

## 6.3100: Dynamic System Modeling and Control Design

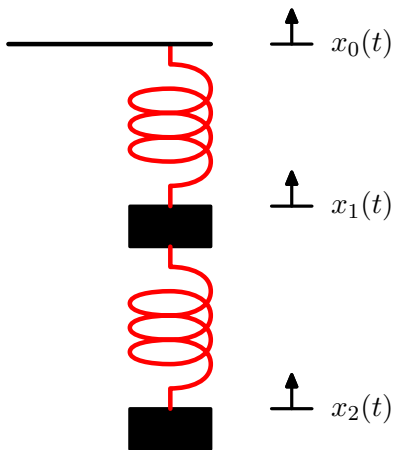
### Controlling a System with an Observer

*May 1, 2023*

## Two-Spring System

---

Last time, we developed classical and state-space controllers for a two-spring system.

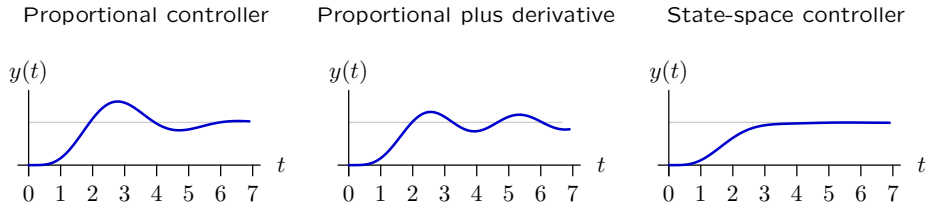


The goal was to move the input  $u(t) = x_0(t)$  so as to position the bottom mass  $y(t) = x_2(t)$  at some desired location  $y_d(t)$ .

## Comparison of Control Schemes

---

We found that the state-space control system allowed much better control of **overshoot** than the classical control systems.



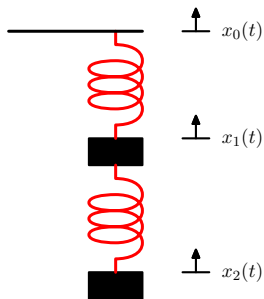
We reasoned that better performance resulted because the state-space controller has access to the motions of **both** masses.

We also outlined a framework for designing an **observer** to provide information about the motion of the center mass without actually measuring that motion.

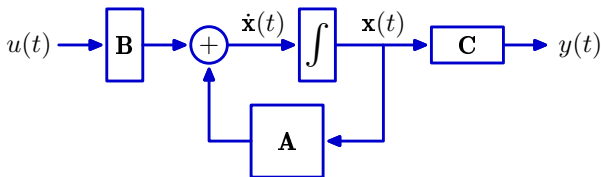
Today we will work through the **implementation** of this design.

## State-Space Model

To apply the state-space approach, we must express the equations of motion in the following matrix form.

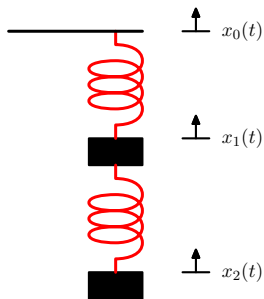


$$f_{m1} = m\ddot{x}_1(t) = k(x_0(t) - x_1(t)) - k(x_1(t) - x_2(t)) - b\dot{x}_1(t)$$
$$f_{m2} = m\ddot{x}_2(t) = k(x_1(t) - x_2(t)) - b\dot{x}_2(t)$$



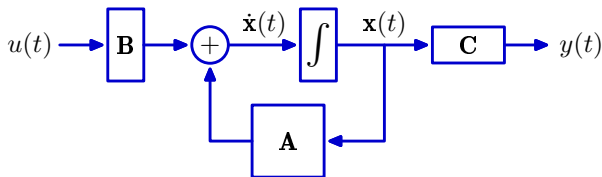
## Check Yourself

Find **A**, **B**, and **C**.



$$f_{m1} = m\ddot{x}_1(t) = k(x_0(t) - x_1(t)) - k(x_1(t) - x_2(t)) - b\dot{x}_1(t)$$

$$f_{m2} = m\ddot{x}_2(t) = k(x_1(t) - x_2(t)) - b\dot{x}_2(t)$$



## State-Space Description

---

Equations of motion:

$$f_{m1} = m\ddot{x}_1(t) = k(x_0(t) - x_1(t)) - k(x_1(t) - x_2(t)) - b\dot{x}_1(t)$$

$$f_{m2} = m\ddot{x}_2(t) = k(x_1(t) - x_2(t)) - b\dot{x}_2(t)$$

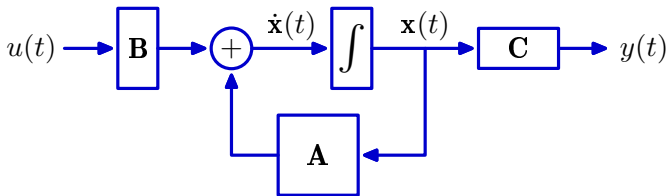
Four state variables (two displacements and their velocities):

$$\frac{d}{dt} \begin{bmatrix} v_1(t) \\ x_1(t) \\ v_2(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} -\frac{b}{m} & -\frac{2k}{m} & 0 & \frac{k}{m} \\ 1 & 0 & 0 & 0 \\ 0 & \frac{k}{m} & -\frac{b}{m} & -\frac{k}{m} \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v_1(t) \\ x_1(t) \\ v_2(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} \frac{k}{m} \\ 0 \\ 0 \\ 0 \end{bmatrix} x_0(t) - \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} g$$

$$y(t) = [0 \ 0 \ 0 \ 1] \begin{bmatrix} v_1(t) \\ x_1(t) \\ v_2(t) \\ x_2(t) \end{bmatrix}$$

## State-Space Model

To apply the state-space approach, we must express the equations of motion in the following matrix form.



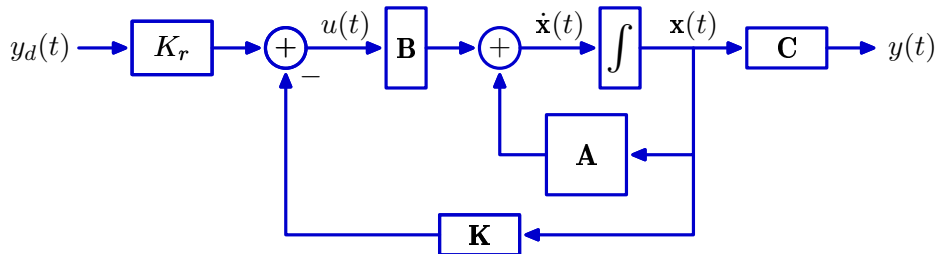
$$\mathbf{A} = \begin{bmatrix} -\frac{b}{m} & -\frac{2k}{m} & 0 & \frac{k}{m} \\ 1 & 0 & 0 & 0 \\ 0 & \frac{k}{m} & -\frac{b}{m} & -\frac{k}{m} \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} \frac{k}{m} \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad \mathbf{C} = [0 \ 0 \ 0 \ 1]$$

$$\mathbf{x}(t) = \begin{bmatrix} v_1(t) \\ x_1(t) \\ v_2(t) \\ x_2(t) \end{bmatrix} \quad u(t) = x_0(t) \quad y(t) = x_2(t)$$

## State-Space Controller

---

A state-space controller can then be expressed as follows.

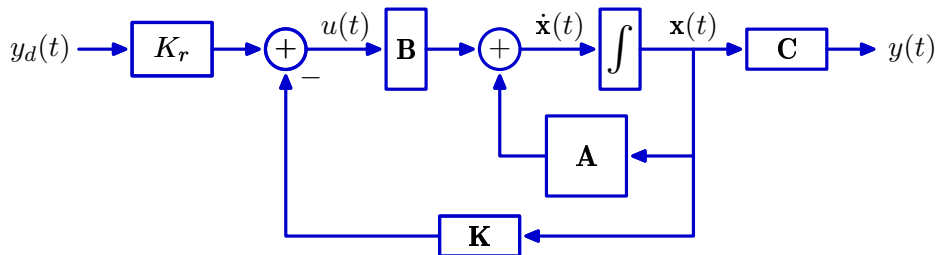


How do we find  $\mathbf{K}$  and  $K_r$ ?



## State-Space Controller

A state-space controller can then be expressed as follows.



We can find  $\mathbf{K}$  using pole placement:

$$\mathbf{K} = \text{place}(\mathbf{A}, \mathbf{B}, [\text{poles}])$$

or LQR:

$$\mathbf{Q} = \text{diag}([1, 1, 1, 1])$$

$$\mathbf{R} = 1$$

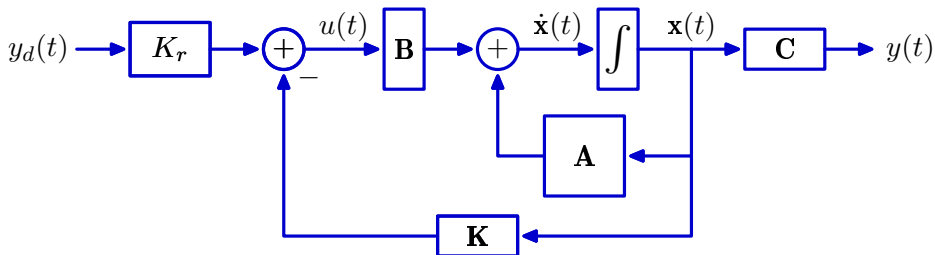
$$\mathbf{K} = \text{lqr}(\mathbf{A}, \mathbf{B}, \mathbf{Q}, \mathbf{R})$$

and

$$K_r = -1/(\mathbf{C} * ((\mathbf{A} - \mathbf{B}\mathbf{K}) \setminus \mathbf{B}))$$

## State-Space Controller

A state-space controller can then be expressed as follows.



We can find  $\mathbf{K}$  using pole placement:

$$\mathbf{K} = \text{place}(\mathbf{A}, \mathbf{B}, [\text{poles}])$$

or LQR:

$$\mathbf{Q} = \text{diag}([1, 1, 1, 1])$$

$$\mathbf{R} = 1$$

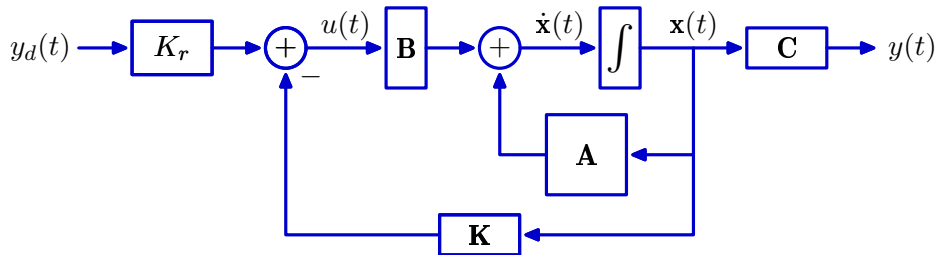
$$\mathbf{K} = \text{lqr}(\mathbf{A}, \mathbf{B}, \mathbf{Q}, \mathbf{R})$$

and

$$\mathbf{K}_r = -1/(\mathbf{C} * ((\mathbf{A} - \mathbf{B}\mathbf{K}) \setminus \mathbf{B})) \quad \leftarrow \text{where does this come from?}$$

## State-Space Controller

Assume that we will implement the controller with a microprocessor.



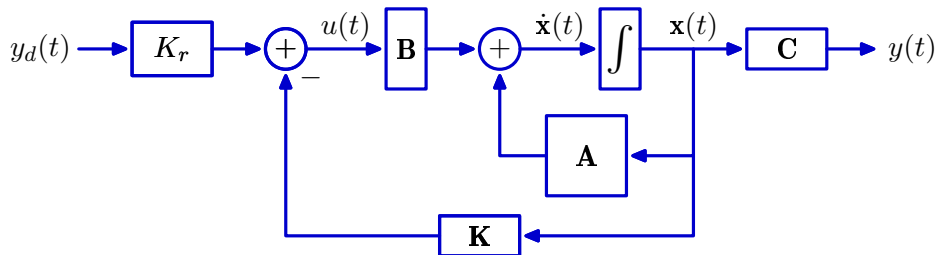
Express the controller algorithm in pseudo-code.

Assume that the step function (below) is executed once every  $\Delta T$  seconds.

```
void step(){
    PUT YOUR CODE HERE
}
```

## State-Space Controller

Assume that we will implement the controller with a microprocessor.



Express the controller algorithm in pseudo-code.

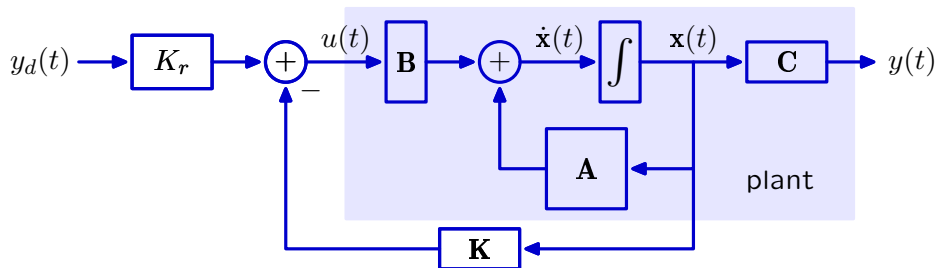
Assume that the step function (below) is executed once every  $\Delta T$  seconds.

```
void step(){
    v1,x1,v2,x2 = get_state_x();
    put_command_u(Kr*yd - (K1*v1 + K2*x1 + K3*v2 + K4*x2));
}
```

Where are **A**, **B**, and **C**? Shouldn't the controller need these?

## State-Space Controller

Assume that we will implement the controller with a microprocessor.



Where are  $A$ ,  $B$  and  $C$ ?

$A$ ,  $B$  and  $C$  are components of our model of the plant (blue shading above). They are used to design  $K$  and  $K_r$ , but do not appear explicitly in a simple state-space controller.

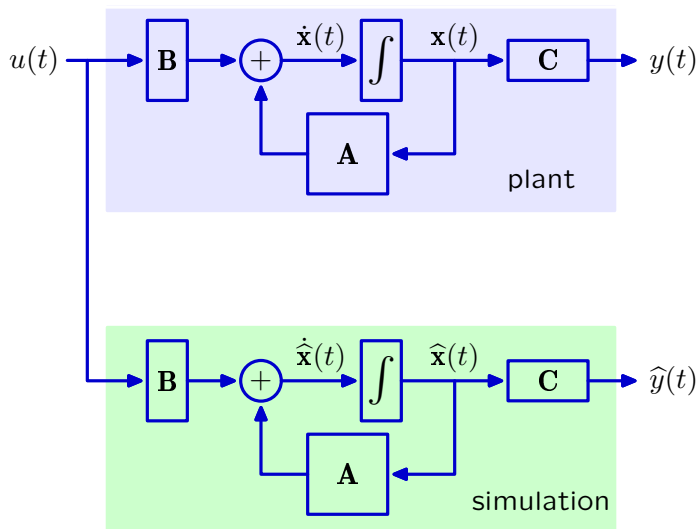
## Observers

---

By contrast, observer-based controllers **explicitly** depend on **A**, **B**, and **C**.

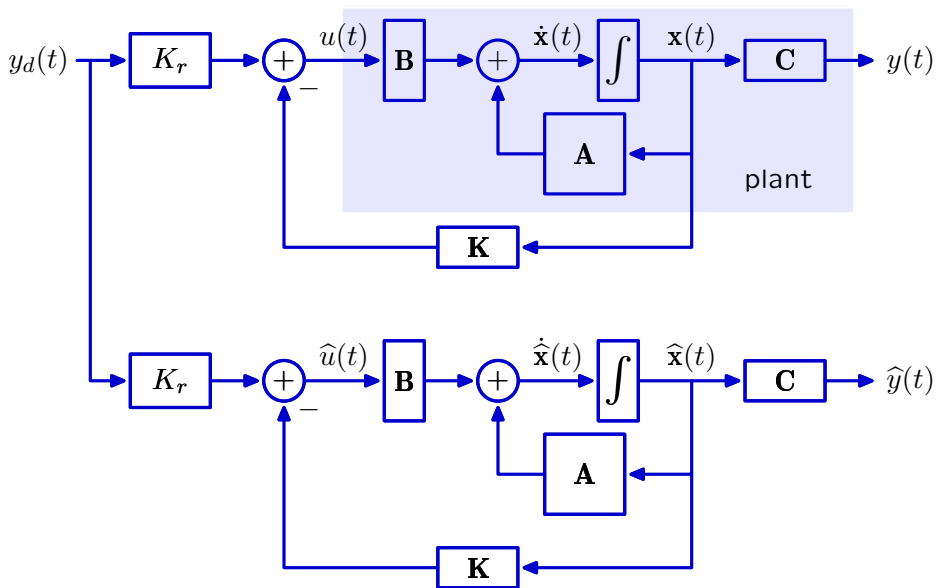
## Observers (Recap)

An **observer** is a **simulation** of the plant that is used by the controller – i.e., the simulation is part of the controller!



## Observers (Recap)

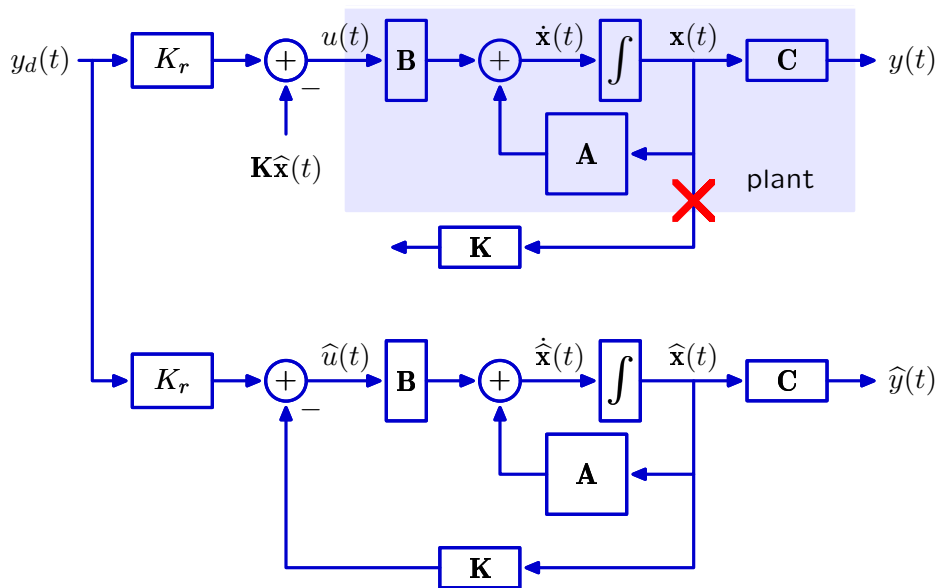
We can build state-space controllers for both the plant and the simulation.





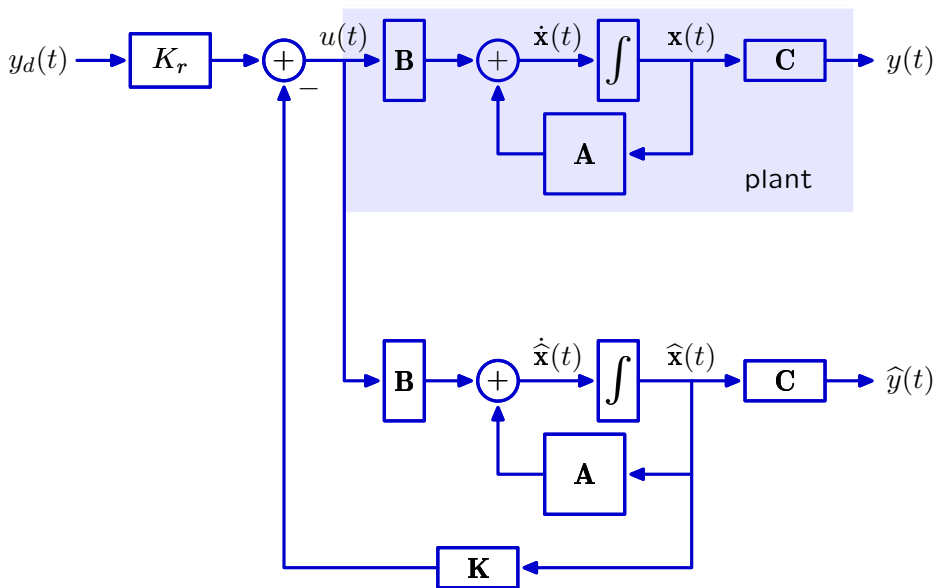
## Observers (Recap)

If our model of the plant ( $\mathbf{A}$ ,  $\mathbf{B}$ ,  $\mathbf{C}$ ) is perfect, then  $\hat{\mathbf{x}}(t) = \mathbf{x}(t)$  and we can replace  $\mathbf{K}\mathbf{x}(t)$  with  $\mathbf{K}\hat{\mathbf{x}}(t)$ . This substitution also makes  $u(t) = \hat{u}(t)$ .



## Observers (Recap)

The resulting structure provides feedback from all **simulated** states  $\hat{\mathbf{x}}(t)$ . Unfortunately even small differences between the plant and simulation can lead to large differences between  $\mathbf{x}(t)$  and  $\hat{\mathbf{x}}(t)$ .

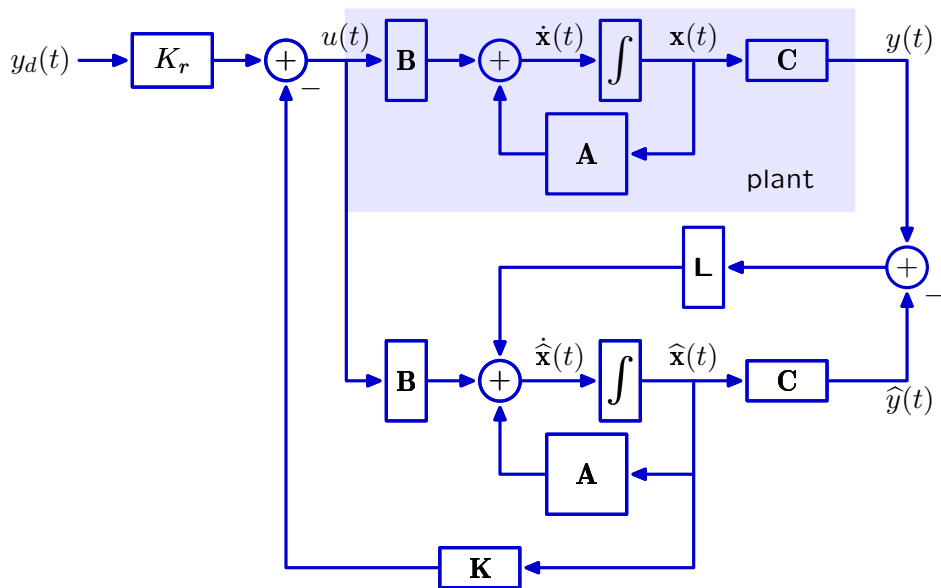


## Observers (Recap)

Fortunately, we can use **feedback** to correct simulation errors!

Calculate the difference between  $y(t)$  and  $\hat{y}(t)$ .

Then use that signal (times  $\mathbf{L}$ ) to correct  $\hat{\mathbf{x}}(t)$ .



## Observers (Recap)

---

Dynamics:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) - \mathbf{BK}\hat{\mathbf{x}}(t) + \mathbf{B}K_r y_d(t)$$

$$\dot{\hat{\mathbf{x}}}(t) = \mathbf{A}\hat{\mathbf{x}}(t) - \mathbf{BK}\hat{\mathbf{x}}(t) + \mathbf{B}K_r y_d(t) + \mathbf{L}\left(y(t) - \hat{y}(t)\right)$$

Matrix form:

$$\begin{bmatrix} \dot{\mathbf{x}}(t) \\ \dot{\hat{\mathbf{x}}}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{A} & -\mathbf{BK} \\ \mathbf{LC} & \mathbf{A}-\mathbf{LC}-\mathbf{BK} \end{bmatrix} \begin{bmatrix} \mathbf{x}(t) \\ \hat{\mathbf{x}}(t) \end{bmatrix} + \begin{bmatrix} \mathbf{B} \\ \mathbf{B} \end{bmatrix} K_r y_d(t)$$

$$y(t) = [\mathbf{C} \quad \mathbf{0}] \begin{bmatrix} \mathbf{x}(t) \\ \hat{\mathbf{x}}(t) \end{bmatrix}$$

Choose  $\mathbf{K}$  to optimize the eigenvalues of  $\mathbf{A} - \mathbf{BK}$ .

Choose  $\mathbf{L}$  to optimize the eigenvalues of  $\mathbf{A}^T - \mathbf{C}^T \mathbf{L}^T$ .

`K = place(A,B,[poles])`

`L = place(A.',C.',[poles]).'`

or

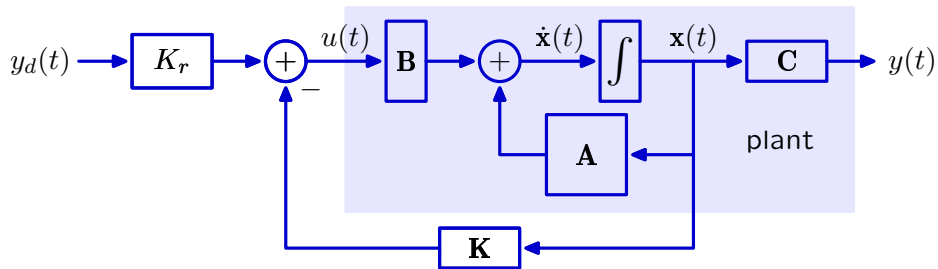
`K = lqr(A,B,Q,R)`

`L = lqr(A.',C.',Q,R).'`

## Noise Performance

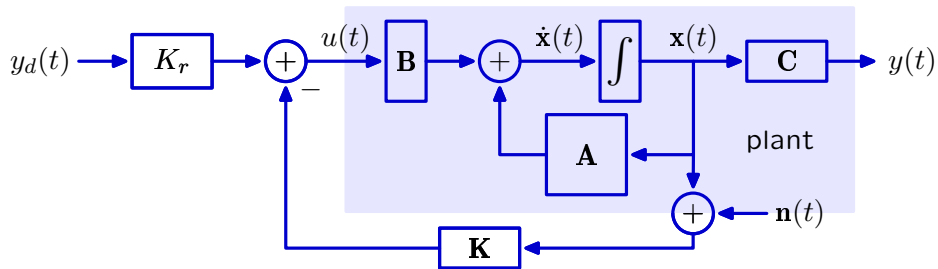
Feedback control can be significantly degraded by noise that is introduced by the sensors that provide information about the plant to the controller.

Suggest a model for the effects of sensor noise on the following state-space control system. Assume that sensor noise is additive.



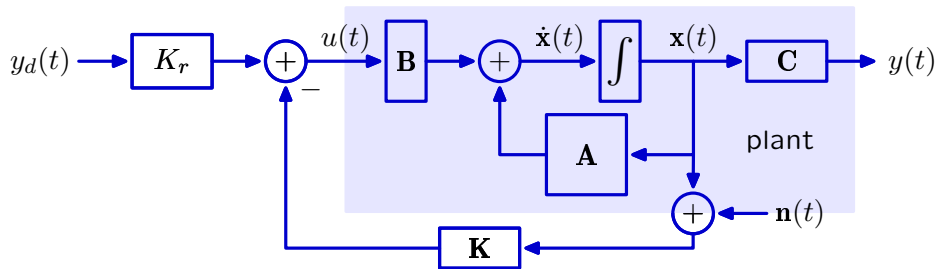
## Effects of Sensor Noise

Sensor noise can contaminate each of the state measurements.



## Effects of Sensor Noise

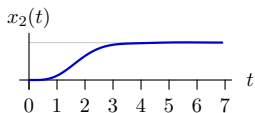
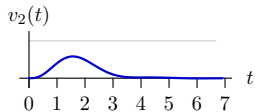
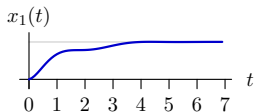
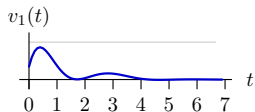
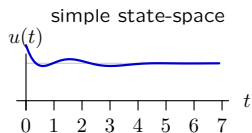
How will this noise affect performance of the control system?



# Results 1

---

Compare with additive noise: amplitude = 0

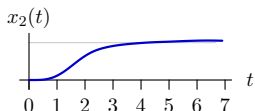
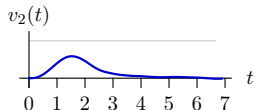
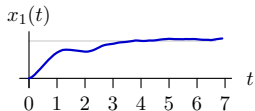
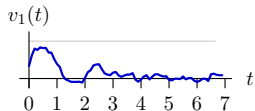
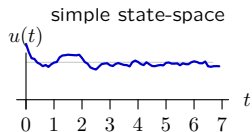




## Results 2

---

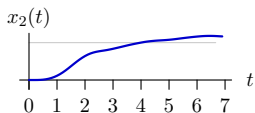
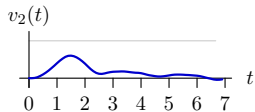
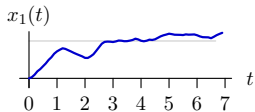
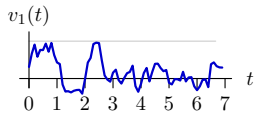
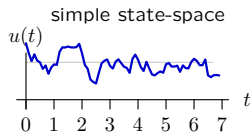
Compare with additive noise: amplitude = 0.3



## Results 3

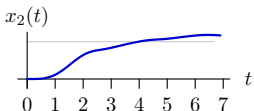
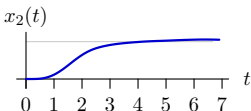
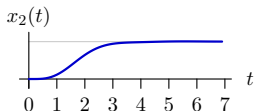
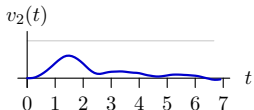
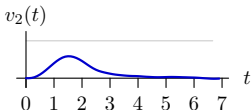
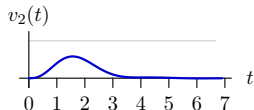
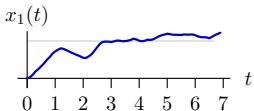
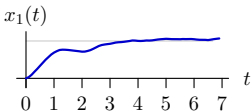
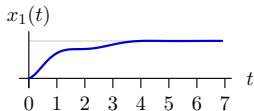
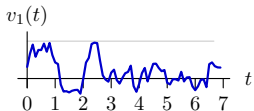
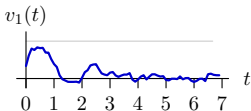
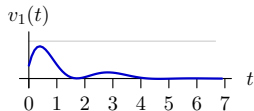
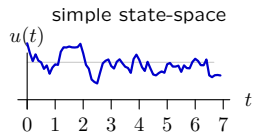
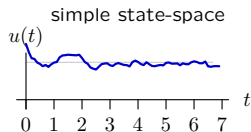
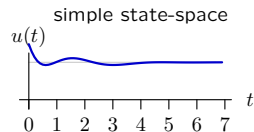
---

Compare with additive noise: amplitude = 1



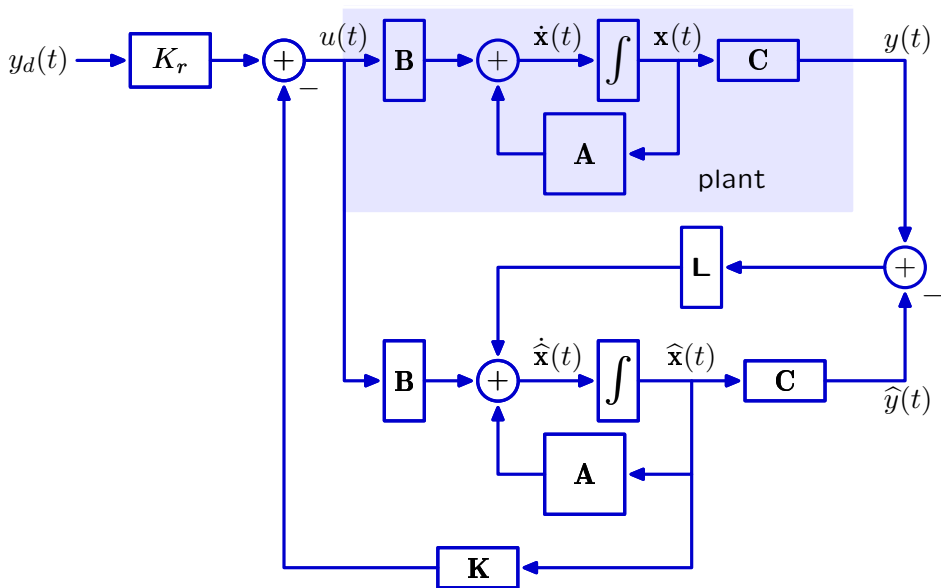
## Results 4

Additive noise: 0, 0.3, and 1:



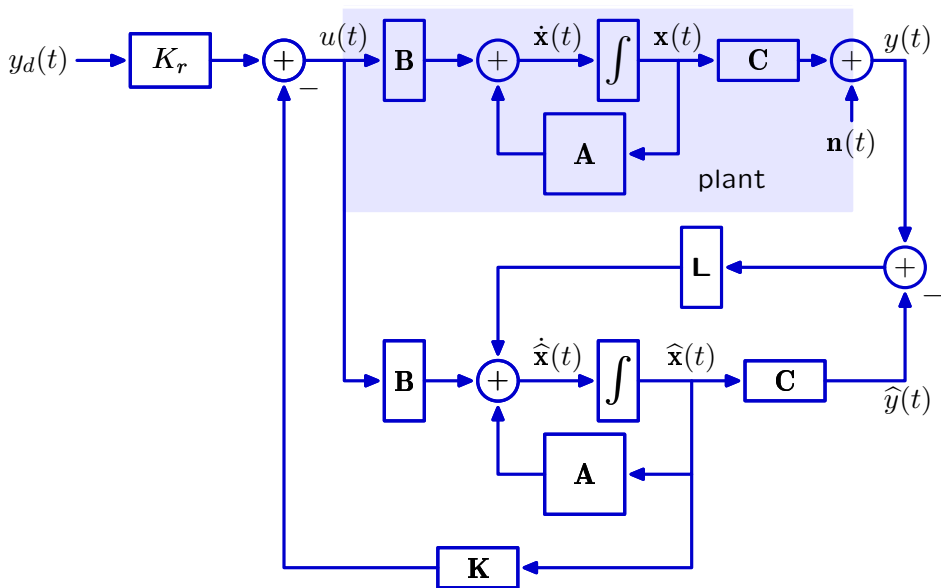
## Effects of Sensor Noise

How should we model sensor noise with an observer?



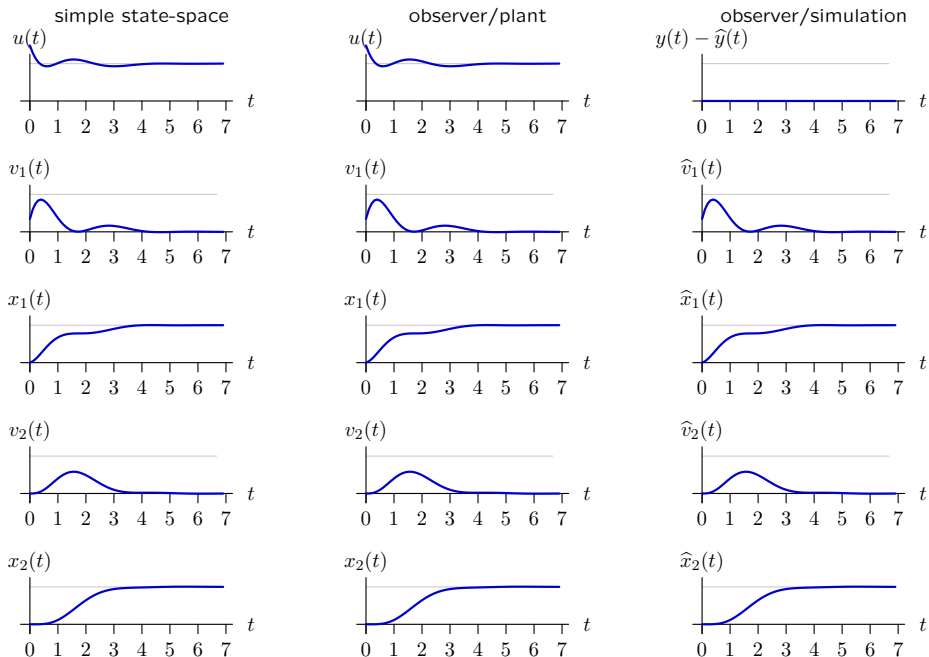
## Effects of Sensor Noise

How will this noise affect performance of the control system?



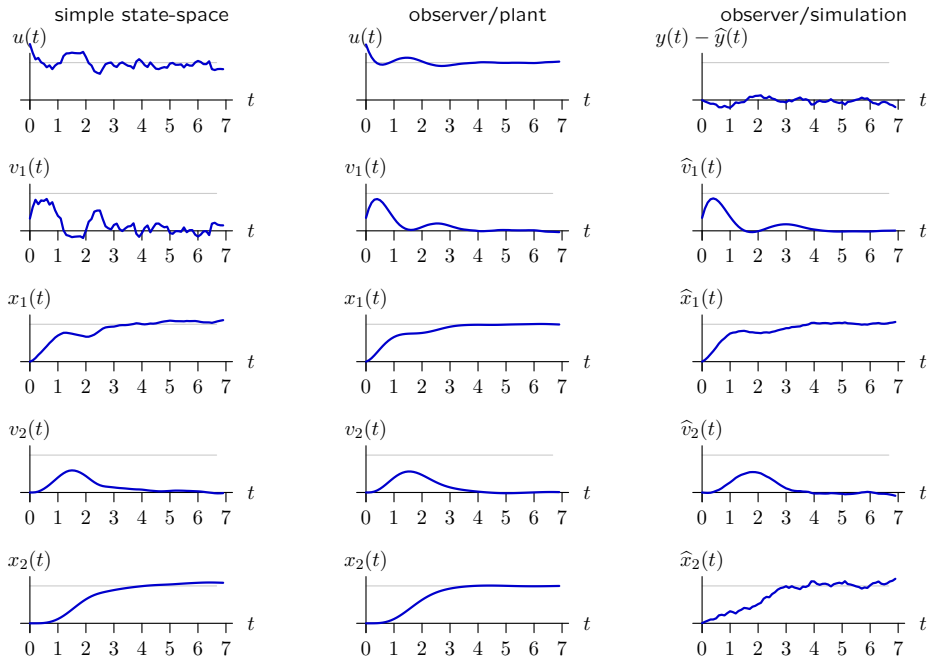
## Results 5

Compare a simple state-space controller with an observer-based controller.



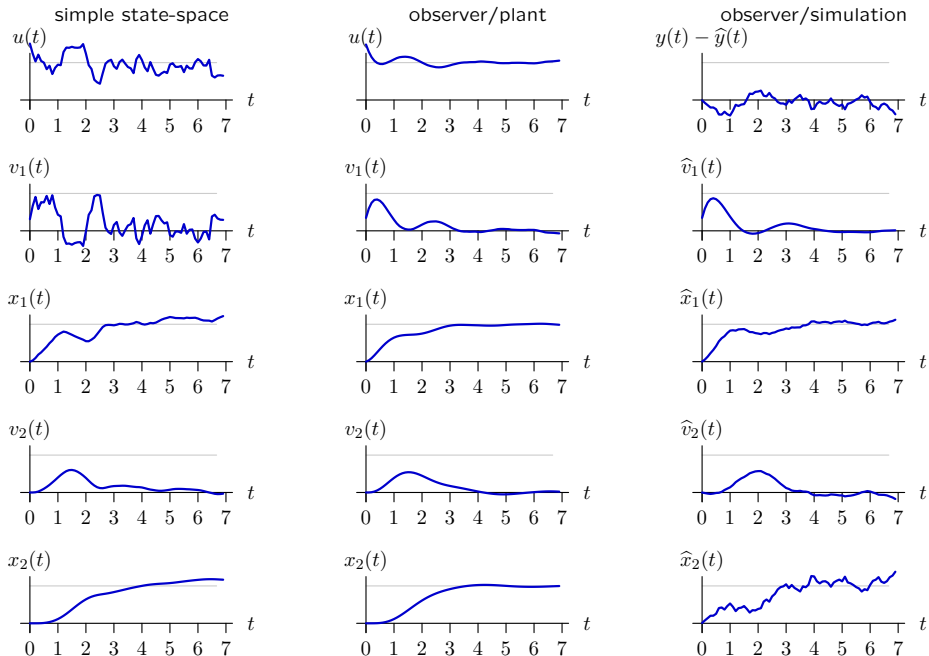
## Results 6

Compare a simple state-space controller with an observer-based controller.



## Results 7

Compare a simple state-space controller with an observer-based controller.





## Effects of Sensor Noise

How will this noise affect performance of the control system?

