

ME 233 – Advanced Control II

Lecture 17

Minimum Variance Regulator

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Outline

Introduction

MVR Problem Statement

MVR Solution

Proof, Special Case: $B(q^{-1})$ Anti-Schur

A-causal but BIBO Systems

Proof, General Case

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Model Form

We consider a state space model of the form

$$\begin{aligned}x(k+1) &= \hat{A}x(k) + \hat{B}u(k) + \hat{B}_w w(k) \\y(k) &= \hat{C}x(k) + v(k)\end{aligned}$$

where

- ▶ $u(k)$ is the **scalar** control signal
- ▶ $y(k)$ is the **scalar** measurement signal
- ▶ $w(k)$ is the input noise
(white, zero-mean, $E\{w(k)w^T(k)\} = W$)
- ▶ $v(k)$ is the measurement noise
(white, zero-mean, $E\{v(k)v^T(k)\} = V$)
- ▶ $E\{w(k)v^T(k)\} = 0$

Stationary Kalman Filter V2 (Review)

The optimal state estimator is given by

$$\hat{x}^o(k+1) = \hat{A}\hat{x}^o(k) + \hat{B}u(k) + \hat{L}\tilde{y}^o(k)$$

$$\tilde{y}^o(k) = y(k) - \hat{C}\hat{x}^o(k)$$

where

$$\hat{L} = \hat{A}M\hat{C}^T[\hat{C}M\hat{C}^T + V]^{-1}$$

$$M = \hat{A}M\hat{A}^T + \hat{B}_wW\hat{B}_w^T - \hat{A}M\hat{C}^T[\hat{C}M\hat{C}^T + V]^{-1}\hat{C}M\hat{A}^T$$

$$\hat{A} - \hat{L}\hat{C} \text{ is Schur}$$

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$$\hat{A} - \hat{L}\hat{C} \text{ is Schur}$$

Also, the signal $\tilde{y}^o(k)$ is zero-mean, white, and has covariance $\hat{C}M\hat{C}^T + V$.

Alternate Model Form

Using the Kalman Filter V2, we can write

$$\begin{aligned}\hat{x}^o(k+1) &= \hat{A}\hat{x}^o(k) + \hat{B}u(k) + \hat{L}\epsilon(k) \\ y(k) &= \hat{C}\hat{x}^o(k) + \epsilon(k)\end{aligned}$$

where $\epsilon(k) = \tilde{y}^o(k)$.

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where $\epsilon(k) = \tilde{y}^o(k)$.

As a transfer function, this is

$$\begin{aligned}Y(z) &= [\hat{C}(zI - \hat{A})^{-1}\hat{B}]U(z) \\ &\quad + [1 + \hat{C}(zI - \hat{A})^{-1}\hat{L}]E(z)\end{aligned}$$

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Recall that $1 + \hat{C}(zI - \hat{A})^{-1}\hat{L} = \frac{\det[zI - (\hat{A} - \hat{L}\hat{C})]}{\det[zI - \hat{A}]}$

Alternate Transfer Function Model

From the previous slide, we have that

$$Y(z) = \frac{\bar{B}(z)}{\bar{A}(z)}U(z) + \frac{\bar{C}(z)}{\bar{A}(z)}E(z)$$

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where

$$\bar{A}(z) = z^n + a_1z^{n-1} + \cdots + a_n \quad = \det[zI - \hat{A}]$$

$$\bar{C}(z) = z^n + c_1z^{n-1} + \cdots + c_n \quad = \det[zI - (\hat{A} - \hat{L}\hat{C})]$$

$$\bar{B}(z) = b_0z^m + \cdots + b_m$$

Alternate Transfer Function Model

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$$\bar{C}(z) = z^n + c_1z^{n-1} + \cdots + c_n = \det[zI - (\hat{A} - \hat{L}\hat{C})]$$

$$\bar{B}(z) = b_0z^m + \cdots + b_m$$

Since $\hat{A} - \hat{L}\hat{C}$ is Schur, the polynomial $\bar{C}(z)$ is Schur

Polynomials in q^{-1}

We now define $d = n - m$ and the polynomials

$$A(z^{-1}) = z^{-n} \bar{A}(z) = 1 + a_1 z^{-1} + \cdots + a_n z^{-n}$$

$$C(z^{-1}) = z^{-n} \bar{C}(z) = 1 + c_1 z^{-1} + \cdots + c_n z^{-n}$$

$$B(z^{-1}) = z^{-m} \bar{B}(z) = b_0 + b_1 z^{-1} + \cdots + b_m z^{-m}$$

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so that we can write the transfer function from the previous slide as

$$Y(z) = \frac{z^{-d} B(z^{-1})}{A(z^{-1})} U(z) + \frac{C(z^{-1})}{A(z^{-1})} E(z)$$

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$$Y(z) = \frac{z^{-d} B(z^{-1})}{A(z^{-1})} U(z) + \frac{C(z^{-1})}{A(z^{-1})} E(z)$$

Note in particular that $C(z^{-1})$ is an anti-Schur polynomial of z^{-1}

ARMAX Plant Model

We have now transformed the original state space plant model to

$$A(q^{-1})y(k) = q^{-d}B(q^{-1})u(k) + C(q^{-1})\epsilon(k)$$

where $C(q^{-1})$ is an anti-Schur polynomial of q^{-1} and $\epsilon(k)$ is zero-mean white noise with covariance $\hat{C}M\hat{C}^T + V$

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This type of model is called an ARMAX model because it is an ARMA model with an eXogenous input.

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Minimum Variance Regulator (MVR) Problem

Given the ARMAX model

$$A(q^{-1})y(k) = q^{-d}B(q^{-1})u(k) + C(q^{-1})\epsilon(k)$$

where

- ▶ $C(q^{-1})$ is an anti-Schur polynomial of q^{-1}
- ▶ $B(q^{-1})$ has no zeros on the unit circle
- ▶ $\epsilon(k)$ is zero-mean white noise
- ▶ The plant has no unstable pole-zero cancelations, i.e. the polynomials $A(q^{-1})$ and $B(q^{-1})$ have no common zeros such that $|q^{-1}| < 1$

Minimum Variance Regulator (MVR) Problem

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- ▶ The plant has no unstable pole-zero cancelations, i.e. the polynomials $A(q^{-1})$ and $B(q^{-1})$ have no common zeros such that $|q^{-1}| < 1$

find the stabilizing feedback control law that minimizes the output variance $E\{y^2(k)\}$

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Factorization of B and \bar{B}

In general, the polynomial $\bar{B}(q) = q^m B(q^{-1})$ has

- ▶ m_s zeros strictly inside the unit circle (stable plant zeros)
- ▶ m_u zeros strictly outside the unit circle (unstable plant zeros)

Factorization of B and \bar{B}

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- ▶ m_u zeros strictly outside the unit circle (unstable plant zeros)

Perform the factorization

$$B(q^{-1}) = B^s(q^{-1})B^u(q^{-1})$$

where

- ▶ $\bar{B}^s(q) = q^{m_s} B^s(q^{-1})$ has its zeros inside the unit circle
(These are the stable plant zeros)
- ▶ $\bar{B}^u(q) = q^{m_u} B^u(q^{-1})$ has its zeros outside the unit circle
(These are the unstable plant zeros)
- ▶ $\bar{B}^u(0) = 1$

Minimum Variance Regulator (MVR) Solution

- ▶ The optimal control $u_*(k)$ is given by

$$B^s(q^{-1})R(q^{-1})u_*(k) = -S(q^{-1})y(k)$$

where $R(q^{-1})$ and $S(q^{-1})$ are found by solving the Diophantine equation

$$C(q^{-1})\bar{B}^u(q^{-1}) = A(q^{-1})R(q^{-1}) + q^{-d}B^u(q^{-1})S(q^{-1})$$

where

$$R(q^{-1}) = 1 + r_1q^{-1} + \dots + r_{n_r}q^{-n_r}$$

$$S(q^{-1}) = s_0 + s_1q^{-1} + \dots + s_{n_s}q^{-n_s}$$

and $n_r = m_u + d - 1$ and $n_s = n - 1$

Minimum Variance Regulator (MVR) Solution

- ▶ The optimal cost is

$$E\{y^2(k)\} = E\{\epsilon_f^2(k)\}$$

where $\epsilon_f(k)$ is defined in terms of $\epsilon(k)$ by the ARMA model

$$\bar{B}^u(q^{-1})\epsilon_f(k) = R(q^{-1})\epsilon(k)$$

Constructing the MVR

1. Find \hat{L} using a stationary Kalman filter design
2. Construct $C(q^{-1}) = q^{-n} \det[qI - (\hat{A} - \hat{L}\hat{C})]$
3. Factor $B(q^{-1}) = B^s(q^{-1})B^u(q^{-1})$ as described previously (don't forget that $\bar{B}^u(0) = 1$)
4. Solve the Diophantine equation

$$C(q^{-1})\bar{B}^u(q^{-1}) = A(q^{-1})R(q^{-1}) + q^{-d}B^u(q^{-1})S(q^{-1})$$

5. Form the optimal controller

$$B^s(q^{-1})R(q^{-1})u_*(k) = -S(q^{-1})y(k)$$

Solution Comments

- ▶ Be careful with $B^u(q^{-1})$, $\bar{B}^u(q)$, and $\bar{B}^u(q^{-1})$

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 - ▶ $\bar{B}^u(q)$ is an anti-Schur polynomial in q

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- ▶ Note that the Diophantine equation involves both $B^u(q^{-1})$ and $\bar{B}^u(q^{-1})$.

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- ▶ Since $\bar{B}^u(q^{-1})$ is anti-Schur, the operator $\frac{R(q^{-1})}{\bar{B}^u(q^{-1})}$ is BIBO.
 $\Rightarrow \epsilon_f(k) = \frac{R(q^{-1})}{\bar{B}^u(q^{-1})} \epsilon(k)$ has bounded covariance

Special Case: $B(q^{-1})$ is anti-Schur

When $B(q^{-1})$ is anti-Schur, we have

- ▶ $B^s(q^{-1}) = B(q^{-1})$
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- ▶ Expressing $R(q^{-1}) = 1 + r_1q^{-1} + \dots + r_{n_r}q^{-n_r}$, the optimal cost is

$$\begin{aligned} E\{y^2(k)\} &= E\{[R(q^{-1})\epsilon(k)]^2\} \\ &= E\{[\epsilon(k) + r_1\epsilon(k-1) + \dots + r_{n_r}\epsilon(k-n_r)]^2\} \\ &= E\{\epsilon^2(k)\} + r_1^2 E\{\epsilon^2(k-1)\} + \dots + r_{n_r}^2 E\{\epsilon^2(k-n_r)\} \\ &= (1 + r_1^2 + \dots + r_{n_r}^2) E\{\epsilon^2(k)\} \end{aligned}$$

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Therefore

$$E\{y^2(k)\} = (1 + r_1^2 + \dots + r_{n_r}^2)(\hat{C}M\hat{C}^T + V)$$

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Comments on the notation in this proof:

- ▶ Capital letters always denote polynomials; lower case letters denote sequences (except d and q)
- ▶ Dependency of polynomials on q^{-1} will be omitted
e.g. \bar{B}^u will refer to $\bar{B}^u(q^{-1})$
- ▶ Dependency of sequences on k will be omitted
e.g. y will refer to $y(k)$

Part 1: Rewrite Dynamics

The plant dynamics are

$$Ay = q^{-d}Bu + C\epsilon$$

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$$R[q^{-d}Bu + C\epsilon] = [C - q^{-d}S]y$$

$$\Rightarrow Cy - q^{-d}(Sy + BRu) - CR\epsilon = 0$$

Part 1: Rewrite Dynamics

From the previous slide:

$$Cy - q^{-d}(Sy + BRu) - CR\epsilon = 0$$

- ▶ Define $z(k)$ in terms of $y(k)$ and $u(k)$ using

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(note that we are not necessarily using the optimal control)

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Since C is anti-Schur, we have $y - q^{-d}z - \epsilon_f \rightarrow 0$

$$y(k) = z(k - d) + \epsilon_f(k)$$

Part 2: $E\{z(k-d)\epsilon_f(k)\} = 0$

- ▶ Since $\epsilon(k) = y(k) - E\{y(k)|y(k-1), y(k-2), \dots\}$, we use least squares property 1 to see that

$$E\{y(k-\ell)\epsilon(k+p)\}, \quad \forall \ell > 0, p \geq 0$$

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- ▶ $\epsilon_f(k+d-1) = \epsilon(k+d-1) + r_1\epsilon(k+d-2) + \dots + r_{d-1}\epsilon(k)$
 $\Rightarrow E\{y(k-\ell)\epsilon_f(k+d-1)\} = 0 \quad \forall \ell > 0$

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$$\Rightarrow E\{y(k-\ell)\epsilon_f(k+d-1)\} = 0 \quad \forall \ell > 0$$

- ▶ Since $u(k)$ is a function of $y(k), y(k-1), \dots$

$$E\{u(k-\ell)\epsilon_f(k+d-1)\} = 0 \quad \forall \ell > 0$$

Part 2: $E\{z(k-d)\epsilon_f(k)\} = 0$

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$$E\{y(k-l)\epsilon(k+p)\}, \quad \forall l > 0, p \geq 0$$

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$$\Rightarrow E\{y(k-l)\epsilon_f(k+d-1)\} = 0 \quad \forall l > 0$$

- ▶ Since $u(k)$ is a function of $y(k), y(k-1), \dots$

$$E\{u(k-l)\epsilon_f(k+d-1)\} = 0 \quad \forall l > 0$$

- ▶ Since $z(k)$ is a function of $y(k), y(k-1), \dots$ and $u(k), u(k-1), \dots$

$$E\{z(k-l)\epsilon_f(k+d-1)\} = 0 \quad \forall l > 0$$

Part 2: $E\{z(k-d)\epsilon_f(k)\} = 0$

- ▶ Since $\epsilon(k) = y(k) - E\{y(k)|y(k-1), y(k-2), \dots\}$, we use least squares property 1 to see that

$$E\{y(k-l)\epsilon(k+p)\}, \quad \forall l > 0, p \geq 0$$

- ▶ $\epsilon_f(k+d-1) = \epsilon(k+d-1) + r_1\epsilon(k+d-2) + \dots + r_{d-1}\epsilon(k)$

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- ▶ Choosing $l = 1$ completes part 2

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- ▶ If we can make $E\{z^2\} = 0$, the control must be optimal

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- ▶ For this control signal, $E\{z^2\} = 0$, which means that $u_*(k)$ is optimal, provided that the closed-loop system is stable
- ▶ Also note that $E\{y^2\} = E\{\epsilon_f^2\}$, provided that the closed-loop system is stable

Part 4: Closed-loop stability

From the plant dynamics and feedback law, we have

$$\begin{bmatrix} A & -q^{-d}B \\ S & BR \end{bmatrix} \begin{bmatrix} y \\ u \end{bmatrix} = \begin{bmatrix} C\epsilon \\ 0 \end{bmatrix}$$

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Since $C(q^{-1})B(q^{-1})$ is an anti-Schur polynomial of q^{-1} , the closed-loop system is stable ■

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A-causal but BIBO Systems

Proof, General Case

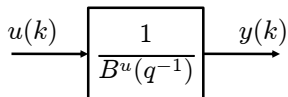
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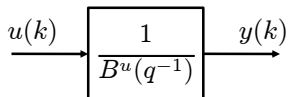
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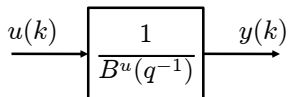


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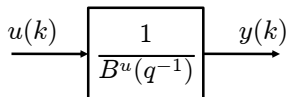
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Interpretation 1: Causal, but Unstable

We are considering the AR model $B^u(q^{-1})y(k) = u(k)$ where

$$B^u(q^{-1}) = 1 + b_1^u q^{-1} + \dots + b_{m_u}^u q^{-m_u}$$

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$$\begin{aligned} y(k) &= u(k) - [b_1^u q^{-1} + \dots + b_{m_u}^u q^{-m_u}]y(k) \\ &= u(k) - b_1^u y(k-1) - \dots - b_{m_u}^u y(k-m_u) \end{aligned}$$

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$$\begin{aligned} \Rightarrow y(k) &= \frac{1}{b_{m_u}^u} [u(k + m_u) - y(k + m_u) - b_1^u y(k + m_u - 1) \\ &\quad - \dots - b_{m_u-1}^u y(k + 1)] \end{aligned}$$

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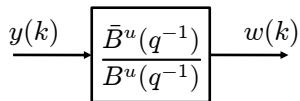
$y(k)$ is a function of $u(k + m_u), u(k + m_u + 1), u(k + m_u + 2), \dots$

A-causal but BIBO All-Pass Filter

Let $w(k)$ be the output of the a-causal, but BIBO ARMAX model

$$B^u(q^{-1})w(k) = \bar{B}^u(q^{-1})y(k)$$

This corresponds to the block diagram

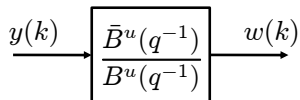


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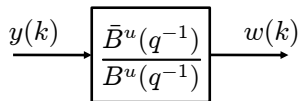
$$\left| \frac{\bar{B}^u(e^{-j\omega})}{B^u(e^{-j\omega})} \right| = 1 \quad \forall \omega \in [0, 2\pi]$$

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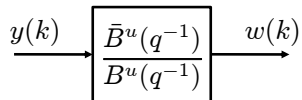
$$\left| \frac{\bar{B}^u(e^{-j\omega})}{B^u(e^{-j\omega})} \right| = 1 \quad \forall \omega \in [0, 2\pi]$$

Proof:

$$\bar{B}^u(q) = q^{m_u} B^u(q^{-1}) \quad \Rightarrow \quad \bar{B}^u(q^{-1}) = q^{-m_u} B^u(q)$$

$$\Rightarrow \quad |\bar{B}^u(e^{-j\omega})| = |e^{-j\omega m_u} B^u(e^{j\omega})| = |B^u(e^{j\omega})| = |B^u(e^{-j\omega})|$$

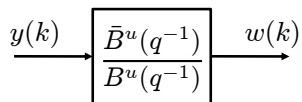
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The power spectral density of $w(k)$ is

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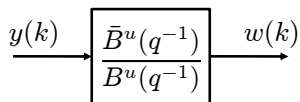
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Comments on the notation in this proof:

- ▶ Capital letters always denote polynomials; lower case letters denote sequences (except d and q)
- ▶ Dependency of polynomials on q^{-1} will be omitted
e.g. \bar{B}^u will refer to $\bar{B}^u(q^{-1})$
- ▶ Dependency of sequences on k will be omitted
e.g. y will refer to $y(k)$

Part 1: Rewrite Dynamics

The plant dynamics are

$$Ay = q^{-d}Bu + C\epsilon$$

and the Diophantine equation gives

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Factoring B^u out of the term in parentheses yields

$$\Rightarrow C\bar{B}^u y - q^{-d}B^u(Sy + B^s Ru) - CR\epsilon = 0$$

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- ▶ From the top equation,

$$\begin{aligned} C B^u w - q^{-d} C B^u z - C B^u \bar{\epsilon}_f &= 0 \\ \Rightarrow C B^u (w - q^{-d} z - \bar{\epsilon}_f) &= 0 \end{aligned}$$

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So far, we know that

$$CB^u(w - q^{-d}z - \bar{\epsilon}_f) = 0$$

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$$w(k) = z(k - d) + \bar{\epsilon}_f(k)$$

- ▶ Also note that, because $w(k) = \frac{\bar{B}^u(q^{-1})}{B^u(q^{-1})}y(k)$

$$E\{w^2(k)\} = E\{y^2(k)\}$$

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- ▶ Since $\epsilon(k) = y(k) - E\{y(k)|y(k-1), y(k-2), \dots\}$, we use least squares property 1 to see that

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- ▶ Choosing $\ell = 1$ yields

$$E\{z(k-d)\bar{\epsilon}_f(k)\} = 0$$

Part 3: Optimal Control

So far, we know

$$w(k) = z(k - d) + \bar{\epsilon}_f(k)$$

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- ▶ \Rightarrow We would like to choose u to minimize $E\{z^2\}$
- ▶ If we can make $E\{z^2\} = 0$, the control must be optimal

Part 3: Optimal Control

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- ▶ For this control signal, $E\{z^2\} = 0$, which means that $u_*(k)$ is optimal, provided that the closed-loop system is stable.
- ▶ Also note that $E\{y^2\} = E\{\tilde{e}_f^2\}$, provided that the closed-loop system is stable

Part 3: Optimal Control

- ▶ Provided that the closed-loop system is stable, we have $E\{y^2\} = E\{\bar{\epsilon}_f^2\}$ where $\bar{\epsilon}_f$ is generated by the BIBO a-causal ARMA model $B^u \bar{\epsilon}_f = R\epsilon$

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(Remember that \bar{B}^u refers to $\bar{B}^u(q^{-1})$)

- ▶ To see this, note that since $\bar{\epsilon}_f$ is the output of the a-causal but BIBO ARMA model $B^u \bar{\epsilon}_f = \bar{B}^u \epsilon_f$ and the operator $\left(\frac{\bar{B}^u}{B^u}\right)$ is an a-causal all-pass filter, we have that $E\{\epsilon_f^2\} = E\{\bar{\epsilon}_f^2\}$

Part 4: Closed-loop stability

From the plant dynamics and feedback law, we have

$$\begin{bmatrix} A & -q^{-d}B \\ S & B^s R \end{bmatrix} \begin{bmatrix} y \\ u \end{bmatrix} = \begin{bmatrix} C\epsilon \\ 0 \end{bmatrix}$$

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Since $C(q^{-1})\bar{B}^u(q^{-1})B^s(q^{-1})$ is an anti-Schur polynomial of q^{-1} , the closed-loop system is stable ■