



# Mechatronics

Week 5 Day 1



# Previous week

We studied

- sampling and discretization
- transformations from  $s$ -plane to  $z$ -plane
- obtaining transfer function of discrete-time system represented by a difference equation
- stability of discrete-time systems
- digital control systems



Today's lecture:

# Optimal Controller Design

The Linear Quadratic Regulator (LQR)



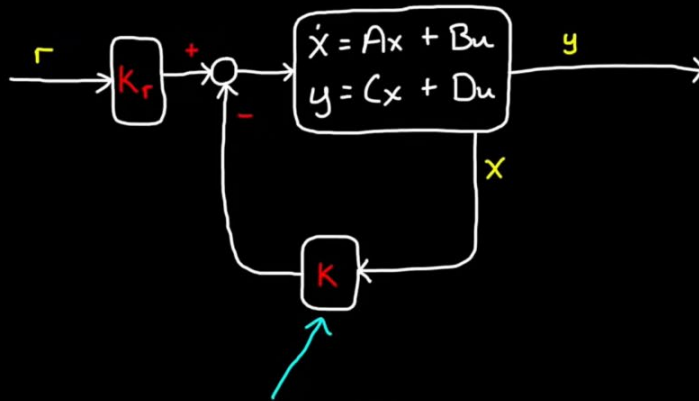
# Learning objectives

After today's lecture, you will be able to

- Design an **optimal controller** via the linear quadratic regulator method (**LQR**)

# Pole Placement vs LQR Method

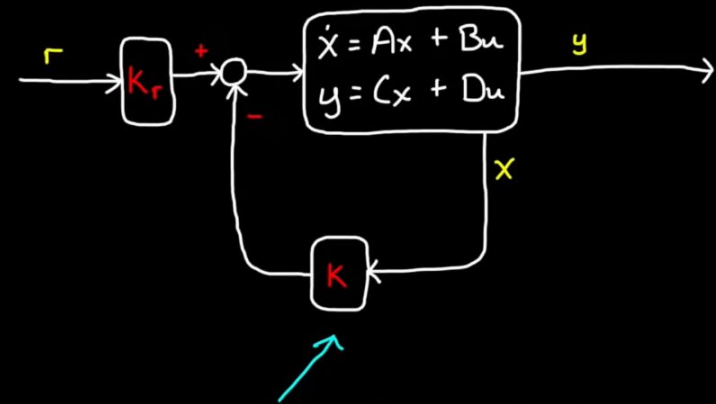
Pole placement  
full state feedback



Solve for  $K$  by choosing  
pole locations

not terribly intuitive

LQR  
full state feedback



Find the optimal  $K$  by  
choosing characteristics

performance & effort



# LQR Method

Initial State



What is optimal?



Desired State



time/trip

\$/trip



20 min

\$7



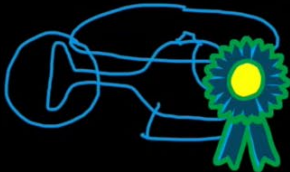
75 min

\$0



30 min

\$2



4 min

\$400

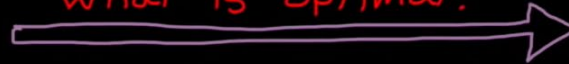


# LQR Method

Initial State



What is optimal?



Desired State



time/trip

\$/trip



20 min

\$ 7



75 min

\$ 0



30 min

\$ 2



4 min

\$ 400



# LQR Method

Initial State







What is optimal?



Desired State



$$J = Q \cdot \text{time} + R \cdot \$$$

	<u>Q</u>	<u>time/trip</u>	<u>R</u>	<u>\$/trip</u>	<u>J(cost)</u>
	2	20 min	10	\$7	= 110
	2	75 min	10	\$0	= 150
	2	30 min	10	\$2	= 80
	2	4 min	10	\$400	= 4008



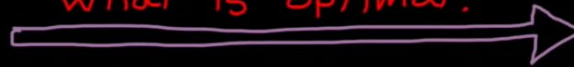


# LQR Method

Initial State



What is optimal?



Desired State



$$J = Q \cdot \text{time} + R \cdot \$$$



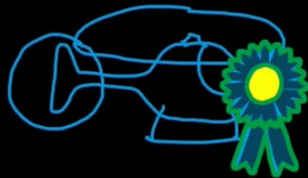
<u>Q</u>	<u>time/trip</u>	<u>R</u>	<u>\$/trip</u>	<u>J(cost)</u>
30	20 min	+	1 · \$7	= 627



30	75 min	+	1 · \$0	= 2250
----	--------	---	---------	--------



30	30 min	+	1 · \$2	= 932
----	--------	---	---------	-------



30	4 min	+	1 · \$400	= 520
----	-------	---	-----------	-------





# LQR Method

For a given state space equation  $\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases}$



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$$u = -Kx$$

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where the gain  $K$  is to be designed such that

- the **closed loop system**  $\dot{x} = (A - BK)x$  is **asymptotically stable**

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The LQR problem aims to **assign a state feedback**

$$u = -Kx,$$

where the gain  $K$  is to be designed such that

- the **closed loop system**  $\dot{x} = (A - BK)x$  is **asymptotically stable**
- it **optimizes** the **cost function**

$$J(x(0)) = \min_u \int_0^{\infty} x^T(\tau)Qx(\tau) + u^T(\tau)Ru(\tau)d\tau,$$

where  $Q$  and  $R$  are symmetric positive definite, i.e.,  $Q = Q^T > 0$  and  $R = R^T > 0$ .

# LQR Method

Remember the system  $\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases}$  with controller  
 $u = -Kx$

and cost function

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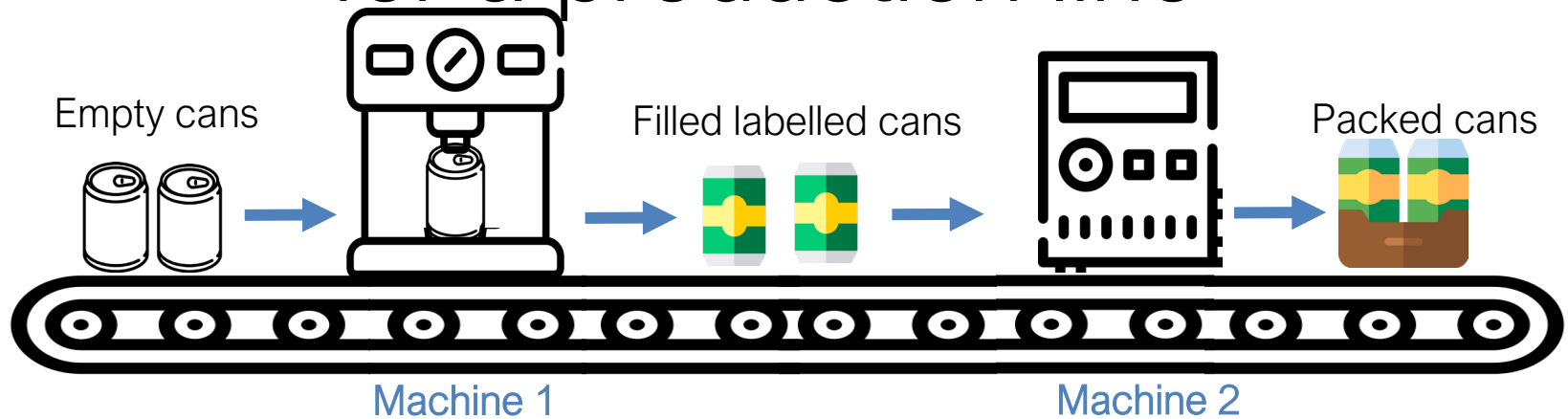
The **solution** to the LQR problem is given by

$$u = \underbrace{-R^{-1}B^T P x}_K,$$




where  **$P$**  is a **symmetric positive definite matrix** ( $P = P^T > 0$ ) that is solution to the algebraic **Riccati equation** (ARE)

$$A^T P + PA - PBR^{-1}B^T P + Q = 0.$$

# Example: Optimal controller design for a production line

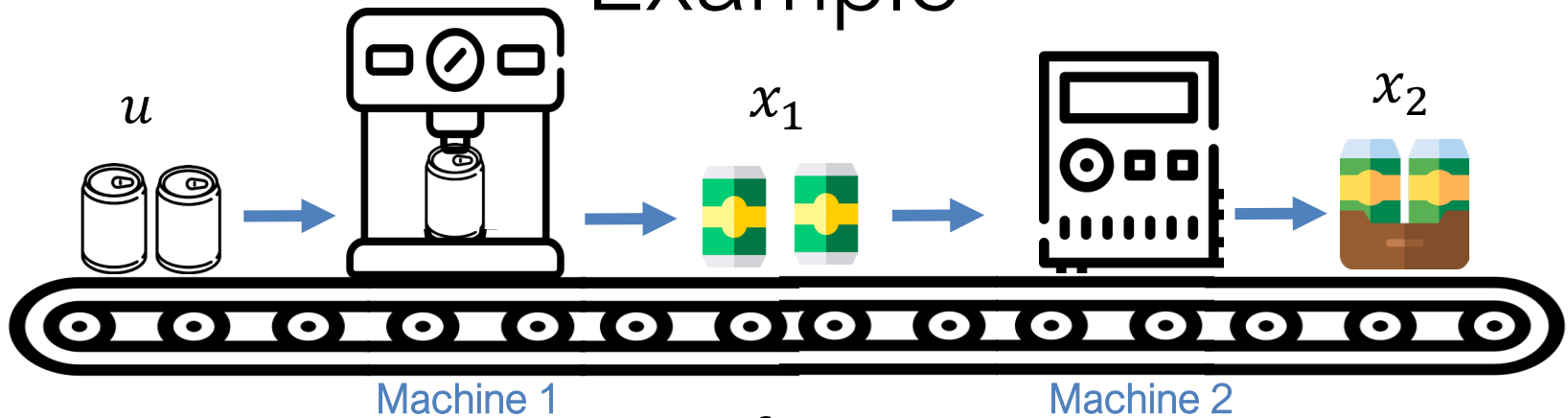


Consider the production line for cans, where

- $u$  is the number of **raw material** (empty unlabelled cans) ,
- $x_1$  is the number of **intermediate product** (filled labelled cans) ,
- $x_2$  is the number of **final product** (can packs) ,
- $r$  is the **demand** (reference signal)



# Example

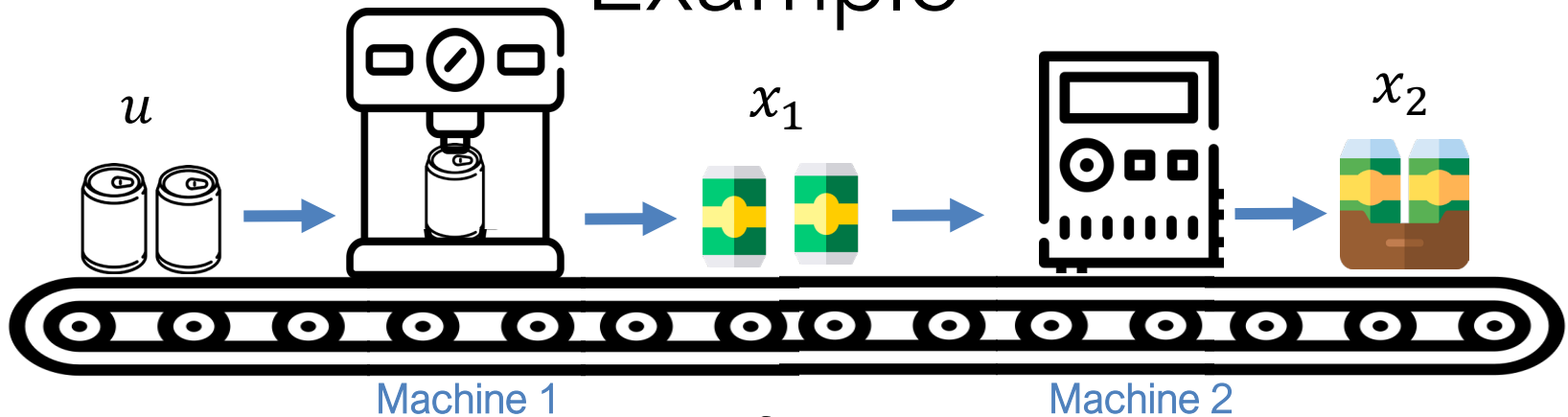


$r$  reference

For maintaining occupancy of machine 2, the **rate of production** of **machine 1**  $\dot{x}_1$  has to be **regulated by**  $u$

$$\dot{x}_1 = -10x_1 - 11x_2 + u$$

# Example



$r$  reference

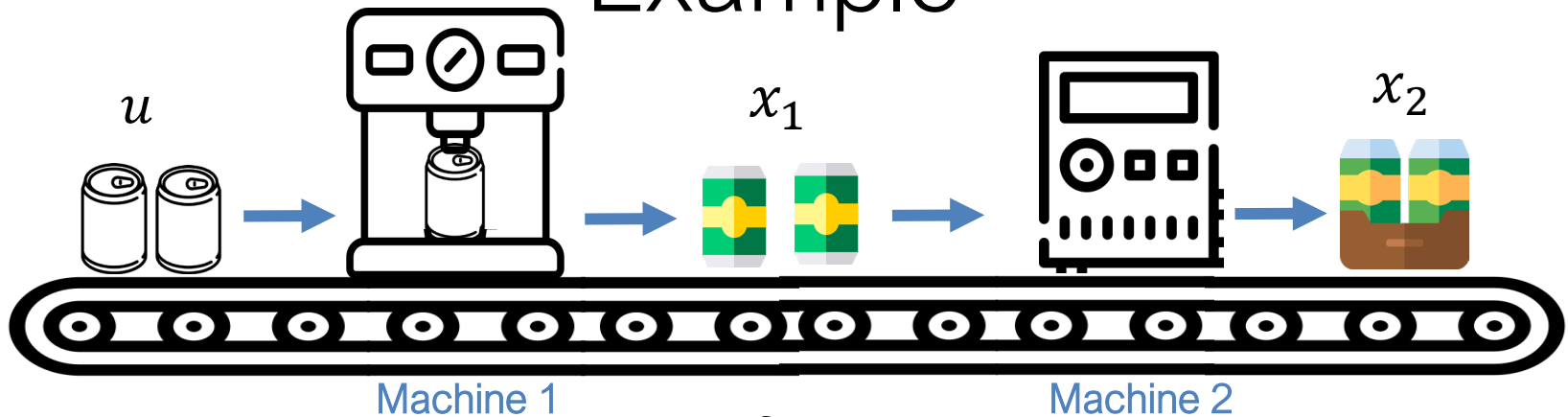
For maintaining occupancy of machine 2, the **rate of production** of **machine 1**  $\dot{x}_1$  has to be **regulated by**  $u$

$$\dot{x}_1 = -10x_1 - 11x_2 + u$$

The **rate of production** of **machine 2**  $\dot{x}_2$  is proportional to the intermediate product

$$\dot{x}_2 = x_1$$

# Example



$r$  reference

Then, with equations  $\dot{x}_1 = -10x_1 - 11x_2 + u$  and  $\dot{x}_2 = x_1$  we can build a **state-space representation**:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} -10 & -11 \\ 1 & 0 \end{bmatrix}}_A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix}}_B u$$

$$y(t) = \underbrace{[0 \quad 1]}_C \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad D = 0,$$

considering the number of final products  $x_2$  as **output**.

# Example

For the given state-space

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} -10 & -11 \\ 1 & 0 \end{bmatrix}}_A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix}}_B u$$

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$$y(t) = \underbrace{[0 \quad 1]}_C \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, D = 0.$$

**LQR Problem:** Find a **regulator**  $u$  in order to control the production such that it **meets** the **demand**  $r$  in an **optimal** manner, i.e.,

1. Optimise **cost function**  $J(x(0)) = \int_0^\infty x^T(\tau) Q x(\tau) + u^T(\tau) R u(\tau) d\tau$ ,

where  $Q = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$  and  $R = 5$  ( $u$  is scalar)

2. Make sure that the system is **asymptotically stable**



# Example

Step 1. Optimise **cost function**

Cost function given by  $J(x(0)) = \int_0^\infty x^T(\tau) Q x(\tau) + u^T(\tau) R u(\tau) d\tau$ ,

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$$J = \int_0^\infty x_1^2 + 2x_2^2 + 5u^2 d\tau$$

# Example

## Step 1. Optimise **cost function**

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Discrepancy in  
production in  
machine 1

Discrepancy in  
production in  
machine 2

Discrepancy in  
supply

**Intuitive meaning:** discrepancy in **machine 2** is **costlier** than machine 1. Discrepancy in **supply** is even **costlier** than the machines





# Example

Step 1. Optimise **cost function**

$$J = \int_0^{\infty} x_1^2 + 2x_2^2 + 5u^2 d\tau$$

**How to optimise?**

There exists a  $u = -Kx$  that will optimise the cost function.

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According to LQR theory

- We first need to solve the following **Ricatti equation**

$$A^T P + PA - PBR^{-1}B^T P + Q = 0$$

for a matrix  $P$  which is symmetric positive definite ( $P = P^T > 0$ ).

Note that  $A, B$  are known from state space; and  $Q$  and  $R$  are known from the cost function.

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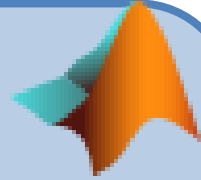
Note that  $A, B$  are known from state space; and  $Q$  and  $R$  are known from the cost function.

- After **solving the Ricatti equation** for  $P$  we can find  $K = R^{-1}B^T P$ , so that  $u = -Kx$  will optimise the cost function



# Example

Step 1. Optimise cost function. Solving Ricatti equation

A decorative graphic consisting of a blue and orange 3D shape, resembling a stylized arrow or a corner piece, located in the top right corner of the light blue note box.

**Note:** In Matlab, you can use command **lqr** to directly solve the Ricatti equation for  $P$ .



# Example

Step 1. Optimise cost function. Solving Ricatti equation  
Manually:

Choose  $P = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}$ , symmetric  $P_{12} = P_{21}$

# Example

Step 1. Optimise cost function. Solving Ricatti equation  
Manually:

Choose  $P = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}$ , symmetric  $P_{12} = P_{21}$

Then  $A^T P + PA - PBR^{-1}B^T P + Q = 0$  becomes

$$\underbrace{\begin{bmatrix} -10 & 1 \\ -11 & 0 \end{bmatrix}}_{A^T} \underbrace{\begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}}_P + \underbrace{\begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}}_P \underbrace{\begin{bmatrix} -10 & -11 \\ 1 & 0 \end{bmatrix}}_A$$
$$- \underbrace{\begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}}_P \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix} \frac{1}{5} \begin{bmatrix} 1 & 0 \end{bmatrix}}_{\underbrace{B R^{-1} B^T}} \underbrace{\begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}}_P + \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}}_Q = 0$$
$$\frac{1}{5} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$

# Example

Step 1. Optimise **cost function**. Solving Ricatti equation

Performing matrix multiplications:

$$\begin{bmatrix} -10P_{11} + P_{12} & -10P_{12} + P_{22} \\ -11P_{11} & -11P_{12} \end{bmatrix} + \begin{bmatrix} -10P_{11} + P_{12} & -11P_{11} \\ -10P_{12} + P_{22} & -11P_{12} \end{bmatrix} \\ -\frac{1}{5} \begin{bmatrix} P_{11}^2 & P_{11}P_{12} \\ P_{11}P_{12} & P_{12}^2 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

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Step 1. Optimise cost function. Solving Ricatti equation

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which gives the system of equations

$$\begin{cases} -20P_{11} + 2P_{12} - \frac{1}{5}P_{11}^2 + 1 = 0 \\ -10P_{12} + P_{22} - 11P_{11} - \frac{1}{5}P_{11}P_{12} = 0 \\ -22P_{12} - \frac{1}{5}P_{12}^2 + 2 = 0 \end{cases}$$

# Example

Step 1. Optimise **cost function**. **Solving Ricatti equation**

The system of equations is solved getting expressions for  $P_{11}$ ,  $P_{12}$ ,  $P_{22}$

$$\begin{cases} -\frac{1}{5}P_{11}^2 - 20P_{11} + 2P_{12} + 1 = 0 & (1) \\ -\frac{1}{5}P_{11}P_{12} - 10P_{12} + P_{22} - 11P_{11} = 0 & (2) \\ -\frac{1}{5}P_{12}^2 - 22P_{12} + 2 = 0 & (3) \end{cases}$$

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From (3),  $P_{12} = -\frac{22}{2/5} \pm \frac{\sqrt{22^2 + 8/5}}{2/5}$

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$$\text{From (3), } P_{12} = -\frac{22}{2/5} \pm \frac{\sqrt{22^2 + 8/5}}{2/5}$$

$$\text{From (1), } P_{11} = -\frac{20}{2/5} \pm \frac{\sqrt{20^2 + 4/5(2P_{12} + 1)}}{2/5}$$

# Example

Step 1. Optimise **cost function**. **Solving Ricatti equation**

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$$\text{From (3), } P_{12} = -\frac{22}{2/5} \pm \frac{\sqrt{22^2 + 8/5}}{2/5}$$

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$$\text{From (2), } P_{22} = \frac{1}{5}P_{11}P_{12} + 10P_{12} + 11P_{11}$$

# Example

Step 1. Optimise cost function. Solving Ricatti equation

There are multiple solution combinations for the system of equations

We need to look for the solution (trial and error) that:

- Makes all entries  $P_{11}$ ,  $P_{12}$ ,  $P_{22}$  real
- Makes  $P$  positive definite

- $P_{11} > 0$

- $P_{22} > 0$

# Example

Step 1. Optimise **cost function**. **Solving Ricatti equation**

There are **multiple solution combinations** for the system of equations

We need to look for the solution (**trial and error**) that:

- Makes **all entries  $P_{11}$ ,  $P_{12}$ ,  $P_{22}$  real**
- Makes  **$P$  positive definite**
  - $P_{11} > 0$
  - $P_{22} > 0$

That solution for the Ricatti equation is

$$P_{12} \approx 0.0908; P_{11} \approx 0.0590; P_{22} \approx 1.5581$$



# Example

Step 1. Optimise **cost function**. **Building optimal controller**

With **solution** for the Ricatti equation:

$$P = \begin{bmatrix} 0.0590 & 0.0908 \\ 0.0908 & 1.5581 \end{bmatrix}$$



# Example

Step 1. Optimise **cost function**. **Building optimal controller**

With **solution** for the Ricatti equation

$$P = \begin{bmatrix} 0.0590 & 0.0908 \\ 0.0908 & 1.5581 \end{bmatrix},$$

we can **build**  $u = -Kx$  that optimises  $J$ , using gain  $K = R^{-1}B^T P$

$$u = -\underbrace{\frac{1}{5}}_{R^{-1}} \underbrace{[1 \quad 0]}_{B^T} \underbrace{\begin{bmatrix} 0.0590 & 0.0908 \\ 0.0908 & 1.5581 \end{bmatrix}}_P \underbrace{\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}}_x$$

$K$

# Example

Step 1. Optimise **cost function**. **Building optimal controller**

With **solution** for the Ricatti equation:

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we can **build**  $u = -Kx$  that optimises  $J$ , using gain  $K = R^{-1}B^T P$

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$K$

$u = -0.012x_1 - 0.02x_2$  **optimises  $J$**



# Example

Step 2. Make sure that the system is **asymptotically stable**

$$\dot{x} = Ax + Bu \text{ with } u = -K\tilde{x} \text{ yields}$$

$$\dot{x} = (A - BK)x$$

So  $(A - BK)$  should be **Hurwitz** or asymptotically stable

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Lets compute  $(A - BK)$

$$(A - BK) = \begin{bmatrix} -10 & -11 \\ 1 & 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \end{bmatrix} [0.012 \quad 0.02] = \begin{bmatrix} -10.012 & -11.020 \\ 1 & 0 \end{bmatrix}$$

# Example

Step 2. Make sure that the system is **asymptotically stable**

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Now to obtain eigenvalues we get the **characteristic equation**

$$|\lambda I - (A - BK)| = \begin{vmatrix} \lambda + 10.012 & 11.02 \\ -1 & \lambda \end{vmatrix} = \lambda^2 + 10.012\lambda + 11.02$$

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Step 2. Make sure that the system is **asymptotically stable**

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Now to obtain eigenvalues we get the **characteristic equation**

$$|\lambda I - (A - BK)| = \begin{vmatrix} \lambda + 10.012 & 11.02 \\ -1 & \lambda \end{vmatrix} = \lambda^2 + 10.012\lambda + 11.02$$

Solving for  $\lambda$

$$\lambda_{1,2} = -\frac{10.012}{2} \pm \frac{1}{2} \sqrt{10.012^2 - 4(11.020)}$$

Since  $\lambda_{1,2} < 0$  the system is **asymptotically stable**



# Proof

How do we know solution to Riccati equation optimises cost function?



# Proof

How do we know solution to Riccati equation optimises cost function?

Step 1. Consider the cost function

$$J(x(t)) = \frac{1}{2} \int_t^{\infty} x^T(\tau) Q x(\tau) + u^T(\tau) R u(\tau) d\tau$$

It will be optimised by the solution where the derivative is minimised ( $\frac{d}{dt} J(x(t)) = 0$ )





# Proof

How do we know solution to Riccati equation optimises cost function?

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$$\frac{d}{dt}J(x(t)) = \left( \frac{d}{dx}J(x(t)) \right)^T \dot{x} = \left( \frac{d}{dx}J(x(t)) \right)^T (Ax + Bu)$$

we can write:

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Step 6. Let us take a **guess solution** for a linear system

$$J(x) = \frac{1}{2}x^T Px, \text{ where } P = P^T > 0 \Rightarrow \frac{dJ}{dx}(x) = Px$$

Then we can write the equation as

$$x^T P(Ax + Bu) + \frac{1}{2}x^T Qx + \frac{1}{2}u^T Ru = 0$$

or

$$x^T P A x + \frac{1}{2}x^T Q x + \frac{1}{2}u^T R u + x^T P B u = 0$$

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Step 7. Using the **completion of squares**

$$x^T PAx + \frac{1}{2}x^T Qx + \frac{1}{2}(u^T R^{\frac{1}{2}} + x^T PBR^{-\frac{1}{2}})(R^{\frac{1}{2}}u + R^{-\frac{1}{2}}B^T Px) - \frac{1}{2}x^T PBR^{-1}B^T Px = 0$$



# Proof

Step 8. For the equation

$$x^T P A x + \frac{1}{2} x^T Q x + \frac{1}{2} (u^T R^{\frac{1}{2}} + x^T P B R^{-\frac{1}{2}}) (R^{\frac{1}{2}} u + R^{-\frac{1}{2}} B^T P x) - \frac{1}{2} x^T P B R^{-1} B^T P x = 0$$

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We can make the parts depending on  $u$  equal to 0 by taking

$$R^{\frac{1}{2}} u + R^{-\frac{1}{2}} B^T P x = 0 ,$$

which results in the input

$$u = -R^{-1} B^T P x$$



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Step 9. Using the input leaves us with an equation only depending on  $x$

$$x^T P A x + \frac{1}{2} x^T Q x - \frac{1}{2} x^T P B R^{-1} B^T P x = 0$$

for which the value of solution  $P$  that minimises the equation will optimise the cost function

# Proof

Step 9. Differentiating twice w.r.t  $x$ , we have

$$PA + A^T P + \underbrace{\frac{1}{2}Q + \frac{1}{2}Q^T}_Q - \underbrace{\frac{1}{2}PBR^{-1}B^T P - \frac{1}{2}PBR^{-1}B^T P}_{-PBR^{-1}B^T P} = 0$$

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Which results in the Ricatti equation:

$$A^T P + PA - PBR^{-1}B^T P + Q = 0$$

where  $P = P^T > 0$

and  $A - BK = A - BR^{-1}B^T P$  is asymptotically stable

Demonstrating we can solve Ricatti equation to  
get  $P$  so that  $u = -R^{-1}B^T Px$  is optimal

# Summary

- An **optimal controller** can be designed with form

$$u = -Kx$$

- The controller has to be defined such that

$$\dot{x} = (A - BK)x \text{ is } \textbf{asymptotically stable}$$

- The **cost function** below is **optimized**

$$J(x(0)) = \min_u \int_0^{\infty} x^T(\tau) Q x(\tau) + u^T(\tau) R u(\tau) d\tau,$$

where  $Q$  and  $R$  are positive definite, i.e.,  $Q = Q^T > 0$  and  $R = R^T > 0$

- The solution to the problem is  $K = R^{-1} B^T P$  with  $P$  **solution** to the **Ricatti equation**.

# Next lecture (Preview)

Optimal state controller  $u = -Kx$  is ideal



PROBLEM: it requires measuring every state



What if we cannot measure every state?



SOLUTION: reconstruct state from input and output

HOW?

Designing an **Observer**