[MEN573] Advanced Control Systems I

Lecture 19 - Optimal Linear Quadratic Regulators (LQR) Continuous Time

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Consider an nth order LTI CT system:

$$\dot{x}(t) = Ax(t) + Bu(t) \qquad x(0) = x_0$$

Assume that the state vector is measurable.

- We are concerned with regulating the state around the origin,
- i.e. bringing the state to the origin from an arbitrary $x(0) = x_0$

$$\dot{x}(t) = Ax(t) + Bu(t) \qquad x(0) = x_0$$

We want to obtain the optimal control, which minimizes:

$$J = \frac{1}{2} x^{T}(t_f) S x(t_f) + \frac{1}{2} \int_{0}^{t_f} \left\{ x^{T} Q x + u^{T} R u \right\} dt$$

$$S = S^T \succeq 0$$
 $Q = Q^T \succeq 0$ $R = R^T \succ 0$

$$J = \frac{1}{2} x^T (\underline{t_f}) S x (\underline{t_f}) + \frac{1}{2} \int_0^{\underline{t_f}} \{ x^T Q x + u^T R u \} dt$$

- ullet t_f
- $\frac{1}{2}x^T(t_f)Sx(t_f)$
- $\frac{1}{2}x^T(t)Qx(t)$
- $\frac{1}{2}u^T(t)Ru(t)$

is the final time

penalizes the final state
deviation from the origin
penalizes the transient state
deviation from the origin
penalizes the control effort

$$J = \frac{1}{2} x^{T}(t_f) S x(t_f) + \frac{1}{2} \int_0^{t_f} \left\{ x^{T} Q x + u^{T} R u \right\} dt$$

Notes:

- S and Q must be at least positive semi-definite
- *R* must be positive definite.
 - Without a weighting on u(t), the optimal control action would yield unbounded control magnitudes.
- All matrices (including A and B) can be time varying.

$$u(t) = -K(t) x(t)$$

where:

$$K(t) = R^{-1}B^T P(t)$$

and P(t) satisfies the following **Riccati** ODE (or **Riccati** eq.):

$$-\frac{d}{dt}P = A^T P + P A + Q - P B R^{-1} B^T P$$
$$P(t_f) = S$$

$$u(t) = -K(t)x(t)$$

where:

$$K(t) = R^{-1}B^T P(t)$$

and P(t) satisfies the following *Riccati* ODE (or *Riccati* eq.):

$$-\frac{d}{dt}P = A^{T}P + PA + Q - PBR^{-1}B^{T}P$$

$$Lyapunov Eq. additional term$$

$$-\frac{d}{dt}P = A^T P + P A + Q - P B R^{-1} B^T P$$
$$P(t_f) = S$$

- The Riccati ODE is integrated backwards,
 - starting from the final time $\,^tf\,$, until $\,^t=0$

$$P(t) = P^{T}(t) \qquad P(t) \succeq 0$$

$$J = \frac{1}{2} x^{T}(t_f) S x(t_f) + \frac{1}{2} \int_{0}^{t_f} \left\{ x^{T} Q x + u^{T} R u \right\} dt$$

The minimum value of the quadratic cost function:

$$J^{0}(x(0)) = \frac{1}{2}x^{T}(0)P(0)x(0)$$

Integration of the Riccati ODE

The **backwards** integration of:

$$-\frac{d}{dt}P = A^T P + P A + Q - P B R^{-1} B^T P$$
$$P(t_f) = S$$

is numerically equivalent to the forward integration of:

$$\frac{d}{dt}P^* = A^T P^* + P^* A + Q - P^* B R^{-1} B^T P^*$$

$$P(t) = P^*(t_f - t)$$

$$P^*(0) = S$$

Numerical integration of the Riccati ODE

$$\frac{d}{dt}P^* = A^T P^* + P^* A + Q - P^* B R^{-1} B^T P^*$$

$$P^*(0) = S$$

This ODE can be integrated using any of matlab's numerical integration functions (e.g. ODE45).

$$P(t) = P^*(t_f - t)$$

Double integrator

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u$$

$$\frac{U(s)}{s} \xrightarrow{X_2(s)} \xrightarrow{X_1(s)} \frac{1}{s}$$

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u$$

$$J = \frac{1}{2} x^{T}(t_f) S x(t_f) + \frac{1}{2} \int_{0}^{t_f} \left\{ x^{T} Q x + R u^{2} \right\} dt$$

with

$$S = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad Q = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \qquad R \succ 0$$

Numerical integration

$$\frac{d}{dt}P^* = A^T P^* + P^* A + Q - P^* B R^{-1} B^T P^*$$

$$P(t) = P^*(t_f - t)$$

with

$$P^*(0) = \left| \begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right|$$

$$R \succ 0$$

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \qquad A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \qquad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Numerical integration

$$\frac{d}{dt}P^* = A^T P^* + P^* A + Q - P^* B R^{-1} B^T P^*$$

$$P(t) = P^*(t_f - t)$$

Define:

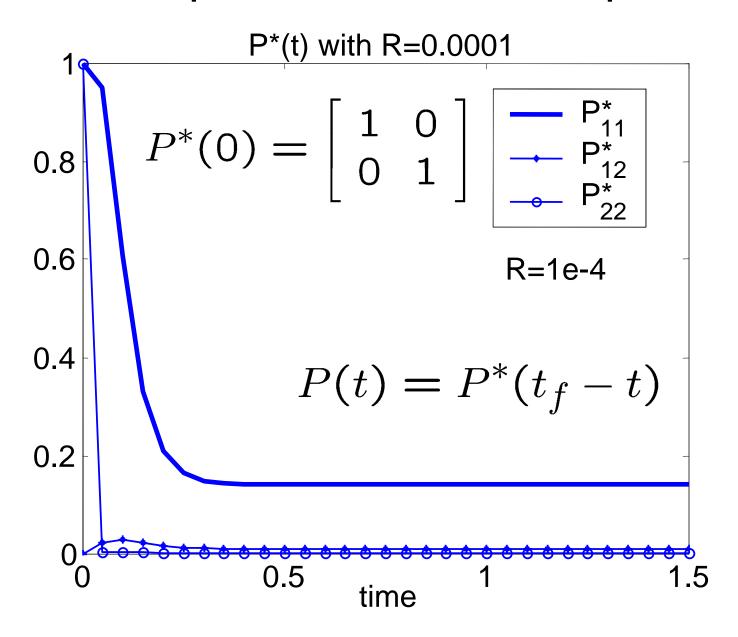
$$P^* = \begin{bmatrix} p_{11}^* & p_{12}^* \\ p_{12}^* & p_{22}^* \end{bmatrix}$$

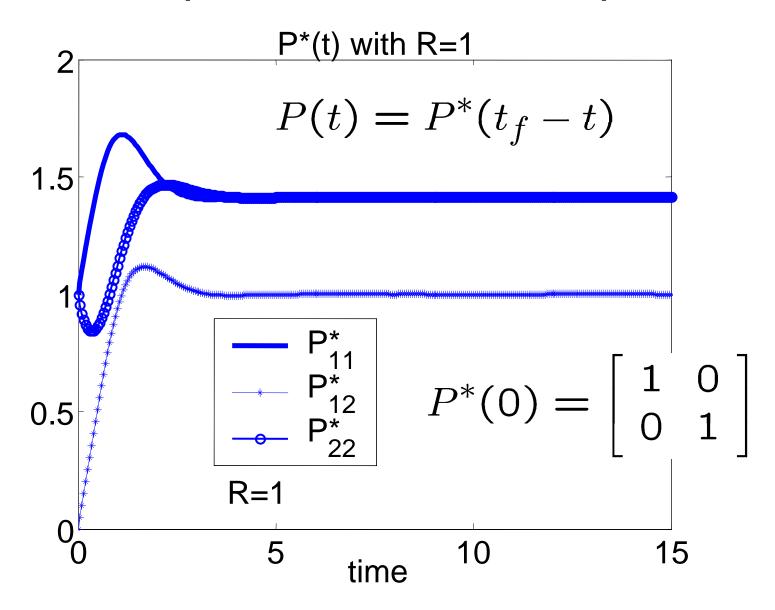
Plugging the matrix parameters into the RHS of the ODE

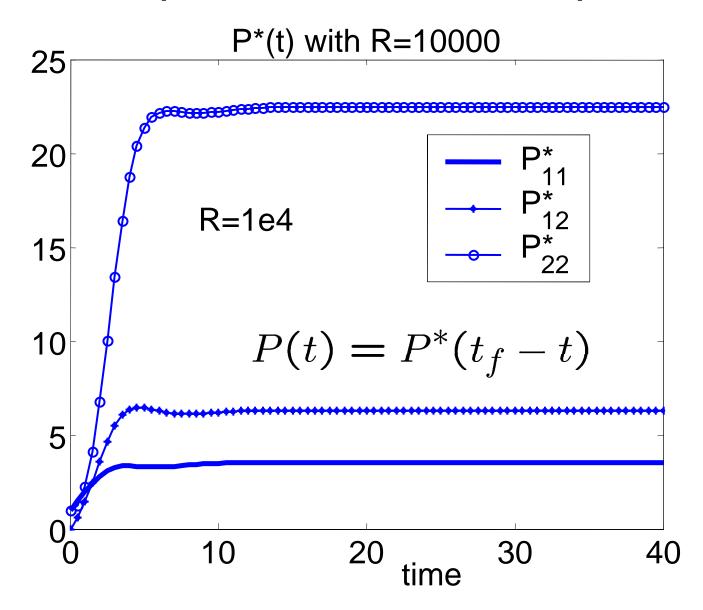
$$\frac{d}{dt}P^* = A^T P^* + P^* A + Q - P^* B R^{-1} B^T P^*$$

yields:

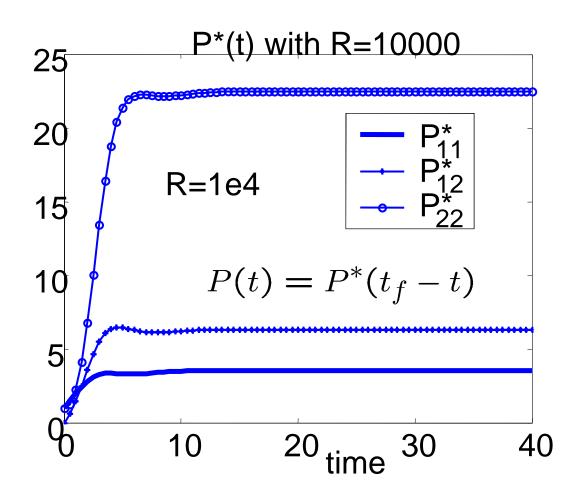
$$\frac{d}{dt} p_{11}^* = 1 - \frac{1}{R} p_{12}^{*2}
\frac{d}{dt} p_{12}^* = p_{11}^* - \frac{1}{R} p_{12}^* p_{22}^*
\frac{d}{dt} p_{22}^* = 2 p_{12}^* - \frac{1}{R} p_{22}^{*2}
p_{11}^*(0) = 1
p_{12}^*(0) = 0
p_{22}^*(0) = 1$$



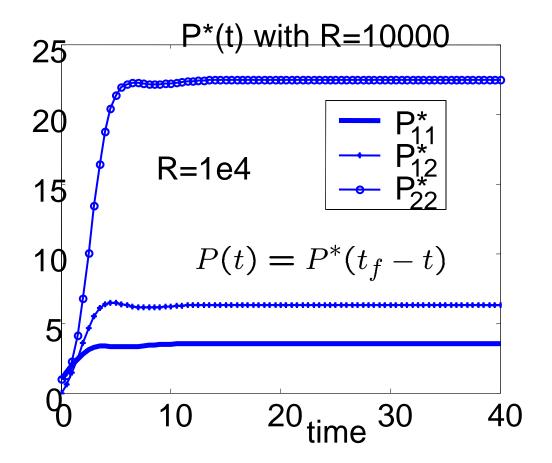




1. If the final time t_f is relatively large, P(t) will be stationary from t=0 until t approaches t_f

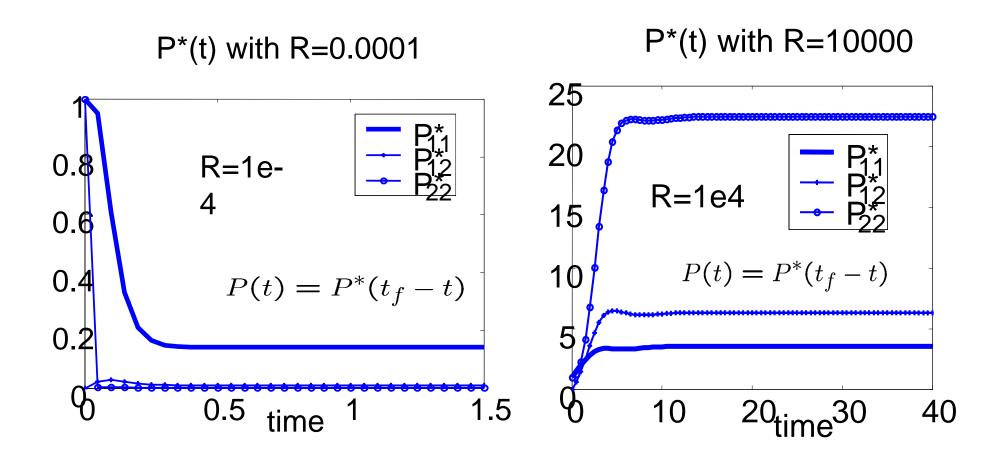


As $t_f o \infty$, P(t) becomes stationary $P(t) o P_+$



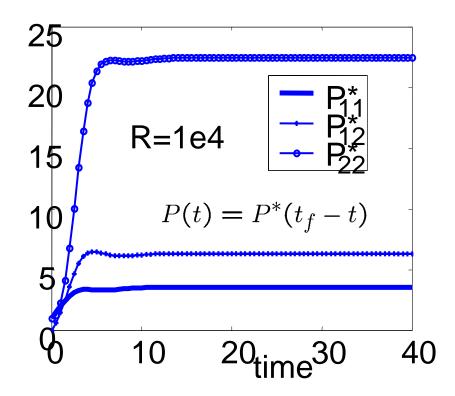
A large input weighting, R results in a longer transient.

A small input weighting, R results in a shorter transient.



$$P(t_f) = S$$
 becomes irrelevant as $t_f \to \infty$

P*(t) with R=10000



- 1. If the final time t_f is relatively large, P(t) will be stationary from t=0 until t approaches t_f
- 2. As $t_f o \infty$, P becomes stationary $P(t) o P_+$
- 3. A large input weighting, R results in a longer transient.
- 4. A small input weighting, R results in a shorter transient.
- 5. $P(t_f) = S$ becomes irrelevant as $t_f \to \infty$

$$\dot{x}(t) = Ax(t) + Bu(t) \qquad x(0) = x_0$$

We want to obtain the optimal control, which minimizes:

$$J = \frac{1}{2} \int_0^\infty \left\{ x^T C^T C x + u^T R u \right\} dt$$

$$Q = C^T C \succ 0 \qquad \qquad R = D^T D \succ 0$$

Conditions for the existence of a LQR solution:

1. The pair $\{A, B\}$ must be controllable or stabilizable.

• This condition is necessary for ${m J}$ to be bounded and for ${m P}(t)$ to converge to a stationary value, P , when integrated backwards from any arbitrary $P(t_f)$

- 2. The pair $\{A,C\}$ must be observable or detectable.
- This condition assures that the optimal closed loop system is asymptotically stable.
- If $\{A,C\}$ is observable, then $P\succ 0$

• If $\{A,C\}$ is detectable, but not observable, then $\dot{P} \succeq \mathbf{0}$

$$\dot{x}(t) = Ax(t) + Bu(t) \qquad x(0) = x_0$$

We want to obtain the optimal control, which minimizes:

$$J = \frac{1}{2} \int_0^\infty \left\{ x^T C^T C x + u^T R u \right\} dt$$

$$Q = C^T C \succ 0 \qquad \qquad R = R^T \succ 0$$

$$u(t) = -Kx(t)$$

where:

$$K = R^{-1} B^T P$$

and $m{P}$ satisfies the following $m{Algebraic\ Riccati\ Equation}$ (ARE):

$$0 = A^{T} P + P A + C^{T} C - P B R^{-1} B^{T} P$$

$$J = \frac{1}{2} \int_0^\infty \left\{ x^T C^T C x + u^T R u \right\} dt$$

Optimal Cost:

$$J^o = \frac{1}{2} x(0)^T P x(0)$$

$$0 = A^{T} P + P A + C^{T} C - P B R^{-1} B^{T} P$$

Theorem

If $\{A,B\}$ is controllable and $\{A,C\}$ observable

$$A_c = A - BK K = R^{-1}B^T P$$

is Hurwitz, and satisfies the following Lyapunov equation

$$A_c^T P + P A_c = -C^T C - P B R^{-1} B^T P$$

There exists a technique for obtaining the solution $m{P}$ of the Algebraic Riccati Equation (ARE)

$$0 = A^{T} P + P A + C^{T} C - P B R^{-1} B^{T} P$$

in close form

$$0 = A^{T} P + P A + C^{T} C - P B R^{-1} B^{T} P$$

1) Define the Hamiltonian matrix:

$$H = \begin{bmatrix} A & -BR^{-1}B^T \\ -C^TC & -A^T \end{bmatrix} \in \mathcal{R}^{2n \times 2n}$$

2) Compute its first n eigenvalues ($\text{Re}(\lambda_i) < 0$):

$$\{\lambda_1, \lambda_2, \cdots, \lambda_n | \lambda_{n+1}, \cdots, \lambda_{2n}\}$$

The first n eigenvalues of H are the eigenvalues of

$$A_c = A - B K$$
 where $K = R^{-1} B^T P$

and are all in the open left complex plane, $\text{Re}(\lambda_i) < 0$ (i.e. asymptotically stable)

The remaining eigenvalues of *H* satisfy:

$$\lambda_{n+i} = -\lambda_i \qquad i = 1, \dots, n$$

3) For each eigenvalue of H in the open left complex plane, compute its associated eigenvector:

$$\operatorname{Re}(\lambda_i) < 0$$
 $i = 1, \dots, n$

$$H\left[\begin{array}{c} f_i \\ g_i \end{array}\right] = \lambda_i \left[\begin{array}{c} f_i \\ g_i \end{array}\right]$$

$$f_i, g_i \in \mathcal{R}^n$$

4) Define the following two $n \times n$ matrices:

$$X_1 = \begin{bmatrix} f_1 & f_2 & \cdots & f_n \end{bmatrix}$$
$$X_2 = \begin{bmatrix} g_1 & g_2 & \cdots & g_n \end{bmatrix}$$

5) Finally, *P* is computed as follows:

$$P = X_2 X_1^{-1}$$

Solution of the ARE using matlab

Matlab command care: (Continuous ARE)

$$[P, \Lambda, K] = \operatorname{care}(A, B, C^T C, R)$$

Solution
$$\boldsymbol{P}$$
 of 0 = $A^T P + P A + C^T C - P B R^{-1} B^T P$

$$\Lambda = {\sf Diag}(\lambda_1, \, \cdots, \, \lambda_n) \quad {\sf Re}(\lambda_i) < 0$$
 eigenvalues of $A_c = A - B \, K$

$$K = R^{-1}B^T P$$

Other matlab commands:

• lqr:
$$[K, P, \Lambda] = lqr(A, B, C^T C, R)$$

• lqry:
$$[K, P, \Lambda] = lqry(sys, Q_y, R)$$

sys:

$$\dot{x} = Ax + Bu$$

$$y = Cx + Du$$

$$J = \frac{1}{2} \int_0^\infty \left\{ y^T \, Q_y \, y + u^T \, R \, u \right\} \, dt$$

Double integrator

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u$$

$$\frac{U(s)}{s} \xrightarrow{X_2(s)} \frac{1}{s} \xrightarrow{X_1(s)}$$

LQR – double integrator

Double integrator

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u$$

$$J = \frac{1}{2} \int_0^\infty \left\{ x^T \, C^T \, C \, x + R \, u^2 \right\} \, dt$$

with

$$C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$
 $R > 0$

LQR – double integrator

Solving the ARE analytically

$$0 = A^{T} P + P A + C^{T} C - P B R^{-1} B^{T} P$$

yields:

$$P = \begin{bmatrix} \sqrt{2} R^{1/4} & R^{1/2} \\ R^{1/2} & \sqrt{2} R^{3/4} \end{bmatrix}$$

$$A_c = A - B K = \begin{bmatrix} 0 & 1 \\ -R^{-1/2} & -\sqrt{2}R^{-1/4} \end{bmatrix}$$

Eigenvalues:

$$\lambda_{1,2} = -\frac{1}{\sqrt{2}R^{1/4}} \pm \frac{1}{\sqrt{2}R^{1/4}}j$$

LQR – double integrator

Close loop eigenvalues a a function of $oldsymbol{R}$

$$\lambda_{1,2} = -\frac{1}{\sqrt{2}R^{1/4}} \pm \frac{1}{\sqrt{2}R^{1/4}}j$$

