

# State Feedback and State Estimators

“Linear System Theory and Design”, Chapter 8

<http://zitompul.wordpress.com>

2 0 1 4

# State Estimator

- In previous section, we have discussed the state feedback, based on the assumption that all state variables are available for feedback.
- Also, we have discussed the output feedback, provided that the output is available for feedback.
- On the purpose of state feedback, practically, the state variables might be not accessible for direct connection.
- The sensing devices or transducers might be not available or very expensive.
- In this case, we need a "**state estimator**" or a "**state observer**". Their output will be the "estimate of the state", provided that the system under consideration is ***observable***.

# State Estimator

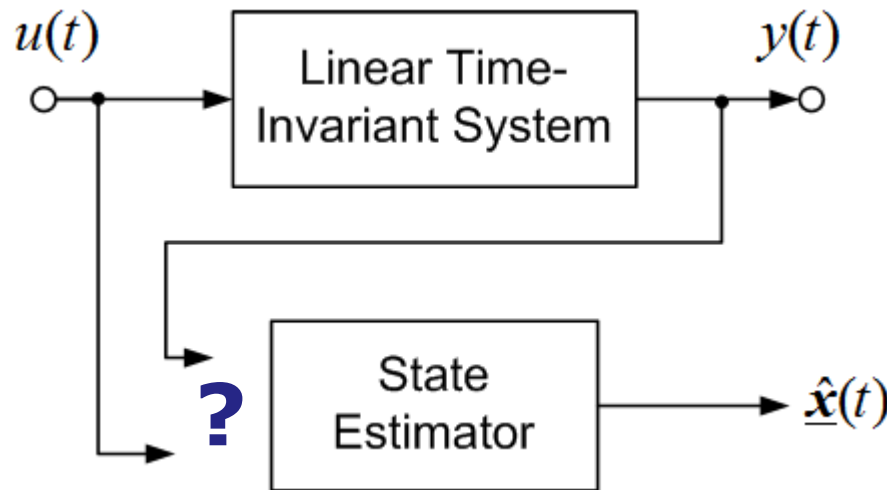
- Consider the  $n$ -dimensional single-variable state space equations:

$$\dot{\underline{x}}(t) = \underline{A}\underline{x}(t) + \underline{b}u(t)$$

$$y(t) = \underline{c}\underline{x}(t)$$

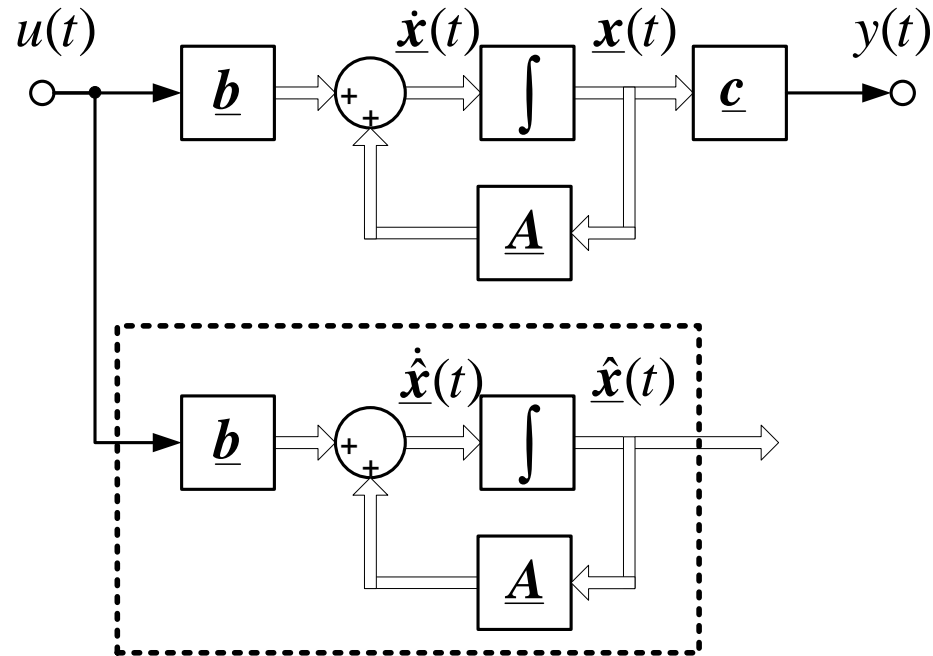
where  $\underline{A}$ ,  $\underline{b}$ ,  $\underline{c}$  are given,  $u(t)$  and  $y(t)$  are available, and the states  $\underline{x}(t)$  are not available.

- Problem:** How to estimate  $\underline{x}(t)$ ?



# Open-Loop State Estimator

- The block diagram of an open-loop state estimator can be seen below:



- The open-loop state estimator duplicates the original system and deliver:

$$\dot{\underline{\hat{x}}}(t) = \underline{A}\underline{\hat{x}}(t) + \underline{b}u(t)$$

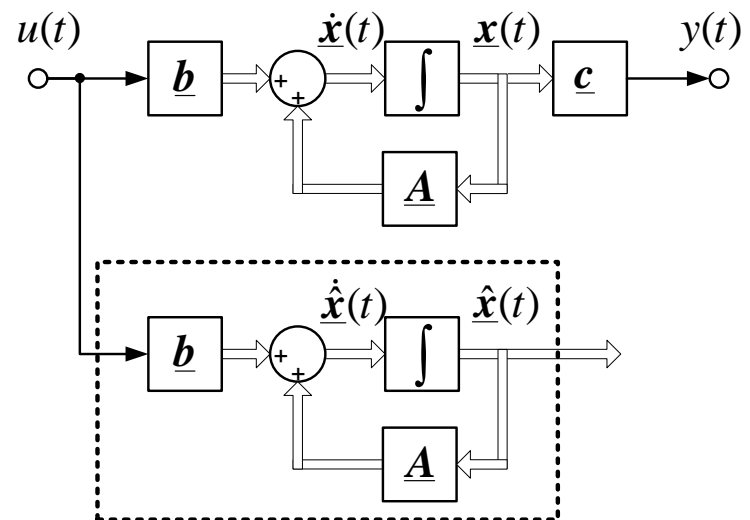
# Open-Loop State Estimator

- Several conclusions can be drawn by comparing both state equations

$$\dot{\underline{x}}(t) = \underline{A}\underline{x}(t) + \underline{b}u(t)$$

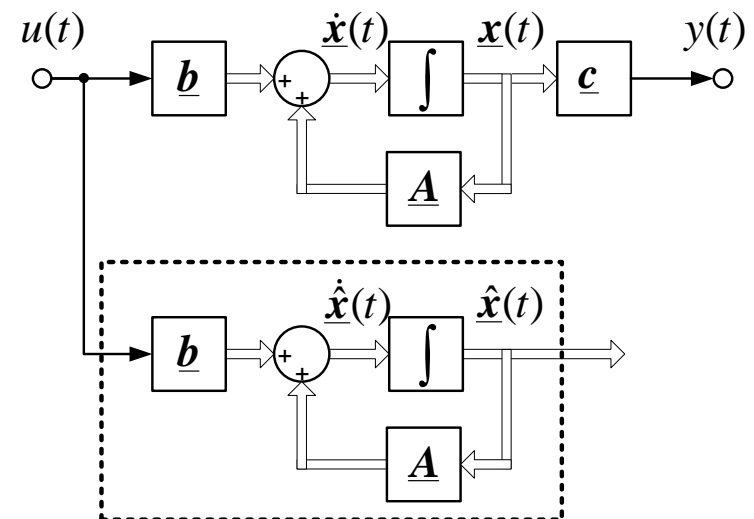
$$\dot{\underline{\hat{x}}}(t) = \underline{A}\underline{\hat{x}}(t) + \underline{b}u(t)$$

- If the initial states of both equations are the same,  $\underline{\hat{x}}_0(t) = \underline{x}_0(t)$ , then for any  $t \geq 0$ ,  $\underline{\hat{x}}(t) = \underline{x}(t)$ .
- If the pair  $(\underline{A}, \underline{c})$  is observable, the initial state can be computed over any time interval  $[0, t_0]$ , and after setting  $\underline{\hat{x}}(t_0) = \underline{x}(t_0)$ , then  $\underline{\hat{x}}(t) = \underline{x}(t)$  for  $t \geq t_0$ .



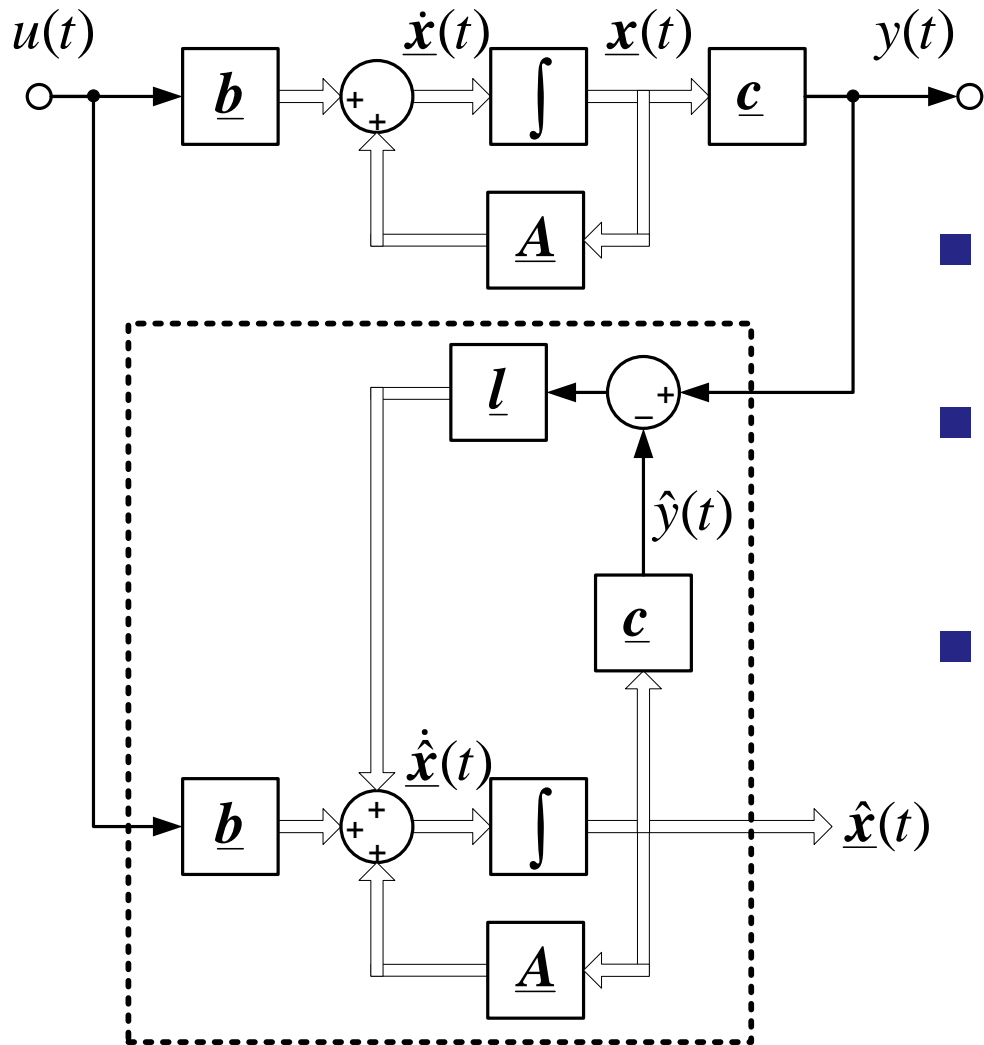
# Open-Loop State Estimator

- The disadvantages of open-loop estimator are:
  - Initial state must be computed and appointed each time the estimator is used.
  - If the system is unstable, any small difference between  $\underline{\mathbf{x}}(t_0)$  and  $\hat{\underline{\mathbf{x}}}(t_0)$  will lead to even bigger difference between  $\underline{\mathbf{x}}(t)$  and  $\hat{\underline{\mathbf{x}}}(t)$ , making  $\hat{\underline{\mathbf{x}}}(t)$  unusable.



# Closed-Loop State Estimator

- The block diagram of a closed-loop state estimator can be seen below:



- In closed-loop estimator,  $y(t) = \mathbf{c}\mathbf{x}(t)$  is compared with  $\hat{y}(t) = \mathbf{c}\hat{\mathbf{x}}(t)$ .
- Their difference, after multiplied by the matrix  $\mathbf{l}$ , is used as a correcting term in the calculation of  $\hat{\mathbf{x}}(t)$ .
- If  $\mathbf{l}$  is properly assigned, the difference will drive  $\hat{\mathbf{x}}(t)$  to  $\mathbf{x}(t)$ .

# Closed-Loop State Estimator

- Following the previous figure,

$$\dot{\hat{\mathbf{x}}}(t) = \underline{\mathbf{A}}\hat{\mathbf{x}}(t) + \underline{\mathbf{b}}u(t) + \underline{\mathbf{l}}(y(t) - \underline{\mathbf{c}}\hat{\mathbf{x}}(t))$$

$$\dot{\hat{\mathbf{x}}}(t) = (\underline{\mathbf{A}} - \underline{\mathbf{l}}\underline{\mathbf{c}})\hat{\mathbf{x}}(t) + \underline{\mathbf{b}}u(t) + \underline{\mathbf{l}}y(t)$$

- "New" inputs

- We now define

$$\underline{\mathbf{e}}(t) = \underline{\mathbf{x}}(t) - \hat{\mathbf{x}}(t)$$

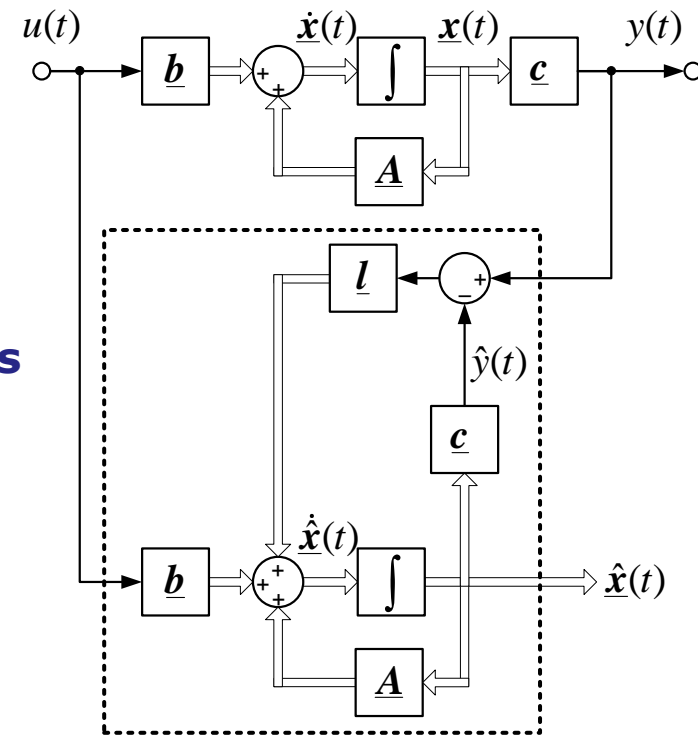
$$\underline{\dot{\mathbf{e}}}(t) = \underline{\dot{\mathbf{x}}}(t) - \dot{\hat{\mathbf{x}}}(t)$$

$$= \{ \underline{\mathbf{A}}\underline{\mathbf{x}}(t) + \underline{\mathbf{b}}u(t) \} - \{ (\underline{\mathbf{A}} - \underline{\mathbf{l}}\underline{\mathbf{c}})\hat{\mathbf{x}}(t) + \underline{\mathbf{b}}u(t) + \underline{\mathbf{l}}y(t) \}$$

$$= (\underline{\mathbf{A}} - \underline{\mathbf{l}}\underline{\mathbf{c}})\underline{\mathbf{x}}(t) - (\underline{\mathbf{A}} - \underline{\mathbf{l}}\underline{\mathbf{c}})\hat{\mathbf{x}}(t)$$

$$= (\underline{\mathbf{A}} - \underline{\mathbf{l}}\underline{\mathbf{c}})(\underline{\mathbf{x}}(t) - \hat{\mathbf{x}}(t))$$

$$\underline{\dot{\mathbf{e}}}(t) = (\underline{\mathbf{A}} - \underline{\mathbf{l}}\underline{\mathbf{c}})\underline{\mathbf{e}}(t)$$





# Closed-Loop State Estimator

$$\dot{\underline{e}}(t) = (\underline{A} - \underline{l}\underline{c})\underline{e}(t) \quad \Longrightarrow \quad \underline{e}(t) = e^{(\underline{A} - \underline{l}\underline{c})t} \underline{e}(0)$$

- The time domain solution of estimation error  $\underline{e}(t)$  depends on  $\underline{e}(0)$ , but not  $u(t)$

Canonical  
Transformation

$$\dot{\underline{\mathcal{E}}}(t) = \underline{A}\underline{\mathcal{E}}(t) \quad \Longrightarrow \quad \underline{\mathcal{E}}(t) = e^{\underline{A}t} \underline{\mathcal{E}}(0)$$

$$\underline{A} = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_n \end{bmatrix}$$

$$e^{\underline{A}t} = \begin{bmatrix} e^{\lambda_1 t} & 0 & \cdots & 0 \\ 0 & e^{\lambda_2 t} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & e^{\lambda_n t} \end{bmatrix}$$

# Closed-Loop State Estimator

- From the fact that  $\underline{\xi}(t) = e^{\underline{\Lambda}t}\underline{\xi}(0)$ , we can conclude that:
  - If all eigenvalues of  $\underline{\Lambda} = (\underline{A} - \underline{lc})$  are negative, then the estimation error  $\underline{e}(t)$  will approach zero as  $t$  increases.
  - There is no need to calculate the initial states each time the closed-loop estimator will be used.
  - After a certain time, the estimation error  $\underline{e}(t)$  will approach zero and the state estimates  $\hat{\underline{x}}(t)$  will be equal to the system's state  $\underline{x}(t)$ .

# Example 1: State Estimators

Consider a linear time-invariant system with the following state equations:

$$\dot{\underline{\mathbf{x}}}(t) = \begin{bmatrix} 0 & 4 \\ -1 & -2 \end{bmatrix} \underline{\mathbf{x}}(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t)$$

$$y(t) = \begin{bmatrix} 1 & 0 \end{bmatrix} \underline{\mathbf{x}}(t)$$

Design a state estimator with eigenvalues of  $-10$  and  $-10$ .

# Example 1: State Estimators

$$\underline{\mathcal{O}} = \begin{bmatrix} \underline{c} \\ \underline{cA} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix}$$

- **Observable** → a state estimator can be designed

$$\alpha(s) = \det(s\underline{I} - \underline{A} + \underline{l}\underline{c})$$

$$= \det \left( \begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} - \begin{bmatrix} 0 & 4 \\ -1 & -2 \end{bmatrix} + \begin{bmatrix} l_1 \\ l_2 \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix} \right)$$

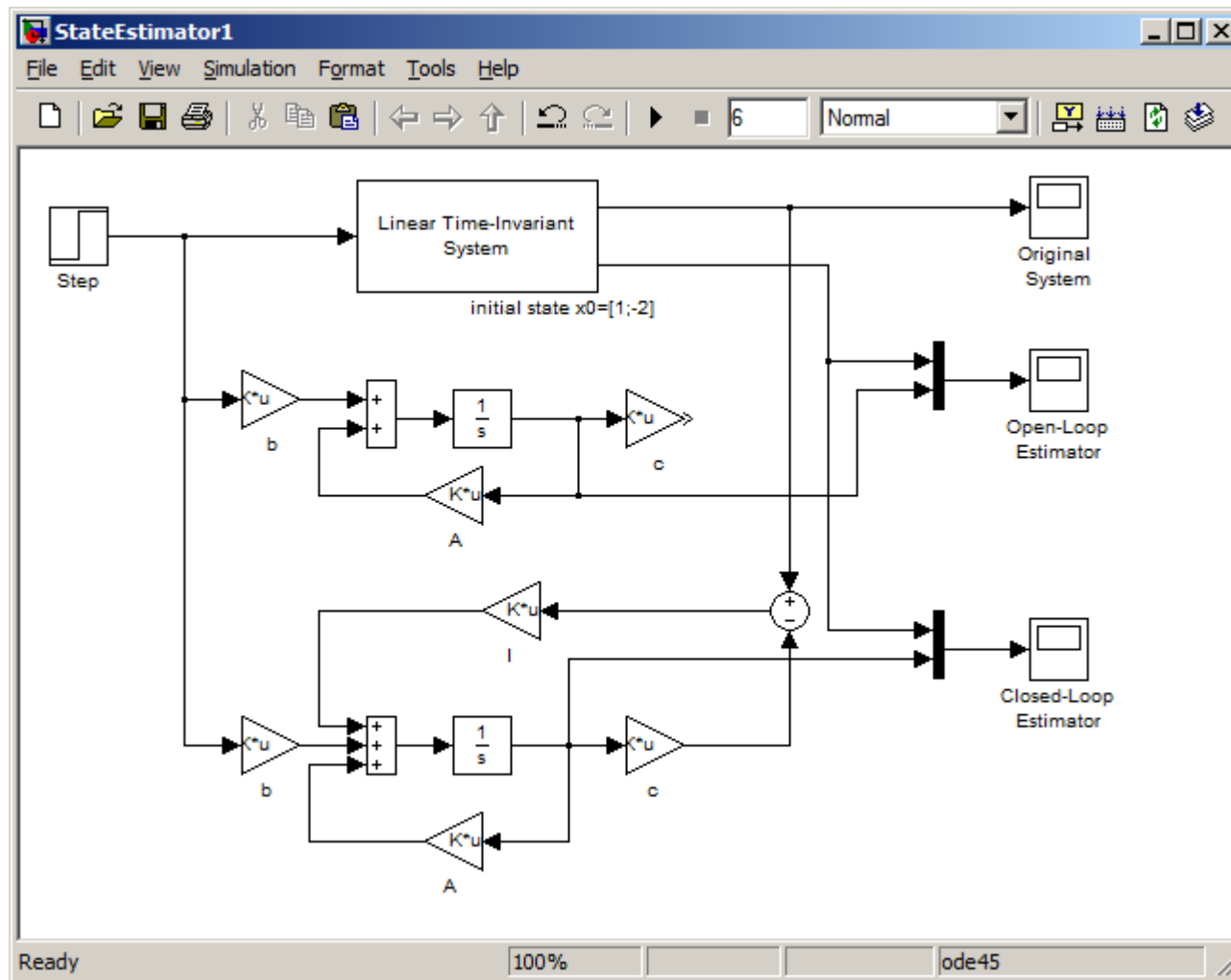
$$= \det \left( \begin{bmatrix} s + l_1 & -4 \\ l_2 + 1 & s + 2 \end{bmatrix} \right)$$

$$= s^2 + (l_1 + 2)s + (2l_1 + 4l_2 + 4)$$

$$\equiv (s + 10)(s + 10)$$

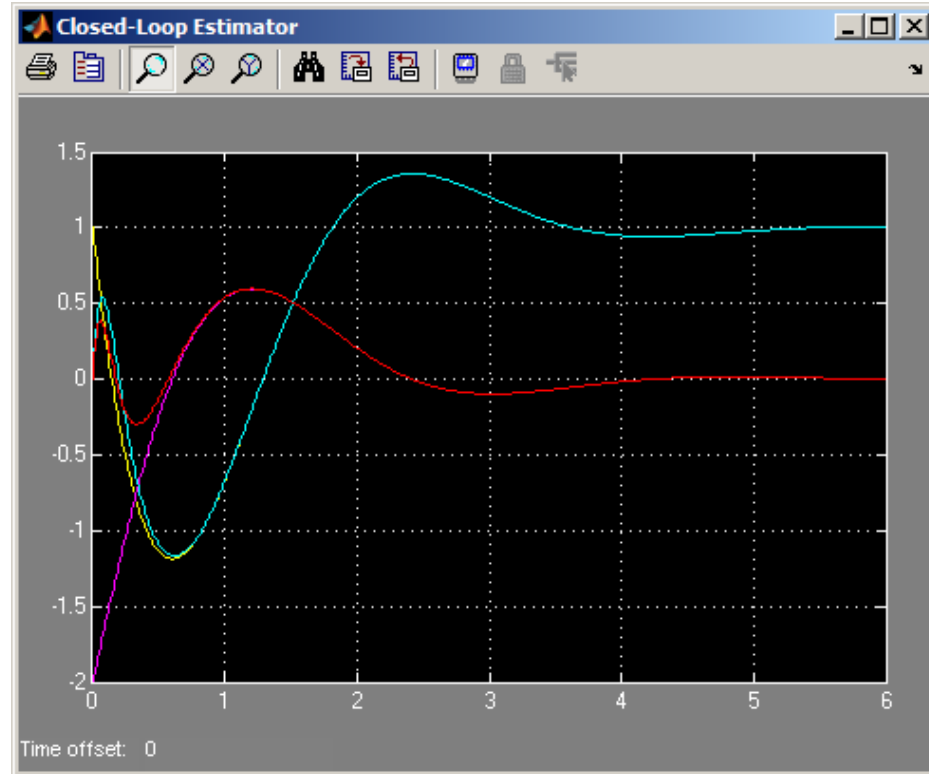
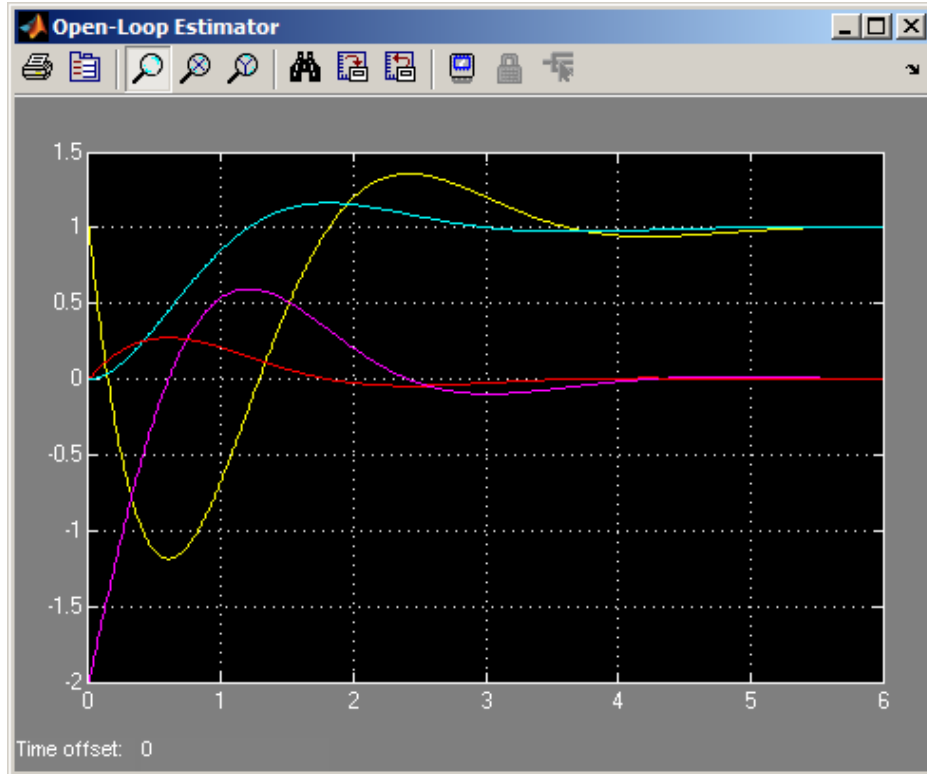
$$\begin{array}{l} l_1 = 18 \\ l_2 = 15 \end{array} \quad \underline{l} = \begin{bmatrix} 18 \\ 15 \end{bmatrix}$$

# Example 1: State Estimators



— :  $X_1$   
— :  $X_2$   
— :  $\hat{X}_1$   
— :  $\hat{X}_2$

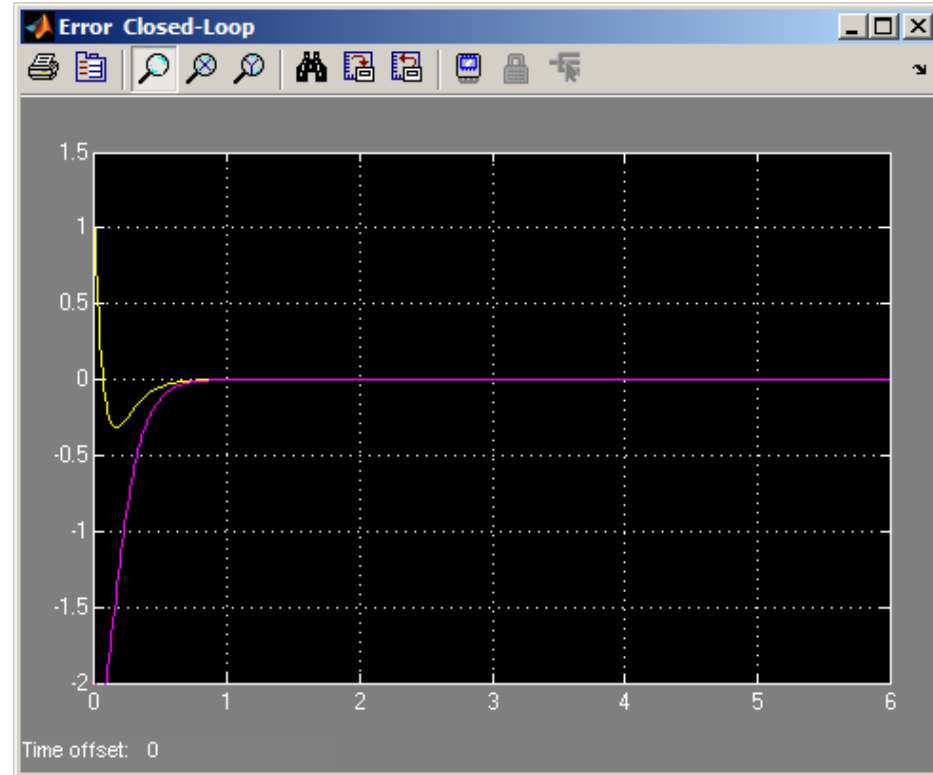
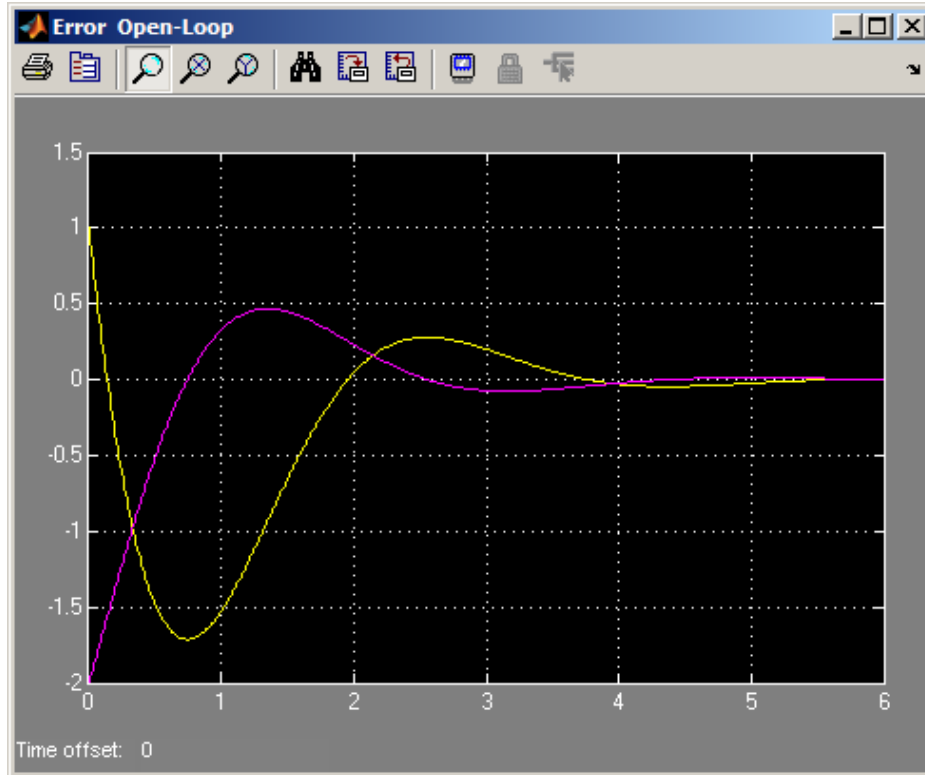
# Example 1: State Estimators



— :  $x_1$   
— :  $x_2$   
— :  $\hat{x}_1$   
— :  $\hat{x}_2$

• **Conclusion: ...**

# Example 1: State Estimators



— :  $x_1 - \hat{x}_1$   
— :  $x_2 - \hat{x}_2$

• **Conclusion: ...**

# Example 2: State Estimators

A system is given in state space form as below:

$$\dot{\underline{\mathbf{x}}}(t) = \begin{bmatrix} 2 & 1 \\ -1 & 1 \end{bmatrix} \underline{\mathbf{x}}(t) + \begin{bmatrix} 1 \\ 2 \end{bmatrix} u(t)$$

$$y(t) = \begin{bmatrix} 1 & 1 \end{bmatrix} \underline{\mathbf{x}}(t)$$

- (a) Find a state feedback gain  $\underline{\mathbf{k}}$ , so that the closed-loop system has  $-1$  and  $-2$  as its eigenvalues.
- (b) Design a closed-loop state estimator for the system, with eigenvalues  $-2 \pm j2$ .



# Example 2: State Estimators

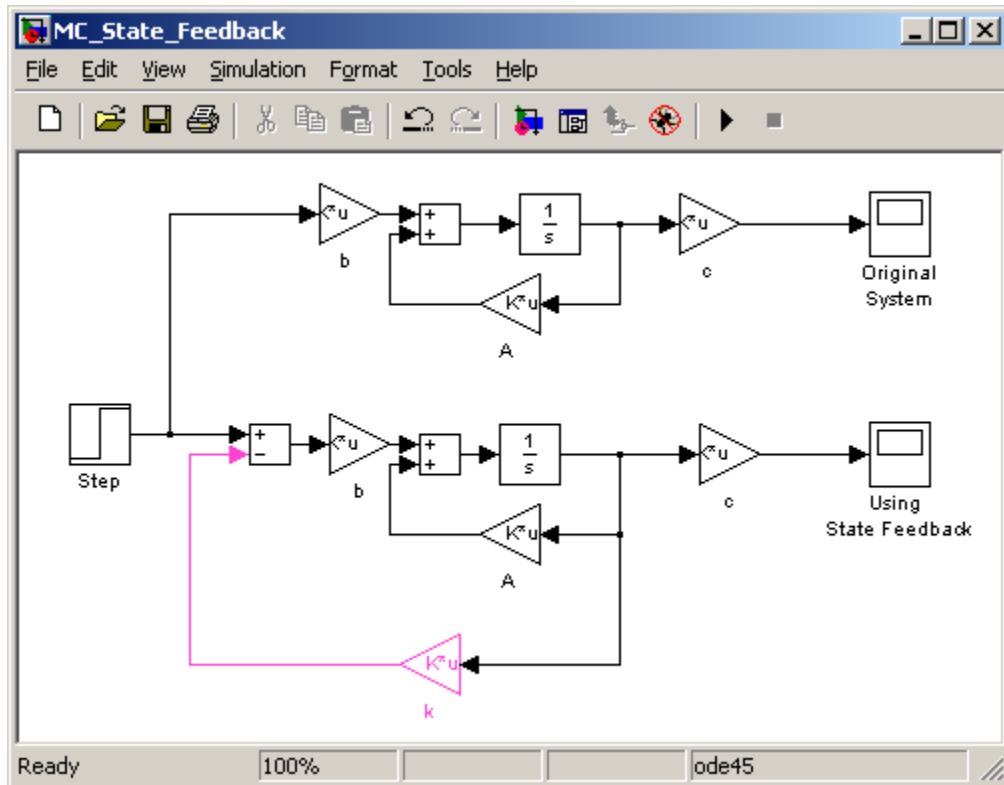
- (a) Find a state feedback gain  $\underline{k}$ , so that the closed-loop system has  $-1$  and  $-2$  as its eigenvalues.

$$\begin{aligned}
 a(s) &= \det(s\underline{I} - \underline{A} + \underline{b}\underline{k}) \\
 &= \det\left(\begin{bmatrix} s-2+k_1 & -1+k_2 \\ 1+2k_1 & s-1+2k_2 \end{bmatrix}\right) \\
 &= s^2 + (k_1 + 2k_2 - 3)s + (k_1 - 5k_2 + 3) \\
 &\equiv (s+1)(s+2)
 \end{aligned}
 \left. \vphantom{\begin{aligned} a(s) &= \det(s\underline{I} - \underline{A} + \underline{b}\underline{k}) \\ &= \det\left(\begin{bmatrix} s-2+k_1 & -1+k_2 \\ 1+2k_1 & s-1+2k_2 \end{bmatrix}\right) \\ &= s^2 + (k_1 + 2k_2 - 3)s + (k_1 - 5k_2 + 3) \\ &\equiv (s+1)(s+2) \end{aligned}} \right\} \begin{array}{l} k_1 = 4 \\ k_2 = 1 \end{array} \quad \underline{k} = \begin{bmatrix} 4 & 1 \end{bmatrix}$$

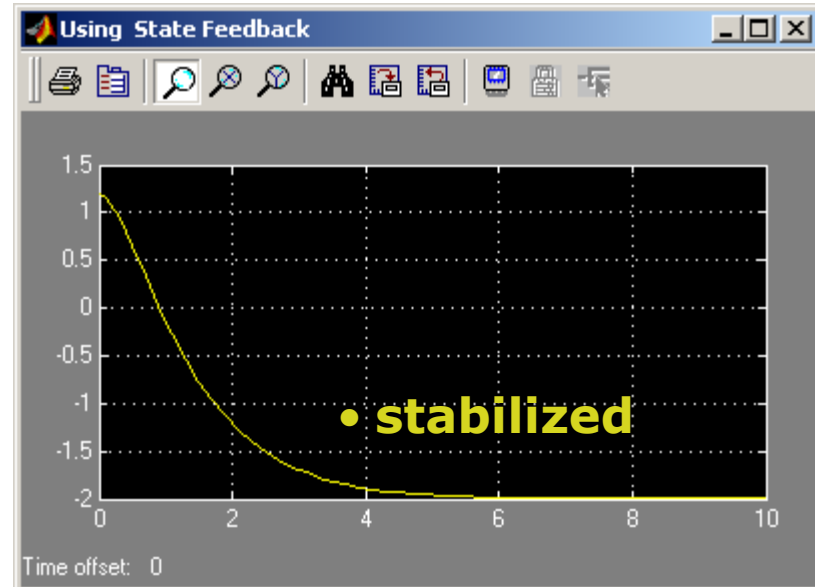
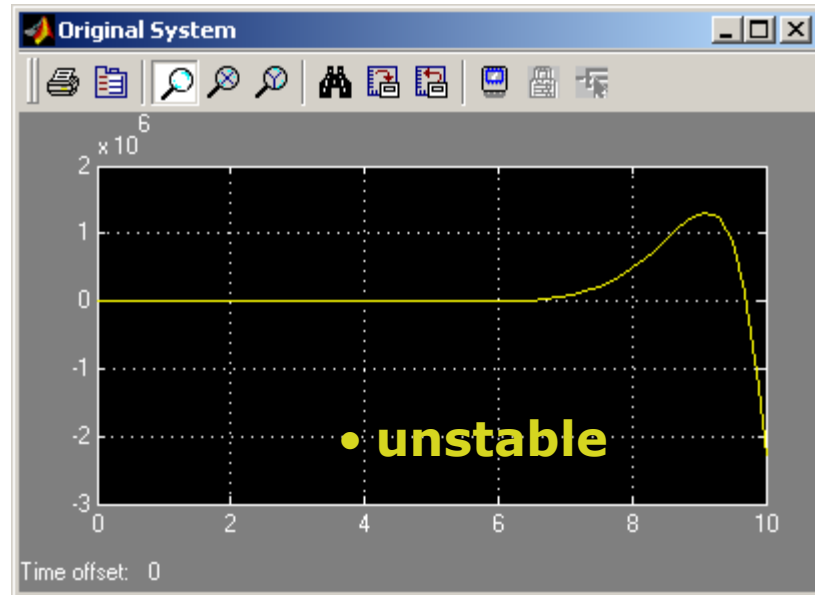
- (b) Design a closed-loop state estimator for the system, with eigenvalues  $-2 \pm j2$ .

$$\begin{aligned}
 \alpha(s) &= \det(s\underline{I} - \underline{A} + \underline{l}\underline{c}) \\
 &= \det\left(\begin{bmatrix} s-2+l_1 & -1+l_1 \\ 1+l_2 & s-1+l_2 \end{bmatrix}\right) \\
 &= s^2 + (l_1 + l_2 - 3)s + (-2l_1 - l_2 + 3) \\
 &\equiv (s+2+j2)(s+2-j2)
 \end{aligned}
 \left. \vphantom{\begin{aligned} \alpha(s) &= \det(s\underline{I} - \underline{A} + \underline{l}\underline{c}) \\ &= \det\left(\begin{bmatrix} s-2+l_1 & -1+l_1 \\ 1+l_2 & s-1+l_2 \end{bmatrix}\right) \\ &= s^2 + (l_1 + l_2 - 3)s + (-2l_1 - l_2 + 3) \\ &\equiv (s+2+j2)(s+2-j2) \end{aligned}} \right\} \begin{array}{l} l_1 = -12 \\ l_2 = 19 \end{array} \quad \underline{l} = \begin{bmatrix} -12 \\ 19 \end{bmatrix}$$

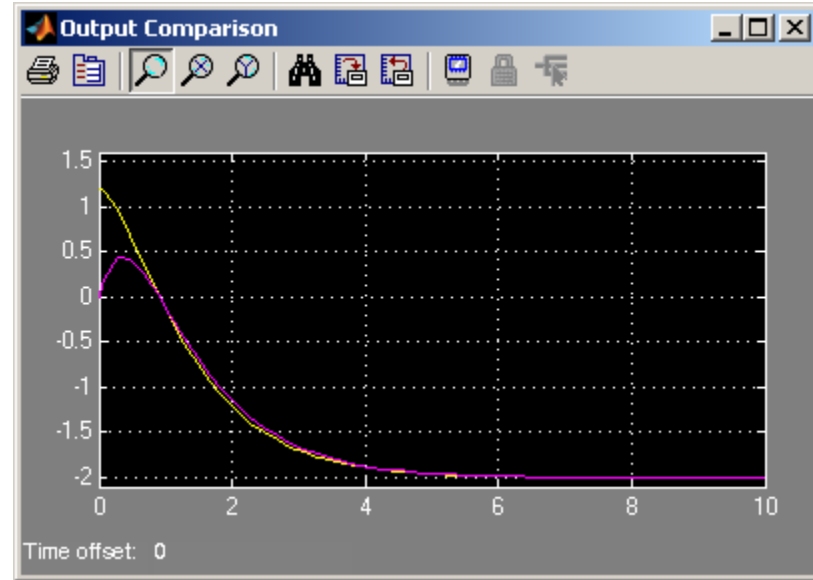
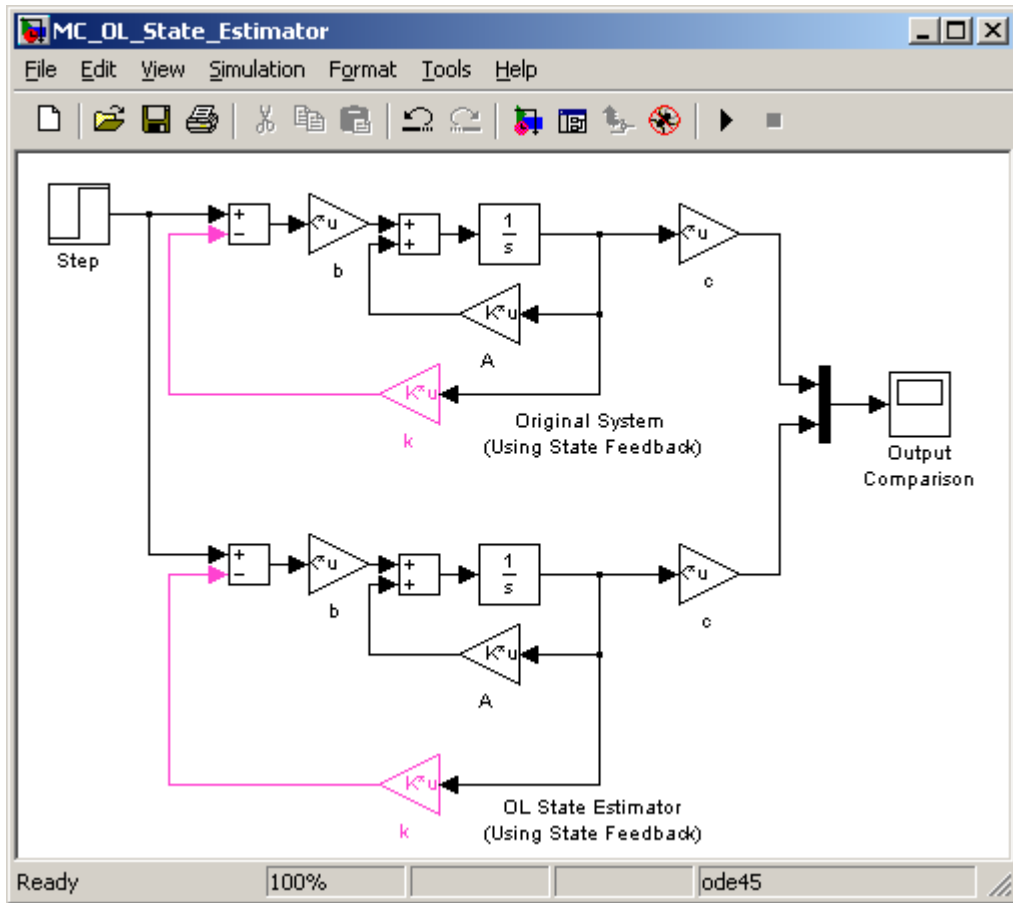
# Example 2: State Estimators



$$\underline{x}_0 = \begin{bmatrix} 0.2 \\ 1 \end{bmatrix}$$



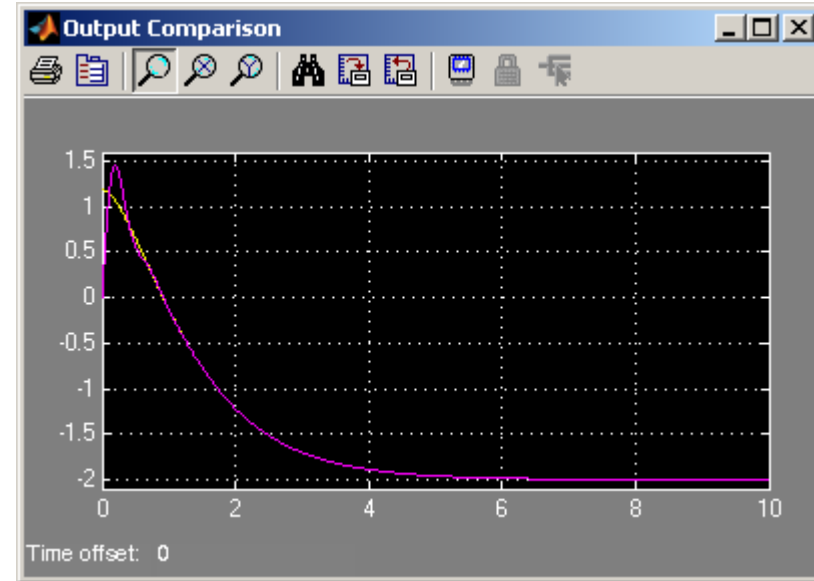
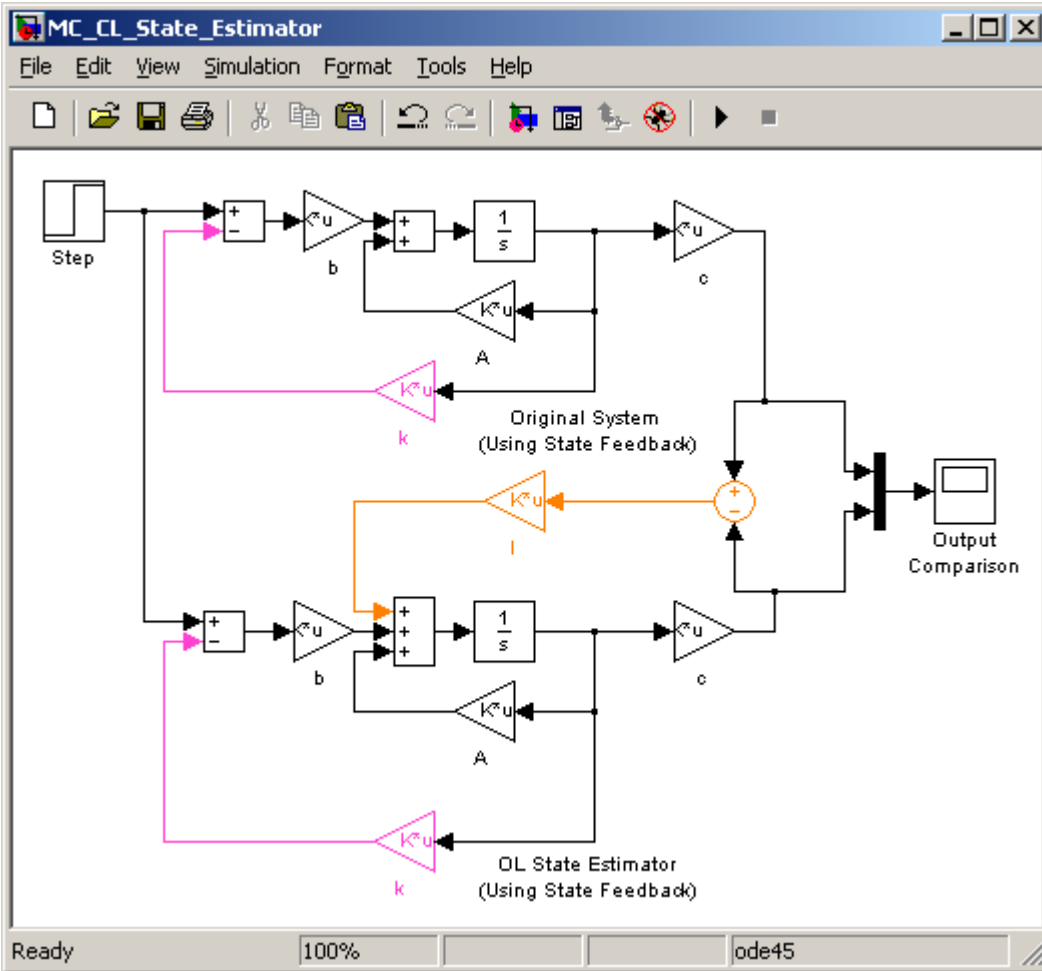
# Example 2: State Estimators



$$\underline{x}_0 = \begin{bmatrix} 0.2 \\ 1 \end{bmatrix}, \quad \hat{\underline{x}}_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

- If  $\hat{\underline{x}}_0 \neq \underline{x}_0$ , then for a certain amount of time there will be estimation error  $e = \underline{x} - \hat{\underline{x}}$ , which in the end will decay to zero
- For unstable system, the estimation error will increase,  $e \rightarrow \infty$ , no decay

# Example 2: State Estimators



- Although  $\hat{\mathbf{x}}_0 \neq \mathbf{x}_0$ , in shorter time the estimation error decays to zero
- Furthermore, in case a system is unstable, the estimation error  $e$  will also decay

$$\underline{\mathbf{x}}_0 = \begin{bmatrix} 0.2 \\ 1 \end{bmatrix}, \quad \hat{\underline{\mathbf{x}}}_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

# Homework 7: State Estimators

- (a) For the same system as discussed in Example 2, design another closed-loop state estimator, with eigenvalues at  $-3$  and  $-4$ .
- (b) Compare the performance of the estimator in the previous slides and the one you have designed. Do simulation using Matlab Simulink.
- (c) Give some explanations of the comparison results.

# Homework 7A: State Estimators

- (a) For the same system as discussed in Example 2, design another closed-loop state estimator, with eigenvalues at  $-0.5 \pm j1$ . This means, the eigenvalues of the estimator is to the right of those of the system, which is  $-1$  and  $-2$ .
- (b) Compare the performance of the estimator in the previous slides and the one you have designed. Do simulation using Matlab Simulink.
- (c) Give some explanations of the comparison results.

- Deadline: Wednesday, 5 November 2014.
- For Johnson, Rayhan, Kristiantho, and Anthony.

# Homework 7B: State Estimators

Consider a second order system.

$$\ddot{x} + 2\zeta\omega_n\dot{x} + \omega_n^2x = u$$

where  $u = 3 + 0.5 \sin(0.75t)$  is the input and  $x$  is the output,  $\zeta = 1$ ,  $\omega_n = 1$  rad/s. The initial states are  $x(0) = 2$ ,  $\dot{x}(0) = 1$ .

- (a) Design an observer with poles at  $-0.25$  and  $-0.5$ .
- (b) Perform simulation in Matlab Simulink and determine the time required by observer states to catch up with the actual system states.