D(q^{-1}) = (1 - q^{-1})^2$$

*Sinus*

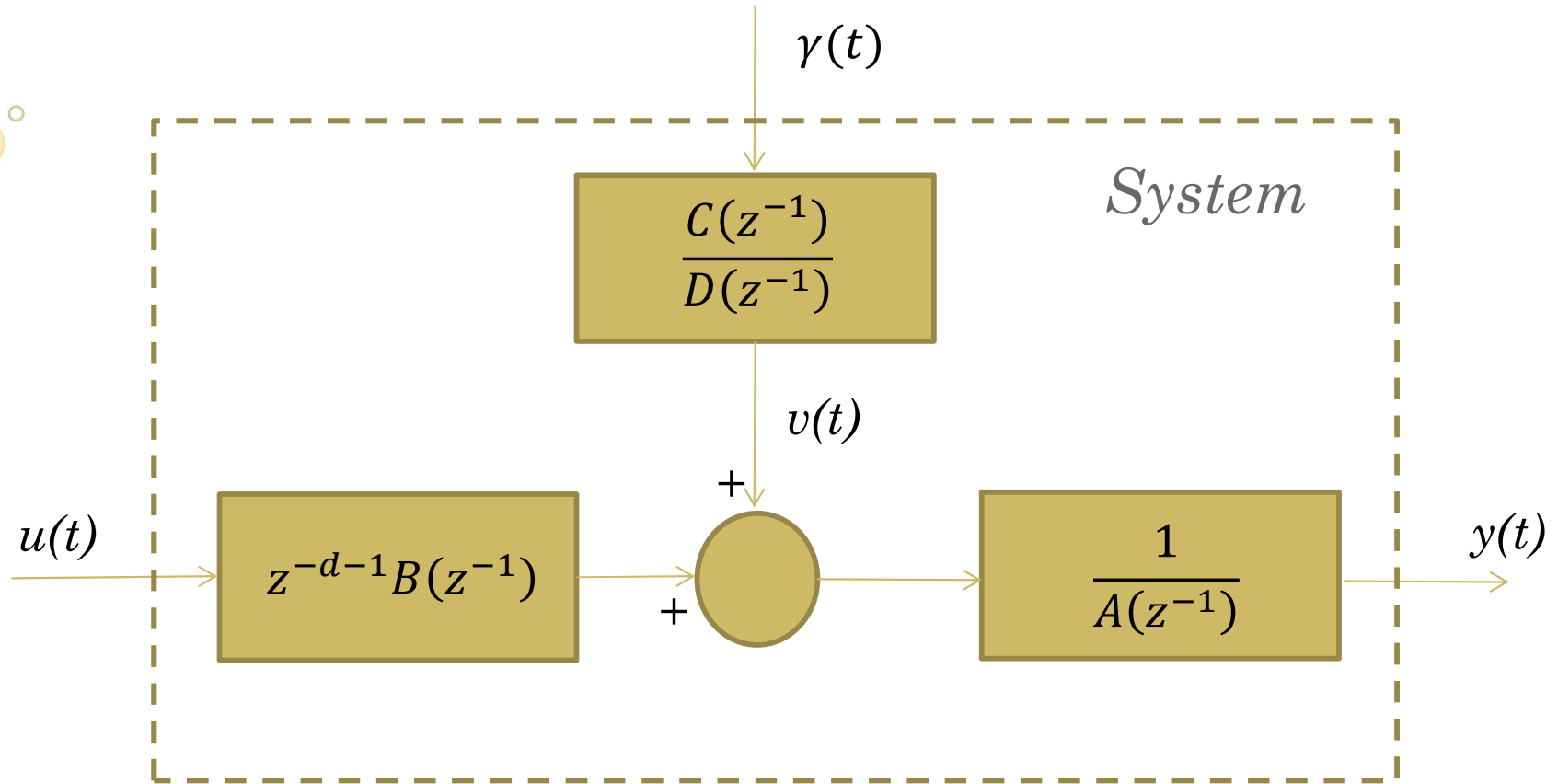
$$D(q^{-1}) = 1 - 2 \cos(\omega T_e) q^{-1} + q^{-2}$$



*The nature of the disturbance is completely described by  $D(q^{-1})$*

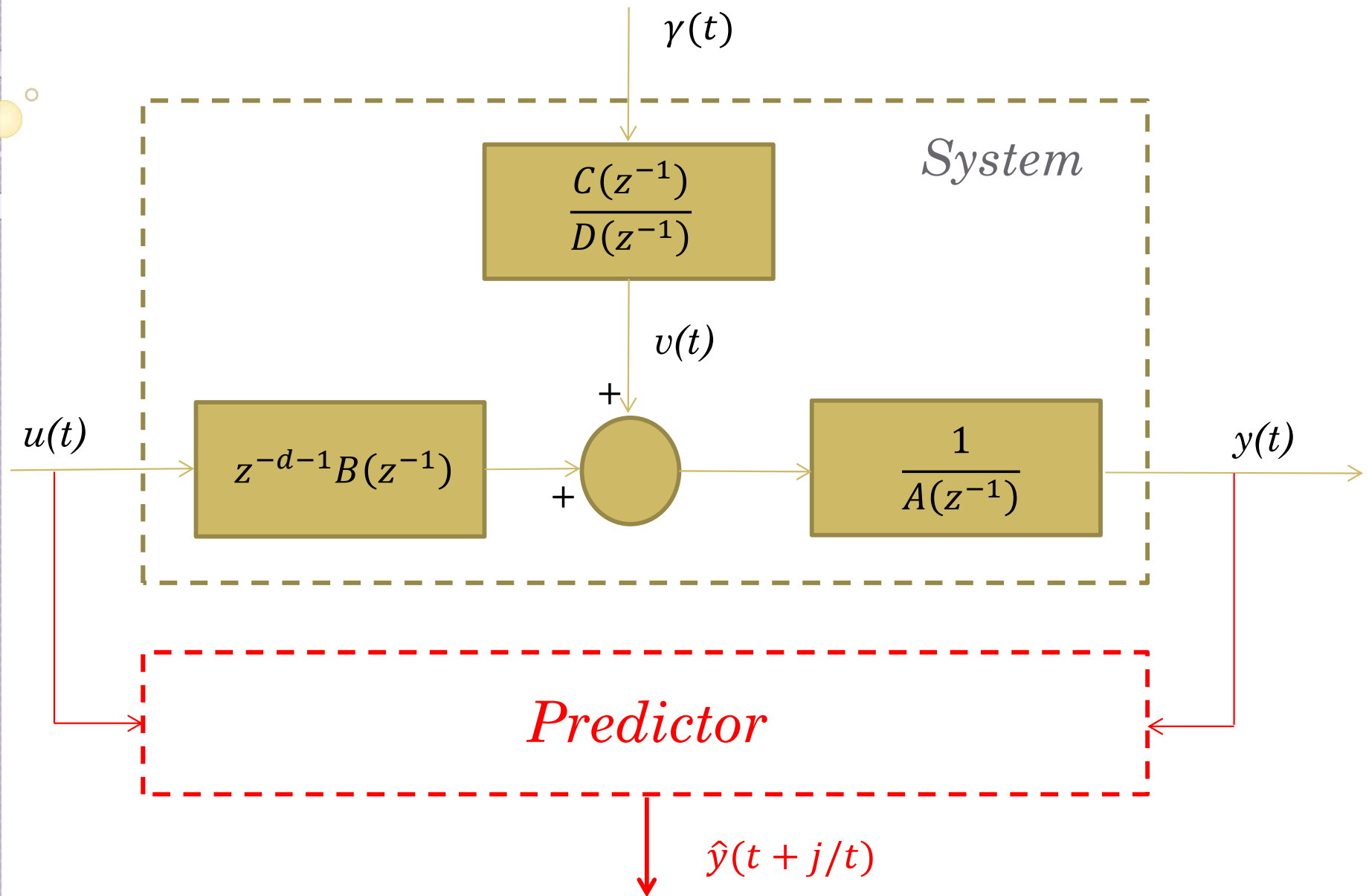
*$C(q^{-1})$  only acts as a filter*

# Class of systems



$$Y(z^{-1}) = \frac{z^{-d-1}B(z^{-1})}{A(z^{-1})}U(z^{-1}) + \frac{C(z^{-1})}{A(z^{-1})D(z^{-1})}\gamma(z^{-1})$$

# Linear prediction



# Optimal Linear Prediction

$\hat{y}(t + j/t)$       *Optimal output prediction of  $y(t + j)$  using the available measurements at time  $t$*

$\tilde{y}(t + j/t) = y(t + j) - \hat{y}(t + j/t)$       *Optimal output prediction **error***

## *Properties of an optimal prediction*

$\varepsilon\{\tilde{y}(t + j/t)\} = 0$       *No bias*

$\varepsilon\{(\tilde{y}(t + j/t))^2\}$  *minimal*



# Decomposition tools

$$A(q^{-1})y(t) = q^{-d-1}B(q^{-1})u(t)+v(t)$$

We operate  
→  
by  $D(q^{-1})$

$$D(q^{-1})A(q^{-1})y(t) = q^{-d-1}D(q^{-1})B(q^{-1})u(t)+ D(q^{-1}) v(t)$$

At  $t = t+j$   
→

$$D(q^{-1})A(q^{-1})y(t + j) = q^{-d-1}D(q^{-1})B(q^{-1})u(t + j)+ D(q^{-1}) v(t+j)$$

Using disturbance  
→  
model

$$D(q^{-1})A(q^{-1})y(t + j) = q^{-d-1}D(q^{-1})B(q^{-1})u(t + j)+ C(q^{-1}) \gamma(t+j)$$

$$y(t + j) = \frac{q^{-d-1}B(q^{-1})}{A(q^{-1})D(q^{-1})}u(t + j)+ \frac{C(q^{-1})}{A(q^{-1})D(q^{-1})}\gamma(t+j)$$

# Decomposition tools

$$y(t+j) = \frac{q^{-d-1}B(q^{-1})}{A(q^{-1})D(q^{-1})}u(t+j) + \frac{C(q^{-1})}{A(q^{-1})D(q^{-1})}\gamma(t+j)$$

Depends on

The past values of  $u(t)$  : *known*

The future values of  $u(t)$  : *can be known*

Depends on

The past values of  $\gamma(t)$  : *available*

The future values of  $\gamma(t)$  : *unknown*

*Why  $\gamma(t)$  is available à time  $t$  ?*

$$A(q^{-1})y(t) = q^{-d-1}B(q^{-1})u(t) + v(t)$$



$$v(t) = A(q^{-1})y(t) - q^{-d-1}B(q^{-1})u(t)$$

## Decomposition tools

*Why  $\gamma(t)$  is available à time  $t$  ?*

$$A(q^{-1})y(t) = q^{-d-1}B(q^{-1})u(t) + v(t)$$



$$v(t) = A(q^{-1})y(t) - q^{-d-1}B(q^{-1})u(t)$$



$$D(q^{-1})v(t) = D(q^{-1})A(q^{-1})y(t) - q^{-d-1}B(q^{-1})D(q^{-1})u(t)$$



$$\gamma(t) = \frac{D(q^{-1})A(q^{-1})}{C(q^{-1})}y(t) - \frac{B(q^{-1})D(q^{-1})}{C(q^{-1})}u(t - d - 1)$$

*$\gamma(t)$  can be calculated using the values of  $y(t)$  and  $u(t)$*

# Decomposition tools

$$y(t + j) = \frac{q^{-d-1}B(q^{-1})}{A(q^{-1})D(q^{-1})}u(t + j) + \frac{C(q^{-1})}{A(q^{-1})D(q^{-1})}\gamma(t+j)$$

$\frac{C(q^{-1})}{A(q^{-1})D(q^{-1})}\gamma(t+j)$  depends on  $\underbrace{\gamma(t+j), \gamma(t+j-1), \dots, \gamma(t+1)}_{\text{unpredictable}}, \underbrace{\gamma(t), \gamma(t-1), \dots}_{\text{Can be calculated}}$

*Objective*

*Separate the unpredictable part  
and the available part*

## *A polynomial division*

$$\frac{C(q^{-1})}{A(q^{-1})D(q^{-1})} = E_j(q^{-1}) + q^{-j} \frac{F_j(q^{-1})}{A(q^{-1})D(q^{-1})}$$

$$E_j(q^{-1}) = e_0 + e_1q^{-1} + e_2q^{-2} + \dots + e_{n_{ej}}q^{-n_{ej}}$$

$$F_j(q^{-1}) = f_0 + f_1q^{-1} + f_2q^{-2} + \dots + f_{n_{fj}}q^{-n_{fj}}$$

*Another useful formulation*

$$C(q^{-1}) = A(q^{-1})D(q^{-1})E_j(q^{-1}) + q^{-j}F_j(q^{-1})$$

***Remark***

***Similar to the diophantine equation  
(useful for Matlab / Simulink implementation)***

# A polynomial division

At which rank do we decide to stop the division ?

$$n_{ej} = j - 1$$

$$\frac{C(q^{-1})}{A(q^{-1})D(q^{-1})} \gamma(t+j) = E_j(q^{-1})\gamma(t+j) + q^{-j} \frac{F_j(q^{-1})}{A(q^{-1})D(q^{-1})} \gamma(t+j)$$

$$E_j(q^{-1})\gamma(t+j) = e_0\gamma(t+j) + e_1\gamma(t+j-1) + \dots + e_{j-1}\gamma(t+1) \quad \text{Unpredictable part}$$

$$q^{-j} \frac{F_j(q^{-1})}{A(q^{-1})D(q^{-1})} \gamma(t+j) = \frac{F_j(q^{-1})}{A(q^{-1})D(q^{-1})} \gamma(t)$$

Available part

$$n_{ej} = j - 1$$

$$n_{ef} \leq \max(n_a + n_d - 1, n_c + j)$$

## Using the polynomial division

$$A(q^{-1})y(t+j) = q^{-d-1}B(q^{-1})u(t+j) + v(t+j)$$

↓

$$D(q^{-1})A(q^{-1})y(t+j) = q^{-d-1}B(q^{-1})D(q^{-1})u(t+j) + D(q^{-1})v(t+j)$$

↓

$$D(q^{-1})A(q^{-1})y(t+j) = q^{-d-1}B(q^{-1})D(q^{-1})u(t+j) + C(q^{-1})\gamma(t+j)$$

↓

$$E(q^{-1})D(q^{-1})A(q^{-1})y(t+j) = q^{-d-1}B(q^{-1})E(q^{-1})D(q^{-1})u(t+j) + E(q^{-1})C(q^{-1})\gamma(t+j)$$

↓

$$\{C(q^{-1}) - q^{-j}F(q^{-1})\}y(t+j) = q^{-d-1}B(q^{-1})E(q^{-1})D(q^{-1})u(t+j) + E(q^{-1})C(q^{-1})\gamma(t+j)$$

↓

$$C(q^{-1})y(t+j) = q^{-j}F(q^{-1})y(t+j) + q^{-d-1}B(q^{-1})E(q^{-1})D(q^{-1})u(t+j) + E(q^{-1})C(q^{-1})\gamma(t+j)$$

## Using the polynomial division

$$y(t+j) = \frac{F(q^{-1})}{C(q^{-1})} y(t) + \frac{B(q^{-1})E(q^{-1})D(q^{-1})}{C(q^{-1})} u(t+j-d-1) + E(q^{-1}) \gamma(t+j)$$

↓  
*unpredictable*

### *The optimal prediction*

$$\hat{y}(t+j/t) = \frac{F(q^{-1})}{C(q^{-1})} y(t) + \frac{B(q^{-1})E(q^{-1})D(q^{-1})}{C(q^{-1})} u(t+j-d-1)$$



## Is the prediction optimal ?

$$\tilde{y}(t + j/t) = y(t + j) - \hat{y}(t + j/t)$$

$$\tilde{y}(t + j/t) = E(q^{-1}) \gamma(t + j) = e_0 \gamma(t + j) + e_1 \gamma(t + j - 1) + \dots + e_{j-1} \gamma(t + 1)$$

*Mean value*

$$\begin{aligned} \varepsilon\{\tilde{y}(t + j/t)\} &= \{e_0 \gamma(t + j) + e_1 \gamma(t + j - 1) + \dots + e_{j-1} \gamma(t + 1)\} \\ &= \varepsilon \left( \sum_{k=0}^{j-1} \{e_k \gamma(t + j - k)\} \right) \\ &= \sum_{k=0}^{j-1} \{e_k \varepsilon(\gamma(t + j - k))\} \\ &= 0 \end{aligned}$$

## Is the prediction optimal ?

$$\begin{aligned} \varepsilon \left\{ (\tilde{y}(t + j/t))^2 \right\} &= \varepsilon \left\{ \left( e_0 \gamma(t + j) + e_1 \gamma(t + j - 1) + \dots + e_{j-1} \gamma(t + 1) \right)^2 \right\} \\ &= \varepsilon \left\{ \sum_{i=0}^{j-1} \sum_{k=0}^{j-1} e_i e_k \gamma(t + j - i) \gamma(t + j - k) \right\} \\ &= \sum_{i=0}^{j-1} e_i^2 \varepsilon \{ (\gamma(t))^2 \} \\ &= \sum_{i=0}^{j-1} e_i^2 \sigma^2 \end{aligned}$$

# Conclusion

*No bias*

$$\varepsilon\{\tilde{y}(t + j/t)\} = 0$$

*Minimal Variance*

$$\varepsilon\{(\tilde{y}(t + j/t))^2\} = \sum_{i=0}^{j-1} e_i^2 \sigma^2$$

*Prediction dynamics imposed by  $C(q^{-1})$*

$$\hat{y}(t + j/t) = \frac{F(q^{-1})}{C(q^{-1})} y(t) + \frac{B(q^{-1})E(q^{-1})D(q^{-1})}{C(q^{-1})} u(t + j - d - 1)$$

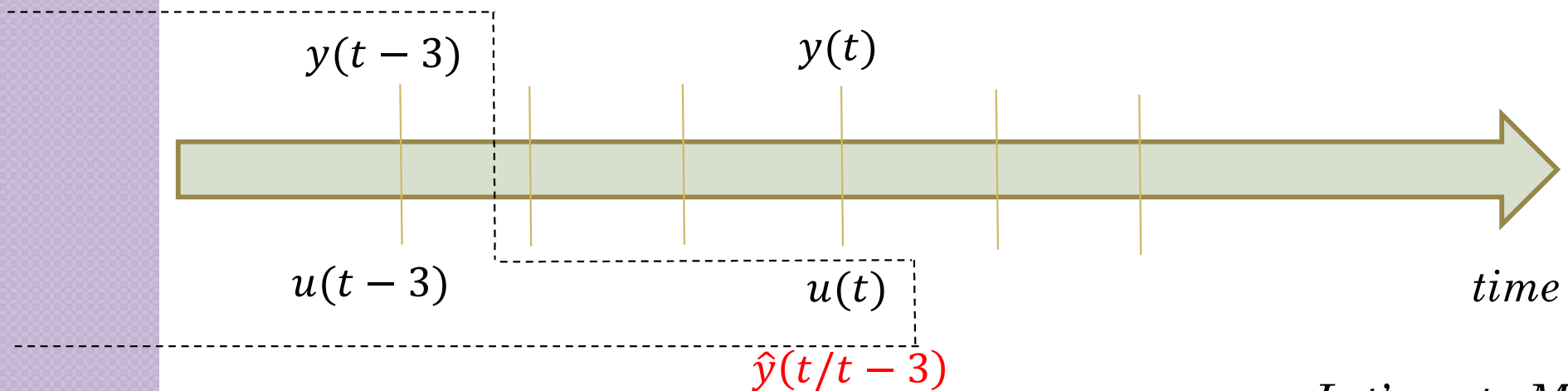
# Exercice using Matlab / Simulink

*The optimal prediction is not causal*

$$\hat{y}(t + j/t) = \frac{F(q^{-1})}{C(q^{-1})}y(t) + \frac{B(q^{-1})E(q^{-1})D(q^{-1})}{C(q^{-1})}u(t + j - d - 1)$$

→ *Depends on the future values of the control variable  
Can not be simulated using Simulink*

*We are going to simulate  $\hat{y}(t/t - j)$*



→ *Let's go to Matlab*