

## 7 LQ Models

We present the LQ regulation model in discrete and continuous time, the Riccati equation, its validity in the model with additive white noise.

### 7.1 The LQ regulation model

The elements needed to define a control optimization problem are specification of (i) the dynamics of the process, (ii) which quantities are observable at a given time, and (iii) an optimization criterion.

In the **LQG model** the plant equation and observation relations are linear, the cost is quadratic, and the noise is Gaussian (jointly normal). The LQG model is important because it has a complete theory and introduces some key concepts, such as controllability, observability and the certainty-equivalence principle.

Begin with a model in which the state  $x_t$  is fully observable and there is no noise. The plant equation of the time-homogeneous  $[A, B, \cdot]$  system has the linear form

$$x_t = Ax_{t-1} + Bu_{t-1}, \quad (7.1)$$

where  $x_t \in \mathbb{R}^n$ ,  $u_t \in \mathbb{R}^m$ ,  $A$  is  $n \times n$  and  $B$  is  $n \times m$ . The cost function is

$$\mathbf{C} = \sum_{t=0}^{h-1} c(x_t, u_t) + \mathbf{C}_h(x_h), \quad (7.2)$$

with one-step and terminal costs

$$c(x, u) = x^\top Rx + u^\top Sx + x^\top S^\top u + u^\top Qu = \begin{bmatrix} x \\ u \end{bmatrix}^\top \begin{bmatrix} R & S^\top \\ S & Q \end{bmatrix} \begin{bmatrix} x \\ u \end{bmatrix}, \quad (7.3)$$

$$\mathbf{C}_h(x) = x^\top \Pi_h x. \quad (7.4)$$

All quadratic forms are non-negative definite, and  $Q$  is positive definite. There is no loss of generality in assuming that  $R$ ,  $Q$  and  $\Pi_h$  are symmetric. This is a model for **regulation** of  $(x, u)$  to the point  $(0, 0)$  (i.e., steering to a critical value).

To solve the optimality equation we shall need the following lemma.

**Lemma 7.1** *Suppose  $x, u$  are vectors. Consider a quadratic form*

$$\begin{pmatrix} x \\ u \end{pmatrix}^\top \begin{pmatrix} \Pi_{xx} & \Pi_{xu} \\ \Pi_{ux} & \Pi_{uu} \end{pmatrix} \begin{pmatrix} x \\ u \end{pmatrix}.$$

*Assume it is symmetric and  $\Pi_{uu} > 0$ , i.e., positive definite. Then the minimum with respect to  $u$  is achieved at*

$$u = -\Pi_{uu}^{-1} \Pi_{ux} x,$$

*and is equal to*

$$x^\top [\Pi_{xx} - \Pi_{xu} \Pi_{uu}^{-1} \Pi_{ux}] x.$$

Proof. Suppose the quadratic form is minimized at  $u$ . Then

$$\begin{aligned} & \begin{pmatrix} x \\ u+h \end{pmatrix}^\top \begin{pmatrix} \Pi_{xx} & \Pi_{xu} \\ \Pi_{ux} & \Pi_{uu} \end{pmatrix} \begin{pmatrix} x \\ u+h \end{pmatrix} \\ &= x^\top \Pi_{xx} x + 2x^\top \Pi_{xu} u + \underbrace{2h^\top \Pi_{ux} x + 2h^\top \Pi_{uu} u}_{\text{underbraced linear term}} + u^\top \Pi_{uu} u + h^\top \Pi_{uu} h. \end{aligned}$$

To be stationary at  $u$ , the underbraced linear term in  $h^\top$  must be zero, so

$$u = -\Pi_{uu}^{-1} \Pi_{ux} x,$$

and the optimal value is  $x^\top [\Pi_{xx} - \Pi_{xu} \Pi_{uu}^{-1} \Pi_{ux}] x$ . ■

**Theorem 7.2** *Assume the structure of (7.1)–(7.4). Then the value function has the quadratic form*

$$F(x, t) = x^\top \Pi_t x, \quad t < h, \quad (7.5)$$

*and the optimal control has the linear form*

$$u_t = K_t x_t, \quad t < h.$$

*The time-dependent matrix  $\Pi_t$  satisfies the Riccati equation*

$$\Pi_t = f \Pi_{t+1}, \quad t < h, \quad (7.6)$$

*where  $f$  is an operator having the action*

$$f \Pi = R + A^\top \Pi A - (S^\top + A^\top \Pi B)(Q + B^\top \Pi B)^{-1} (S + B^\top \Pi A), \quad (7.7)$$

*and  $\Pi_h$  has the value prescribed in (7.4). The  $m \times n$  matrix  $K_t$  is given by*

$$K_t = -(Q + B^\top \Pi_{t+1} B)^{-1} (S + B^\top \Pi_{t+1} A), \quad t < h.$$

Proof. Assertion (7.5) is true at time  $h$ . Assume it is true at time  $t+1$ . Then

$$\begin{aligned} F(x, t) &= \inf_u [c(x, u) + (Ax + Bu)^\top \Pi_{t+1} (Ax + Bu)] \\ &= \inf_u \left[ \begin{pmatrix} x \\ u \end{pmatrix}^\top \begin{pmatrix} R + A^\top \Pi_{t+1} A & S^\top + A^\top \Pi_{t+1} B \\ S + B^\top \Pi_{t+1} A & Q + B^\top \Pi_{t+1} B \end{pmatrix} \begin{pmatrix} x \\ u \end{pmatrix} \right] \end{aligned}$$

By Lemma 7.1 the minimum is achieved by  $u = K_t x$ , and the form of  $f$  comes from this also. ■

## 7.2 The Riccati recursion

The backward recursion (7.6)–(7.7) is called the **Riccati equation**. Note that

(i)  $S$  can be normalized to zero by choosing a new control  $u^* = u + Q^{-1}Sx$ , and setting  $A^* = A - BQ^{-1}S$ ,  $R^* = R - S^\top Q^{-1}S$ .

(ii) The optimally controlled process obeys  $x_{t+1} = \Gamma_t x_t$ . Here  $\Gamma_t$  is called the **gain matrix** and is given by

$$\Gamma_t = A + BK_t = A - B(Q + B^\top \Pi_{t+1} B)^{-1} (S + B^\top \Pi_{t+1} A).$$

(iii) An equivalent expression for the Riccati equation is

$$f\Pi = \inf_K [R + K^\top S + S^\top K + K^\top QK + (A + BK)^\top \Pi (A + BK)].$$

(iv) We might have carried out exactly the same analysis for a time-heterogeneous model, in which the matrices  $A, B, Q, R, S$  are replaced by  $A_t, B_t, Q_t, R_t, S_t$ .

(v) We do not give details, but comment that it is possible to analyse models in which

$$x_{t+1} = Ax_t + Bu_t + \alpha_t,$$

for a known sequence of disturbances  $\{\alpha_t\}$ , or in which the cost function is

$$c(x, u) = \begin{bmatrix} x - \bar{x}_t \\ u - \bar{u}_t \end{bmatrix}^\top \begin{bmatrix} R & S^\top \\ S & Q \end{bmatrix} \begin{bmatrix} x - \bar{x}_t \\ u - \bar{u}_t \end{bmatrix},$$

so that the aim is to track a sequence of values  $(\bar{x}_t, \bar{u}_t)$ ,  $t = 0, \dots, h-1$ .

## 7.3 White noise disturbances

Suppose the plant equation (7.1) is now

$$x_{t+1} = Ax_t + Bu_t + \epsilon_t,$$

where  $\epsilon_t \in \mathbb{R}^n$  is vector **white noise**, defined by the properties  $E\epsilon = 0$ ,  $E\epsilon_t \epsilon_s^\top = N$  and  $E\epsilon_t \epsilon_s^\top = 0$ ,  $t \neq s$ . The DP equation is then

$$F(x, t) = \inf_u [c(x, u) + E_\epsilon [F(Ax + Bu + \epsilon, t + 1)]].$$

By definition  $F(x, h) = x^\top \Pi_h x$ . Try a solution  $F(x, t) = x^\top \Pi_t x + \gamma_t$ . This holds for  $t = h$ . Suppose it is true for  $t + 1$ , then

$$\begin{aligned} F(x, t) &= \inf_u [c(x, u) + E(Ax + Bu + \epsilon)^\top \Pi_{t+1} (Ax + Bu + \epsilon) + \gamma_{t+1}] \\ &= \inf_u [c(x, u) + E(Ax + Bu)^\top \Pi_{t+1} (Ax + Bu) \\ &\quad + 2E[\epsilon^\top (Ax + Bu)] + E[\epsilon^\top \Pi_{t+1} \epsilon] + \gamma_{t+1}] \\ &= \inf_u [\dots] + 0 + \text{tr}(N\Pi_{t+1}) + \gamma_{t+1}. \end{aligned}$$

Here we use the fact that

$$E[\epsilon^\top \Pi \epsilon] = E \left[ \sum_{ij} \epsilon_i \Pi_{ij} \epsilon_j \right] = E \left[ \sum_{ij} \epsilon_j \epsilon_i \Pi_{ij} \right] = \sum_{ij} N_{ji} \Pi_{ij} = \text{tr}(N\Pi).$$

Thus (i)  $\Pi_t$  follows the same Riccati equation as before, (ii) the optimal control is  $u_t = K_t x_t$ , and (iii)

$$F(x, t) = x^\top \Pi_t x + \gamma_t = x^\top \Pi_t x + \sum_{j=t+1}^h \text{tr}(N\Pi_j).$$

The final term can be viewed as the cost of correcting future noise. In the infinite horizon limit of  $\Pi_t \rightarrow \Pi$  as  $t \rightarrow \infty$ , we incur an average cost per unit time of  $\text{tr}(N\Pi)$ , and a transient cost of  $x^\top \Pi x$  that is due to correcting the initial  $x$ .

## 7.4 LQ regulation in continuous-time

In continuous-time we take  $\dot{x} = Ax + Bu$  and

$$\mathbf{C} = \int_0^h \begin{pmatrix} x \\ u \end{pmatrix}^\top \begin{pmatrix} R & S^\top \\ S & Q \end{pmatrix} \begin{pmatrix} x \\ u \end{pmatrix} dt + (x^\top \Pi x)_h.$$

We can obtain the continuous-time solution from the discrete time solution by moving forward in time in increments of  $\Delta$ . Make the following replacements.

$$x_{t+1} \rightarrow x_{t+\Delta}, \quad A \rightarrow I + A\Delta, \quad B \rightarrow B\Delta, \quad R, S, Q \rightarrow R\Delta, S\Delta, Q\Delta.$$

Then as before,  $F(x, t) = x^\top \Pi x$ , where  $\Pi$  obeys the Riccati equation

$$\frac{\partial \Pi}{\partial t} + R + A^\top \Pi + \Pi A - (S^\top + \Pi B)Q^{-1}(S + B^\top \Pi) = 0.$$

This is simpler than the discrete time version. The optimal control is

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

where

$$K(t) = -Q^{-1}(S + B^\top \Pi).$$

The optimally controlled plant equation is  $\dot{x} = \Gamma(t)x$ , where

$$\Gamma(t) = A + BK = A - BQ^{-1}(S + B^\top \Pi).$$