

Institute of Systems Science and Intelligent Control Technology 系统科学与智能控制研究所

鲁棒控制： 建模、跟踪、抗扰、容错

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爱眼无窮

提纲

- 1 古典控制基础
- 2 鲁棒控制理论基础
- 3 鲁棒控制在迟滞系统中应用
- 4 高精度跟踪与抗扰控制
- 5 故障诊断与容错控制
- 6 教材2-16章

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State Space Formula

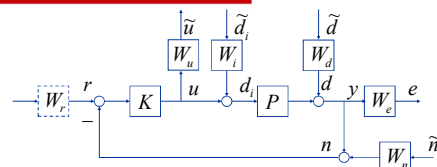
- Let $P = \begin{bmatrix} A & B \\ C & D \end{bmatrix}$ be a stabilizable and detectable realization, and let F and L be such that $A+BF$ and $A+LC$ are both stable.

- Define

$$\begin{bmatrix} M \\ N \end{bmatrix} = \begin{bmatrix} A+BF & B \\ F & I \end{bmatrix} \quad \begin{bmatrix} \tilde{N} & \tilde{M} \end{bmatrix} = \begin{bmatrix} A+LC & B+LD & L \\ C & D & I \end{bmatrix}$$

Then $P = NM^{-1} = \tilde{M}^{-1}\tilde{N}$ are rcf and lcf, respectively.

Weighted H_2 and H_∞



H_2 Performance: Assume $d_1(t) = \eta \delta(t)$ and $E(\eta\eta^*) = I$
Minimize the expected energy of the error e :

$$E\{\|e\|_2^2\} = E\left\{\int_0^\infty \|e\|^2 dt\right\} = \|W_e S_o W_d\|_2^2$$

Include the control signal u in the cost function:

$$E\{\|e\|_2^2 + \rho^2 \|u\|_2^2\} = \left\| \begin{bmatrix} W_e S_o W_d \\ \rho W_u K S_o W_d \end{bmatrix} \right\|_2^2$$

Robustness problem????

H_∞ Performance: under worst possible case

$$\sup_{\|d\|_2 \leq 1} \|e\|_2 = \|W_e S_o W_d\|_\infty$$

restrictions on the control energy or control bandwidth:

$$\sup_{\|u\|_2 \leq 1} \|u\|_2 = \|W_u K S_o W_d\|_\infty$$

Combined cost:

$$\sup_{\|d\|_2 \leq 1} \left\{ \|e\|_2^2 + \rho^2 \|u\|_2^2 \right\} = \left\| \begin{bmatrix} W_e S_o W_d \\ \rho W_u K S_o W_d \end{bmatrix} \right\|_\infty^2$$

Chapter 7: Balanced Model Reduction

- Lyapunov Equations
- Gramians
- Controllable Decomposition
- Observable Decomposition
- Balanced Realization
- Computing Balanced Realization
- Balanced Truncation and Matlab
- Bounds of Functions Norms
- Balanced Model Reduction
- Frequency Weighted Balanced Model Reduction
- Relative Reduction

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Lyapunov Equations

Consider the following Lyapunov equation

$$A^*X + XA + Q = 0$$

- Assume that A is stable, then the following statements hold:

- $X = \int_0^\infty e^{A^*t} Q e^{At} dt$.
- $X > 0$ if $Q > 0$ and $X \geq 0$ if $Q \geq 0$.
- if $Q \geq 0$, then (Q, A) is observable iff $X > 0$.

- Proof:

$$\begin{aligned} A^*X + XA &= A^* \int_0^\infty e^{A^*t} Q e^{At} dt + \int_0^\infty e^{A^*t} Q e^{At} A dt \\ &= \int_0^\infty (A^* e^{A^*t} Q e^{At} + e^{A^*t} Q e^{At} A) dt = \int_0^\infty \frac{d}{dt} (e^{A^*t} Q e^{At}) dt = -Q \end{aligned}$$

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Let $Q = C^*C$ for some C matrix and let $v \in \mathbb{C}$.
Then $X \geq 0$ and

$$v^* X v = \int_0^\infty v^* e^{A^* t} Q e^{A t} v dt = \int_0^\infty \|C e^{A t} v\|^2 dt$$

Thus X is singular

\Leftrightarrow there is a $v \in \mathbb{C}$ such that $C e^{A t} v = 0, \forall t$

$$\Leftrightarrow \text{there is a } v \in \mathbb{C} \text{ such that } \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix} v = 0$$

$\Leftrightarrow (C, A)$ is not observable

$\Leftrightarrow (Q, A)$ is not observable.

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$$A^*X + XA + Q = 0$$

□ Suppose X is the solution of the Lyapunov equation, then

■ $\operatorname{Re} \lambda_i(A) \leq 0$ if $X > 0$ and $Q \geq 0$.

■ A is stable if $X > 0$ and $Q > 0$.

■ A is stable if $X \geq 0, Q \geq 0$ and (Q, A) is detectable.

□ Proof: Let λ be an eigenvalue and v be a corresponding eigenvector of A , i.e., $Av = \lambda v$. Then

$$0 = v^*(A^*X + XA)v = (\lambda^* + \lambda)v^*Xv + v^*Qv = 2 \operatorname{Re} \lambda v^*Xv + v^*Qv$$

$$\geq 2 \operatorname{Re} \lambda v^*Xv \text{ since } Q \geq 0. \text{ Thus } \operatorname{Re} \lambda \leq 0.$$

If $\operatorname{Re} \lambda = 0$, then $v^*Qv = 0$. Thus $Qv = 0$ and $Av = \lambda v$. By PBH test, (Q, A) is not detectable.

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Gramians



□ Let A be stable. Then a pair (C, A) is observable iff the observability Gramian $Q > 0$

$$A^*Q + QA + C^*C = 0.$$

Similarly, (A, B) is controllable iff the controllability Gramian $P > 0$

$$AP + PA^* + BB^* = 0$$

□ When A is not necessarily stable, the above Lyapunov equations may still have solutions. But they are not gramians.

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Controllable Decomposition



Let $\begin{bmatrix} A & B \\ C & D \end{bmatrix}$ be a state space realization of a (not necessarily stable) transfer matrix $G(s)$. Suppose that there exists a symmetric matrix

$$P = P^* = \begin{bmatrix} P_1 & 0 \\ 0 & 0 \end{bmatrix}$$

(P is not necessarily the Gramian) with P_1 nonsingular such that

$$AP + PA^* + BB^* = 0$$

Now partition the realization (A, B, C, D) compatibly with P as

$$\begin{bmatrix} A_{11} & A_{12} & B_1 \\ A_{21} & A_{22} & B_2 \\ C_1 & C_2 & D \end{bmatrix}$$

Then $\begin{bmatrix} A_{11} & B_1 \\ C_1 & D \end{bmatrix}$ is also a realization of G .

Moreover, (A_{11}, B_1) is controllable if A_{11} is stable.

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Controllable Decomposition



Proof Using the partitioned equation $0 = AP + PA^* + BB^*$ to get

$$A_{11}P_1 + P_1A_{11}^* + B_1B_1^* = 0, \quad P_1A_{21}^* + B_1B_2^* = 0, \text{ and } B_2B_2^* = 0$$

then we conclude that $B_2 = 0$ and $A_{21} = 0$. Hence, part of the realization is not controllable:

$$\begin{bmatrix} A_{11} & A_{12} & B_1 \\ A_{21} & A_{22} & B_2 \\ C_1 & C_2 & D \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & B_1 \\ 0 & A_{22} & 0 \\ C_1 & C_2 & D \end{bmatrix} = \begin{bmatrix} A_{11} & B_{11} \\ C_1 & D \end{bmatrix}$$

$P_1 > 0$ if A_{11} is stable. So (A_{11}, B_1) is controllable.

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Observable Decomposition



Let $\begin{bmatrix} A & B \\ C & D \end{bmatrix}$ be a state space realization of a (not necessarily stable) transfer matrix $G(s)$. Suppose that there exists a symmetric matrix

$$Q = Q^* = \begin{bmatrix} Q_1 & 0 \\ 0 & 0 \end{bmatrix}$$

(Q is not necessarily the Gramian) with Q_1 nonsingular such that

$$A^*Q + QA + C^*C = 0$$

Now partition the realization (A, B, C, D) compatibly with Q as

$$\begin{bmatrix} A_{11} & A_{12} & B_1 \\ A_{21} & A_{22} & B_2 \\ C_1 & C_2 & D \end{bmatrix}$$

Then $\begin{bmatrix} A_{11} & B_1 \\ C_1 & D \end{bmatrix}$ is also a realization of G .

Moreover, (C_1, A_{11}) is observable if A_{11} is stable.

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Balanced Realization

- Let P and Q be the controllability and observability Gramians,

$$AP+PA^*+BB^*=0, \quad A^*Q+QA+C^*C=0$$

Suppose $P=Q=\Sigma=\text{diag}(\sigma_1, \sigma_2, \dots, \sigma_n)$. Then the state space realization is called *internally balanced realization* and $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0$, are called the *Hankel singular values* of the system.

- Two other closely related realizations are called

input normal realization with $P = I$ and $Q = \Sigma^2$

and

output normal realization with $P = \Sigma^2$ and $Q = I$.

Both realizations can be obtained easily from the balanced realization by a suitable scaling on the states.

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Computing Balanced Realization

- In the special case where $\begin{bmatrix} A & B \\ C & D \end{bmatrix}$ is a minimal realization, a balanced realization can be obtained through the following simplified procedure:

1. Compute $P>0$ and $Q>0$.
2. Find a matrix R such that $P=R^*R$.
3. Diagonalize RQR^* to get $RQR^*=U\Sigma^2U^*$.
4. Let $T^{-1}=R^*U\Sigma^{-1/2}$. Then $TPR^*=(T^*)^{-1}QT^{-1}=\Sigma$ and $\begin{bmatrix} TAT^{-1} & TB \\ CT^{-1} & D \end{bmatrix}$ is balanced.

- In general, let P and Q be two positive semidefinite matrices. Then there exists a nonsingular matrix T such that

$$TPR^* = \begin{bmatrix} \Sigma_1 & & \\ & \Sigma_2 & \\ & & 0 \end{bmatrix} \quad (T^{-1})^*QT^{-1} = \begin{bmatrix} \Sigma_1 & & \\ & 0 & \\ & & \Sigma_3 \end{bmatrix}$$

respectively with $\Sigma_1, \Sigma_2, \Sigma_3$ diagonal and positive definite.

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Balanced Truncation and Matlab

- Suppose $\sigma_r \gg \sigma_{r+1}$ for some r then the balanced realization implies that those states corresponding to the singular values of $\sigma_{r+1}, \dots, \sigma_n$ are less controllable and observable than those states corresponding to $\sigma_1, \dots, \sigma_r$. Therefore, truncating those less controllable and observable states will not lose much information about the system.

- MATLAB:

```
>>[G,ss(A,B,C,D);
>>[Gb,sig,T,Tinv]=balreal(G); %sig is a vector of Hankel
    singular values and Tinv=T^-1;
>>[Gred,redinfo] = balancmr(G,r); %r=reduced order
>>[Gred,redinfo] =
    reduce(G,'ErrorType','add','MaxError',[0.01,0.05]);
>>[Gred,redinfo] = reduce(G,[5:10],'ErrorType','mult')
```

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Bounds of Function Norms

- Suppose $G(s) = \begin{bmatrix} A & B \\ C & 0 \end{bmatrix} \in RH_\infty$ is a balanced realization: that is, there exists

$$\Sigma = \text{diag}(\sigma_1 I_{S_1}, \sigma_2 I_{S_2}, \dots, \sigma_N I_{S_N}) \quad \text{with} \quad \sigma_1 > \sigma_2 > \dots > \sigma_N \geq 0,$$

such that

$$A\Sigma + \Sigma A^* + BB^* = 0, \quad A^*\Sigma + \Sigma A + C^*C = 0$$

Then

$$\sigma_1 \leq \|G\|_\infty \leq \int_0^\infty \|g(t)\|^2 dt \leq 2 \sum_{i=1}^N \sigma_i$$

where $g(t) = Ce^{At}B$.

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Bounds (proof)

- Proof: Consider $\dot{x} = Ax + Bw$
 $z = Cx$

where (A,B) is controllable and (C,A) is observable.

$$\frac{d}{dt}(x^* \Sigma^{-1} x) = x^* \Sigma^{-1} \dot{x} + \dot{x}^* \Sigma^{-1} x = x^* (A^* \Sigma^{-1} + \Sigma^{-1} A)x + 2\langle w, B^* \Sigma^{-1} x \rangle$$

$$\frac{d}{dt}(x^* \Sigma^{-1} x) = \|w\|^2 - \|w - B^* \Sigma^{-1} x\|^2$$

Integration from $t = -\infty$ to $t = 0$ with $x(-\infty) = 0$ and $x(0) = x_0$ gives

$$x_0^* \Sigma^{-1} x_0 = \|w\|_2^2 - \|w - B^* \Sigma^{-1} x\|_2^2 \leq \|w\|_2^2$$

$$\inf_{w \in L_2(-\infty, 0)} \left\{ \|w\|_2^2 : x(0) = x_0 \right\} = x_0^* \Sigma^{-1} x_0.$$

Given $x(0) = x_0$ and $w = 0$ for $t \geq 0$, the norm of $z(t) = Ce^{At}x_0$ can be found from

$$\int_0^\infty \|z(t)\|^2 dt = \int_0^\infty x_0^* e^{A^* t} C^* C e^{-At} x_0 dt = x_0^* \Sigma x_0$$

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To show $\sigma_1 \leq \|G\|_\infty$, note that

$$\|G\|_\infty = \sup_{\|u\|_2=1} \left\| \int_0^\infty e^{At} B u dt \right\|_2 = \sup_{\|u\|_2=1} \sqrt{\int_0^\infty \|e^{At} B u\|_2^2 dt} \geq \sup_{\|u\|_2=1} \sqrt{\int_0^\infty \|e^{At} B u\|_2^2 dt}$$

$$\geq \sup_{\|u\|_2=1} \sqrt{\int_0^\infty \|e^{At} B u\|_2^2 dt} = \sup_{\|u\|_2=1} \sqrt{x_0^* \Sigma x_0} = \sigma_1$$

We shall now show the other inequalities. Since

$$G(s) = \int_0^\infty g(t) e^{-st} dt, \quad \text{Re}(s) > 0,$$

by the definition of H_∞ norm, we have

$$\|G\|_\infty = \sup_{\text{Re}(s) > 0} \left\| \int_0^\infty g(t) e^{-st} dt \right\| \leq \sup_{\text{Re}(s) > 0} \int_0^\infty \|g(t) e^{-st}\| dt \leq \int_0^\infty \|g(t)\| dt.$$

See next page for the proof of the last inequality.

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To prove the last inequality, let e_i be the i th unit vector and note that $\sum e_i e_i^* = I$ and consider the case $s_i = 1$ (general case with a suitable change)

$$\begin{aligned} \int_0^\infty \|g(t)\|^2 dt &= \int_0^\infty \left\| C e^{A_1 t/2} \sum_{j=1}^n e_j e_j^* e^{A_1 t/2} B \right\|^2 dt \leq \sum_{j=1}^n \int_0^\infty \left\| C e^{A_1 t/2} e_j e_j^* e^{A_1 t/2} B \right\|^2 dt \\ &\leq \sum_{j=1}^n \int_0^\infty \left\| C e^{A_1 t/2} e_j \right\|^2 \int_0^\infty \left\| e_j^* e^{A_1 t/2} B \right\|^2 dt \\ &\leq 2 \sum_{j=1}^n \sigma_j \end{aligned}$$

where we have used Cauchy-Schwarz inequality and the following relations

$$\begin{aligned} \int_0^\infty \left\| C e^{A_1 t/2} e_j \right\|^2 dt &= \int_0^\infty e_j^* e^{A_1 t} C^* C e^{A_1 t/2} e_j dt = 2 e_j^* \Sigma e_j = 2 \sigma_j \\ \int_0^\infty \left\| e_j^* e^{A_1 t/2} B \right\|^2 dt &= \int_0^\infty e_j^* e^{A_1 t} B B^* e^{A_1 t/2} e_j dt \end{aligned}$$

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Balanced Model Reduction



Additive Model Reduction

$$G = G_r + \Delta_r \Rightarrow \inf_{\deg(G_r) \leq r} \|G - G_r\|_\infty$$

□ Suppose

$$G(s) = \begin{bmatrix} A_{11} & A_{12} & B_1 \\ A_{21} & A_{22} & B_2 \\ C_1 & C_2 & D \end{bmatrix}$$

is a balanced realization with Gramian $\Sigma = \text{diag}(\Sigma_1, \Sigma_2)$

$$A \Sigma + \Sigma A^* + B B^* = 0, \quad A^* \Sigma + \Sigma A + C^* C = 0$$

where

$$\Sigma_1 = \text{diag}(\sigma_1 I_{s_1}, \sigma_2 I_{s_2}, \dots, \sigma_r I_{s_r}), \quad \Sigma_2 = \text{diag}(\sigma_{r+1} I_{s_{r+1}}, \sigma_{r+2} I_{s_{r+2}}, \dots, \sigma_N I_{s_N})$$

and

$$\sigma_1 > \sigma_2 > \dots > \sigma_r > \sigma_{r+1} > \sigma_{r+2} > \dots > \sigma_N \geq 0,$$

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where σ_i has multiplicity s_i , $i = 1, 2, \dots, N$ and $s_1 + s_2 + \dots + s_N = n$.

Then the truncated system

$$G_r(s) = \begin{bmatrix} A_{11} & B_1 \\ C_1 & D \end{bmatrix}$$

is balanced and asymptotically stable. Furthermore

$$\|G(s) - G_r(s)\|_\infty \leq 2(\sigma_{r+1} + \sigma_{r+2} + \dots + \sigma_N),$$

$$\|G(s) - G(\infty)\|_\infty \leq 2(\sigma_1 + \sigma_2 + \dots + \sigma_N),$$

$$\|G(s) - G_{N-1}(s)\|_\infty = 2\sigma_N.$$

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Additive Reduction (proof)



□ Proof. We shall first show the one step model reduction. Hence we shall assume $\Sigma_2 = \sigma_N I_{s_N}$. Define the approximation error

$$E_{11} = \begin{bmatrix} A_{11} & A_{12} & B_1 \\ A_{21} & A_{22} & B_2 \\ C_1 & C_2 & D \end{bmatrix} - \begin{bmatrix} A_{11} & B_1 \\ C_1 & D \end{bmatrix} = \begin{bmatrix} A_{11} & 0 & 0 & B_1 \\ 0 & A_{11} & A_{12} & B_1 \\ 0 & A_{21} & A_{22} & B_2 \\ -C_1 & C_1 & C_2 & 0 \end{bmatrix}$$

Apply a similarity transformation T to the preceding state-space realization with

$$T = \begin{bmatrix} I/2 & I/2 & 0 \\ I/2 & -I/2 & 0 \\ 0 & 0 & I \end{bmatrix}, \quad T^{-1} = \begin{bmatrix} I & I & 0 \\ I & -I & 0 \\ 0 & 0 & I \end{bmatrix}$$

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to get

$$E_{11} = \begin{bmatrix} A_{11} & 0 & A_{12}/2 & B_1 \\ 0 & A_{11} & -A_{12}/2 & 0 \\ A_{21} & -A_{21} & A_{22} & B_2 \\ 0 & -2C_1 & C_2 & 0 \end{bmatrix}$$

Consider a dilation of $E_{11}(s)$:

$$\begin{aligned} E(s) = \begin{bmatrix} E_{11}(s) & E_{12}(s) \\ E_{21}(s) & E_{22}(s) \end{bmatrix} &= \begin{bmatrix} A_{11} & 0 & A_{12}/2 & B_1 & 0 \\ 0 & A_{11} & -A_{12}/2 & 0 & \sigma_N \Sigma_1^{-1} C_1^* \\ A_{21} & -A_{21} & A_{22} & B_2 & -C_2^* \\ 0 & -2C_1 & C_2 & 0 & 2\sigma_N I \\ -2\sigma_N B_1^* \Sigma_1^{-1} & 0 & -B_2^* & -2\sigma_N I & 0 \end{bmatrix} \\ &= \begin{bmatrix} \tilde{A} & \tilde{B} \\ \tilde{C} & \tilde{D} \end{bmatrix} \end{aligned}$$

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Then it is easy to verify that

$$\tilde{P} = \begin{bmatrix} \Sigma_1 & 0 & 0 \\ 0 & \sigma_N^2 \Sigma_1^{-1} & 0 \\ 0 & 0 & 2\sigma_N I_{s_N} \end{bmatrix}, \quad \tilde{A} \tilde{P} + \tilde{P} \tilde{A}^* + \tilde{B} \tilde{B}^* = 0, \quad \tilde{P} \tilde{C}^* + \tilde{B} \tilde{D}^* = 0$$

Using these equations, we have

$$\begin{aligned} E(s)E^*(s) &= \begin{bmatrix} \tilde{A} & -\tilde{B}\tilde{B}^* & \tilde{B}\tilde{D}^* \\ 0 & -\tilde{A} & \tilde{C} \\ \tilde{C} & -\tilde{D}\tilde{B}^* & \tilde{D}\tilde{D}^* \end{bmatrix} \begin{bmatrix} \tilde{A}^* & -\tilde{A}\tilde{P} - \tilde{P}\tilde{A}^* - \tilde{B}\tilde{B}^* & \tilde{P}\tilde{C}^* + \tilde{B}\tilde{D}^* \\ 0 & -\tilde{A}^* & \tilde{C}^* \\ \tilde{C}^* & -\tilde{C}\tilde{P} - \tilde{D}\tilde{B}^* & \tilde{D}\tilde{D}^* \end{bmatrix} \\ &= \begin{bmatrix} \tilde{A} & 0 & 0 \\ 0 & -\tilde{A} & \tilde{C} \\ \tilde{C} & 0 & \tilde{D}\tilde{D}^* \end{bmatrix} = \tilde{D}\tilde{D}^* = 4\sigma_N^2 I \end{aligned}$$

where a second equality is obtained by applying a similarity transformation

$$T = \begin{bmatrix} I & \tilde{P} \\ 0 & I \end{bmatrix}$$

Hence $\|E_{11}\|_\infty \leq \|E\|_\infty = 2\sigma_N$, which is the desired result.

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The remainder of the proof is achieved by using the order reduction by one-step results and by noting that

$$G_k(s) = \begin{bmatrix} A_{11} & B_1 \\ C_1 & D \end{bmatrix}$$

obtained by the "kth" order partitioning is internally balanced with balanced Gramian given by $\Sigma_k = \text{diag}(\sigma_1 I_{s_1}, \sigma_2 I_{s_2}, \dots, \sigma_k I_{s_k})$

Let $E_k(s) = G_{k+1}(s) - G_k(s)$ for $k=1, 2, \dots, N-1$ and let $G_N(s) = G(s)$. Then

$$\bar{\sigma}[E_k(j\omega)] \leq 2\sigma_{k+1}$$

Since $G_k(s)$ is a reduced-order model obtained from the internally balanced realization of $G_{k+1}(s)$ and the bound for one-step order reduction holds.

Noting that $G(s) - G_r(s) = \sum_{k=r}^{N-1} E_k(s)$

by the definition of $E_k(s)$, we have

$$\bar{\sigma}[G(j\omega) - G_r(j\omega)] \leq \sum_{k=r}^{N-1} \bar{\sigma}[E_k(j\omega)] \leq 2 \sum_{k=r}^{N-1} \sigma_{k+1}$$

This is the desired upper bound.

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Tightness of the Bounds



□ Bound can be tight. For example,

$$G(s) = \sum_{j=1}^n \frac{b_j}{s + a_j} = \begin{bmatrix} -a_1 & & & \sqrt{b_1} \\ & -a_2 & & \sqrt{b_2} \\ & & \ddots & \vdots \\ & & & -a_n \\ \sqrt{b_1} & \sqrt{b_2} & \cdots & \sqrt{b_n} & 0 \end{bmatrix}$$

with $a_j > 0$ and $b_j > 0$. Then

$$P = Q = \begin{bmatrix} \sqrt{b_1 b_j} \\ a_j + a_j \end{bmatrix} \text{ and } \|G(s)\|_\infty = G(0) = \sum_{i=1}^n \frac{b_i}{a_i} = 2 \text{trace}(P) = 2 \sum_{i=1}^n \sigma_i$$

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□ Bound can also be loose for systems with Hankel singular values close to each other. For example,

$$G(s) = \begin{bmatrix} -19.9579 & -5.4682 & 9.6954 & 0.9160 & -6.3180 \\ 5.4682 & 0 & 0 & 0.2378 & 0.0020 \\ -9.6954 & 0 & 0 & -4.0051 & -0.0067 \\ 0.9160 & -0.2378 & 4.0051 & -0.0420 & 0.2893 \\ -6.3180 & -0.0020 & 0.0067 & 0.2893 & 0 \end{bmatrix}$$

with Hankel singular values given by

$$\sigma_1=1, \sigma_2=0.9977, \sigma_3=0.99570, \sigma_4=0.9952$$

| r | 0 | 1 | 2 | 3 |
|-------------------------------------|--------|--------|--------|--------|
| $\ G - G_r\ _\infty$ | 2 | 1.996 | 1.991 | 1.9904 |
| Bounds: $2 \sum_{i=r+1}^4 \sigma_i$ | 7.9772 | 5.9772 | 3.9818 | 1.9904 |
| $2\sigma_{r+1}$ | 2 | 1.9954 | 1.9914 | 1.9904 |

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Frequency-Weighted Reduction



□ General Case: given weights W_o and W_i , find G_r such that

$$\inf_{\deg(G_r) \leq r} \|W_o(G - G_r)W_i\|$$

Let

$$G = \begin{bmatrix} A & B \\ C & 0 \end{bmatrix}, W_i = \begin{bmatrix} A_i & B_i \\ C_i & D_i \end{bmatrix}, W_o = \begin{bmatrix} A_o & B_o \\ C_o & D_o \end{bmatrix},$$

$$W_o G W_i = \begin{bmatrix} A & 0 & B C_i & B D_i \\ B_o C & A_o & 0 & 0 \\ 0 & 0 & A_i & B_i \\ D_o C & C_o & 0 & 0 \end{bmatrix} = \begin{bmatrix} \tilde{A} & \tilde{B} \\ \tilde{C} & 0 \end{bmatrix}$$

and solving the following Lyapunov equations

$$\tilde{A} \tilde{P} + \tilde{P} \tilde{A}^* + \tilde{B} \tilde{B}^* = 0$$

$$\tilde{Q} \tilde{A} + \tilde{A}^* \tilde{Q} + \tilde{C}^* \tilde{C} = 0.$$

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Frequency-Weighted Reduction



The input/output weighted Gramians P and Q are defined by

$$P := \begin{bmatrix} I_n & 0 \end{bmatrix} \tilde{P} \begin{bmatrix} I_n \\ 0 \end{bmatrix}, \quad Q := \begin{bmatrix} I_n & 0 \end{bmatrix} \tilde{Q} \begin{bmatrix} I_n \\ 0 \end{bmatrix}.$$

P and Q satisfy the following lower order equations

$$\begin{bmatrix} A & B C_i \\ 0 & A_i \end{bmatrix} \begin{bmatrix} P & P_{12} \\ P_{12}^* & P_{22} \end{bmatrix} + \begin{bmatrix} P & P_{12} \\ P_{12}^* & P_{22} \end{bmatrix} \begin{bmatrix} A & B C_i \\ 0 & A_i \end{bmatrix}^* + \begin{bmatrix} B D_i & B_i \\ B_i^* & D_i \end{bmatrix} \begin{bmatrix} P & P_{12} \\ P_{12}^* & P_{22} \end{bmatrix}^* = 0$$

$$\begin{bmatrix} Q & Q_{12} \\ Q_{12}^* & Q_{22} \end{bmatrix} \begin{bmatrix} A & 0 \\ B_o C & A_o \end{bmatrix} + \begin{bmatrix} A & 0 \\ B_o C & A_o \end{bmatrix} \begin{bmatrix} Q & Q_{12} \\ Q_{12}^* & Q_{22} \end{bmatrix}^* + \begin{bmatrix} C^* D_o^* & C^* D_o^* \\ C_o^* & C_o^* \end{bmatrix} \begin{bmatrix} Q & Q_{12} \\ Q_{12}^* & Q_{22} \end{bmatrix} = 0.$$

If $W_i = I$, then P can be obtained from

$$P A^* + A P + B B^* = 0$$

If $W_o = I$, then Q can be obtained from

$$Q A + A^* Q + C^* C = 0$$

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Frequency-Weighted Reduction



Now let T be a nonsingular matrix such that

$$T P T^* = (T^{-1})^* Q T^{-1} = \begin{bmatrix} \Sigma_1 & \\ & \Sigma_2 \end{bmatrix}$$

(i.e., balanced) and partition the system accordingly as

$$\begin{bmatrix} T A T^{-1} & T B \\ C T^{-1} & 0 \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & B_1 \\ A_{21} & A_{22} & B_2 \\ C_1 & C_2 & 0 \end{bmatrix}.$$

Then a reduced order model G_r is obtained as

$$G_r = \begin{bmatrix} A_{11} & B_1 \\ C_1 & 0 \end{bmatrix}.$$

Works well but without guarantee in general.

```
>>[Gred, redinfo] =
    reduce(G,'weight',{wo,wi},'order',[4:2:10])
```

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Relative Reduction

- Consider a special frequency-weighted model reduction problem:

$$G_r = G(I + \Delta_{rel}), \Rightarrow \inf_{\deg(G_r) \leq n} \|G^{-1}(G - G_r)\|_\infty$$

This is a relative error approximation problem.

Consider also a related multiplicative error reduction problem

Let $G(s) = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \in RH_\infty$ be minimum phase and D be nonsingular.

Then
$$W_0 = G^{-1}(s) = \begin{bmatrix} A - BD^{-1}C & -BD^{-1} \\ D^{-1}C & D^{-1} \end{bmatrix}.$$

Now apply the frequency-weighted model reduction to get

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- (a) Then the input/output weighted Gramians P and Q are given by

$$PA^* + AP + BB^* = 0 \\ Q(A - BD^{-1}C) + (A - BD^{-1}C)^*Q + C^*(D^{-1})^*D^{-1}C = 0$$

- (b) Suppose P and Q are balanced:

$$P = Q = \Sigma = \text{diag}(\Sigma_1, \Sigma_2) = \text{diag}(\sigma_1 I_{s_1}, \dots, \sigma_r I_{s_r}, \sigma_{r+1} I_{s_{r+1}}, \dots, \sigma_N I_{s_N})$$

and let G be partitioned compatibly with Σ_1, Σ_2 as

$$G(s) = \begin{bmatrix} A_{11} & A_{12} & B_1 \\ A_{21} & A_{22} & B_2 \\ C_1 & C_2 & D \end{bmatrix} \gg [\text{Gr, redinfo}] = \text{bstmr}(G, r)$$

Then $G_r(s) = \begin{bmatrix} A_{11} & B_1 \\ C_1 & D \end{bmatrix}$ is stable and minimum phase.

Furthermore
$$\|\Delta_{rel}\|_\infty \leq \prod_{i=r+1}^N (1 + 2\sigma_i(\sqrt{1 + \sigma_i^2} + \sigma_i)) - 1$$

$$\|\Delta_{mul}\|_\infty \leq \prod_{i=r+1}^N (1 + 2\sigma_i(\sqrt{1 + \sigma_i^2} + \sigma_i)) - 1$$

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Chapter 8 Uncertainty and Robustness

- model uncertainty
- small gain theorem
- additive uncertainty
- multiplicative uncertainty
- coprime factor uncertainty
- other tests
- robust performance
- skewed specifications
- example: siso vs mimo

Model Uncertainty

Suppose P is the nominal model and K is a controller.

Nominal Stability (NS): if K stabilizes the nominal P .

Robust Stability (RS): if K stabilizes every plant in Π .

Nominal Performance (NP): if the performance objectives are satisfied for the nominal plant P .

Robust Performance (RP): if the performance objectives are satisfied for every plant in Π .

$$P_N(s) = P(s) + w(s)\Delta(s), \quad \|\Delta(j\omega)\| < 1, \forall \omega$$

$$P_N(s) = (I + w(s)\Delta(s))P(s).$$

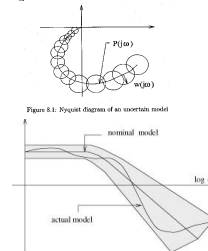


Figure 8.1: Nyquist diagram of an uncertain model

Example 1: Consider a uncertain transfer function

$$P(s, \alpha, \beta) = \frac{10((2 + 0.2\alpha)s^2 + (2 + 0.3\alpha + 0.4\beta)s + (1 + 0.2\beta))}{(s^2 + 0.5s + 1)(s^2 + 2s + 3)(s^2 + 3s + 6)}, \quad \alpha, \beta \in [-1, 1]$$

$$P(s, \alpha, \beta) \in \{P_0 + W\Delta \mid \|\Delta\| \leq 1\}$$

with $P_0 := P(s, 0, 0)$ and

$$W(s) = P(s, 1, 1) - P(s, 0, 0) = \frac{10(0.2s^2 + 0.7s + 0.2)}{(s^2 + 0.5s + 1)(s^2 + 2s + 3)(s^2 + 3s + 6)}$$

The frequency response $P_0 + W\Delta$ is shown in Figure 8.14 as circles

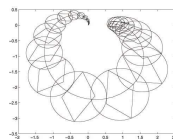


Figure 8.14: Nyquist diagram of uncertain system and disk covering

Another way to bound the frequency response is to treat and as norm bounded uncertainties; that is,

$$P(s, \alpha, \beta) \in \{P_0 + W_1\Delta_1 + W_2\Delta_2 \mid \|\Delta_1\|_\infty \leq 1\}$$

with $P_0 = P(s, 0, 0)$ and

$$W_1 = \frac{10(0.2s^2 + 0.3s)}{(s^2 + 0.5s + 1)(s^2 + 2s + 3)(s^2 + 3s + 6)}, \quad W_2 = \frac{10(0.4s + 0.2)}{(s^2 + 0.5s + 1)(s^2 + 2s + 3)(s^2 + 3s + 6)}$$

It is in fact easy to show that

$$\{P_0 + W_1\Delta_1 + W_2\Delta_2 \mid \|\Delta_1\|_\infty \leq 1\} = \{P_0 + W\Delta \mid \|\Delta\|_\infty \leq 1\}$$

with $|W| = |W_1| + |W_2|$.

The frequency response $P_0 + W\Delta$ is shown in Figure 8.15. This bounding is clearly more conservative.

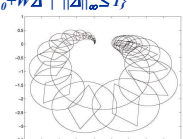


Figure 8.15: A conservative covering

Example 2: Consider a process control model

$$G(s) = \frac{ke^{-\tau s}}{Ts + 1}, 4 \leq k \leq 9, 2 \leq T \leq 3, 1 \leq \tau \leq 2.$$

Take the nominal model as

$$G_0(s) = \frac{6.5}{(2.5s + 1)(1.5s + 1)}$$

Then for each frequency, all possible frequency responses are in a box, as shown in Figure 8.16.

$$\Delta_a(j\omega) = G(j\omega) - G_0(j\omega)$$

To get an additive weighting W_a , use the following Matlab procedure:

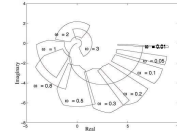


Figure 8.16: uncertain delay system and G_0

```
>> mf=input(50) % pick 50 points:
the first column of mf is the
frequency points and the second
column of mf is the
corresponding magnitude
responses.
```

```
>> magg=vpck(mf(:,2),mf(:,1)); %
pack them as a varying matrix.
```

```
>> Wa=fitmag(magg); % choose the
order of W_a online. A third-
order W_a is sufficient for this
example.
```

```
>> [A,B,C,D]=unpck(W_a)
%converting into state-space.
```

```
>> [Z,P,K]=ss2zp(A,B,C,D) %
converting into zero/pole/gain
form.
```

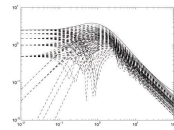


Figure 8.17: Δ_a (dashed line) and a bound W_a (solid line)

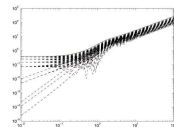


Figure 8.18: Δ_m (dashed line) and a bound W_m (solid line)

We get

$$W_a(s) = \frac{0.0376(s + 116.4808)(s + 7.4514)(s + 0.2674)}{(s + 1.2436)(s + 0.5575)(s + 4.95081)}$$

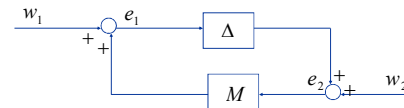
And the frequency response of W_a is also plotted in Figure 8.17. Similarly, define the multiplicative uncertainty

$$\Delta_m(s) := \frac{G(s) - G_0(s)}{G_0(s)}$$

and a W_m can be found such that $|\Delta_m(j\omega)| \leq |W_m(j\omega)|$ as shown in Figure 8.18. A W_m is given by

$$W_m = \frac{2.8169(s + 0.212)(s^2 + 2.6128s + 1.732)}{s^2 + 2.2425s + 2.6319}$$

Small Gain Theorem



□ Small Gain Theorem: Suppose $M \in (RH_\infty)^{p \times q}$. Then the system is well-posed and internally stable for all $\Delta \in RH_\infty$ with

(a) $\|\Delta\|_\infty \leq 1/\gamma$ if and only if $\|M\|_\infty < \gamma$;

(b) $\|\Delta\|_\infty < 1/\gamma$ if and only if $\|M\|_\infty \leq \gamma$.

□ Proof: Assume $\gamma = 1$. System is stable iff $\det(I - M\Delta)$ has no zero in the closed right-half plane for all $\Delta \in RH_\infty$ and $\|\Delta\|_\infty \leq 1$.

(\Leftarrow) $\det(I - M\Delta) \neq 0$ for all $\Delta \in RH_\infty$ and $\|\Delta\|_\infty \leq 1$ since

$$|\lambda(I - M\Delta)| \geq 1 - \max |\lambda(M\Delta)| \geq 1 - \|M\|_\infty > 0$$

(\Rightarrow) Suppose $\|M\|_\infty \geq 1$. There exists a $\Delta \in RH_\infty$ with $\|\Delta\|_\infty \leq 1$ such that $\det(I - M\Delta(s))$ has a zero on the imaginary axis, so the system is unstable. Suppose $\omega \in \mathbb{R}_+ \cup \{\infty\}$ is such that $\sigma_1(M(j\omega_0)) \geq 1$. Let $M(j\omega_0) = U(j\omega_0)\Sigma(j\omega_0)V^*(j\omega_0)$ be a singular value decomposition with

$$U(j\omega_0) = [u_1, u_2, \dots, u_p], \quad V(j\omega_0) = [v_1, v_2, \dots, v_p], \\ \Sigma(j\omega_0) = \text{diag}[\sigma_1, \sigma_2, \dots]$$

We shall construct a $\Delta \in RH_\infty$ such that $\Delta(j\omega_0) = (1/\sigma_1) v_1 u_1^*$ and $\|\Delta\|_\infty \leq 1$. Indeed, for such $\Delta(s)$,

$$\det(I - M(j\omega_0)\Delta(j\omega_0)) = \det(I - U(j\omega_0)\Sigma(j\omega_0)V^*(j\omega_0)(1/\sigma_1)v_1 u_1^*) \\ = I - u_1^* U(j\omega_0)\Sigma(j\omega_0)V^*(j\omega_0)v_1 (1/\sigma_1) = 0$$

and thus the closed-loop system is either not well-posed (if $\omega_0 = \infty$) or unstable (if $\omega_0 \in \mathbb{R}_+$). There are two different cases:

(1) $\omega_0 = 0$ or ∞ : Then U and V are real matrices. Choose

$$\Delta = (1/\sigma_1) v_1 u_1^* \in \mathbb{R}^{q \times p}$$

(2) $0 < \omega_0 < \infty$: write u_i and v_i in the following form

$$u_i^* = \begin{bmatrix} u_{i1} e^{j\theta_{i1}} & u_{i2} e^{j\theta_{i2}} & \dots & u_{ip} e^{j\theta_{ip}} \end{bmatrix}, \quad v_i = \begin{bmatrix} v_{i1} e^{j\phi_i} \\ v_{i2} e^{j\phi_i} \\ \vdots \\ v_{iq} e^{j\phi_i} \end{bmatrix}$$

where $u_{ij}, v_{ij} \in \mathbb{R}$ are chosen so that $\theta_i, \phi_i \in [-\pi, 0]$.

Choose $\beta_i \geq 0$ and $\alpha_j \geq 0$ so that

$$\angle \left(\frac{\beta_i - j\omega_0}{\beta_i + j\omega_0} \right) = \theta_i, \quad \angle \left(\frac{\alpha_j - j\omega_0}{\alpha_j + j\omega_0} \right) = \phi_j$$

Let

$$\Delta(s) = \frac{1}{\sigma_1} \begin{bmatrix} v_{11} \frac{\alpha_1 - s}{\alpha_1 + s} \\ \vdots \\ v_{1q} \frac{\alpha_q - s}{\alpha_q + s} \end{bmatrix} \begin{bmatrix} u_{11} \frac{\beta_1 - s}{\beta_1 + s} & \cdots & u_{1p} \frac{\beta_p - s}{\beta_p + s} \end{bmatrix} \in RH_\infty.$$

Then $\|\Delta\|_\infty = 1/\sigma_1 \leq 1$ and $\Delta(j\omega_0) = (1/\sigma_1) v_1 u_1^*$.

The small gain theorem still holds even if Δ and M are infinite dimensional. This is summarized as the following corollary.

□ Corollary: The following statements are equivalent:

- (i) The system is well-posed and internally stable for all $\Delta \in RH_\infty$ with $\|\Delta\|_\infty \leq 1/\gamma$.
- (ii) The system is well-posed and internally stable for all $\Delta \in RH_\infty$ with $\|\Delta\|_\infty \leq 1/\gamma$.
- (iii) The system is well-posed and internally stable for all $\Delta \in C^{qp}$ with $\|\Delta\| \leq 1/\gamma$.
- (iv) $\|M\|_\infty \leq \gamma$

It can be shown that the small gain condition is sufficient to guarantee internal stability even if Δ is a nonlinear and time varying "stable" operator with an appropriately defined stability notion, see Desoer and Vidyasagar [1975].

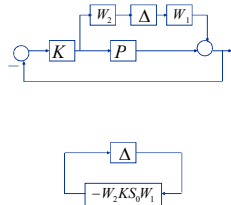
Additive Uncertainty

Define

$$S_o = (I + PK)^{-1}, \quad T_o = PK(I + PK)^{-1}$$

$$S_i = (I + KP)^{-1}, \quad T_i = KP(I + KP)^{-1}$$

- Let $\Pi = \{P + W_1 \Delta W_2 : \Delta \in RH_\infty\}$ and let K stabilize P . Then the closed-loop system is well-posed and internally stable for all $\|\Delta\|_\infty < 1$ if and only if $\|W_2 K S_o W_1\|_\infty \leq 1$.



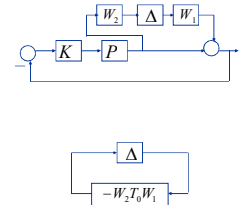
Multiplicative Uncertainty

Define

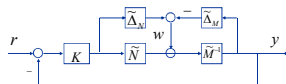
$$S_o = (I + PK)^{-1}, \quad T_o = PK(I + PK)^{-1}$$

$$S_i = (I + KP)^{-1}, \quad T_i = KP(I + KP)^{-1}$$

- Let $\Pi = \{(I + W_1 \Delta W_2)P : \Delta \in RH_\infty\}$ and let K stabilize P . Then the closed-loop system is well-posed and internally stable for all $\|\Delta\|_\infty < 1$ if and only if $\|W_2 T_o W_1\|_\infty \leq 1$.



Coprime Factor Uncertainty



- Let $P = \tilde{M}^{-1} \tilde{N}$ be stable left coprime factorization and let K stabilize P . Suppose $\Pi = (\tilde{M} + \tilde{\Delta}_M)^{-1} (\tilde{N} + \tilde{\Delta}_N)$, $\Delta = \begin{bmatrix} \tilde{\Delta}_N & \tilde{\Delta}_M \end{bmatrix}$ with $\tilde{\Delta}_M, \tilde{\Delta}_N \in RH_\infty$. Then the closed-loop system is well-posed and internally stable for all $\|\Delta\|_\infty < 1$ if and only if

$$\left\| \begin{bmatrix} K \\ I \end{bmatrix} (I + PK)^{-1} \tilde{M}^{-1} \right\|_\infty \leq 1.$$

Other Tests

| $W_1 \in RH_\infty, W_2 \in RH_\infty, \Delta \in RH_\infty, \ \Delta\ _\infty < 1$ | | |
|---|--|---------------------------------|
| Perturbed Model Sets Π | Representative Types of Uncertainty Characterized | Robust Stability Tests |
| $(I + W_1 \Delta W_2)P$ | output (sensor) errors neglected HF dynamics uncertain rhp zeros | $\ W_2 T_o W_1\ _\infty \leq 1$ |
| $P(I + W_1 \Delta W_2)$ | Input (actuators) errors neglected HF dynamics uncertain rhp zeros | $\ W_2 T_i W_1\ _\infty \leq 1$ |
| $(I + W_1 \Delta W_2)^{-1} P$ | LF parameter errors uncertain rhp poles | $\ W_2 S_o W_1\ _\infty \leq 1$ |

| | | |
|---|--|--|
| $P(I + W_1 \Delta W_2)^{-1}$ | LF parameter errors uncertain rhp poles | $\ W_2 S_0 W_1\ _\infty \leq 1$ |
| $P + W_1 \Delta W_2$ | Additive plant errors neglected HF dynamics uncertain rhp zeros | $\ W_2 K S_0 W_1\ _\infty \leq 1$ |
| $P(I + W_1 \Delta W_2 P)^{-1}$ | LF parameter errors uncertain rhp poles | $\ W_2 S_0 P W_1\ _\infty \leq 1$ |
| $(\tilde{M} + \tilde{\Delta}_u)^{-1}(\tilde{N} + \tilde{\Delta}_s)$ $P = \tilde{M}^{-1} \tilde{N}$ $\Delta = \begin{bmatrix} \tilde{\Delta}_s & \tilde{\Delta}_u \end{bmatrix}$ | LF parameter errors neglected HF dynamics uncertain rhp poles & zeros | $\left\ \begin{bmatrix} K \\ I \end{bmatrix} S_0 \tilde{M}^{-1} \right\ _\infty \leq 1$ |
| $(N + \Delta_s)(M + \Delta_u)^{-1}$ $P = NM^{-1}$ $\Delta = \begin{bmatrix} \Delta_s \\ \Delta_u \end{bmatrix}$ | LF parameter errors neglected HF dynamics uncertain rhp poles & zeros | $\ M^{-1} S_0 [K \quad I]\ _\infty \leq 1$ |

Robust Performance

- Consider a feedback system with uncertain plant P_Δ , the weighted sensitivity function is defined as the transfer function from d to e :

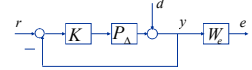
$$T_{ed} = W_e(I + P_\Delta K)^{-1}$$

Suppose our performance objective is

$$\|T_{ed}\|_\infty = \sup_{\|d\|_2 \leq 1} \|e\|_2 \leq 1$$

- Suppose $P_\Delta \in \{(I + \Delta W_2)P : \Delta \in RH_\infty, \|\Delta\|_\infty < 1\}$ and K stabilizes P . Then the

$$\bar{\sigma}(W_e S_0) + \bar{\sigma}(W_2 T_0) \leq 1.$$



Proof:

$$\begin{aligned} \bar{\sigma}(T_{ed}) &\leq \bar{\sigma}(W_e S_0) \bar{\sigma}[(I + \Delta W_2 T_0)^{-1}] \\ &= \frac{\bar{\sigma}(W_e S_0)}{\underline{\sigma}(I + \Delta W_2 T_0)} \\ &\leq \frac{\bar{\sigma}(W_e S_0)}{1 - \bar{\sigma}(\Delta W_2 T_0)} \leq \frac{\bar{\sigma}(W_e S_0)}{1 - \bar{\sigma}(W_2 T_0)}. \end{aligned}$$

Skewed Specifications

- Suppose $P_\Delta \in \{(I + w\Delta)P : \Delta \in RH_\infty, \|\Delta\|_\infty < 1\}$ and K stabilizes P .

robust stability:

$$\|wT\|_\infty \leq 1$$

nominal performance:

$$\|W_e S_0\|_\infty \leq 1.$$

robust performance is guaranteed if

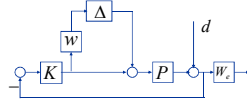
$$\bar{\sigma}(W_e S_0) + \kappa(P) \bar{\sigma}(wT_0) \leq 1$$

$$\bar{\sigma}(W_e S_0) + \kappa(P) \bar{\sigma}(wT_0) \leq 1.$$

Condition number!!!!

Proof: Note that

$$\begin{aligned} T_{ed} &= W_e S_0 (I + P \Delta W K S_0)^{-1} \\ &= W_e S_0 (I + P \Delta P^{-1} w T_0)^{-1} \end{aligned}$$



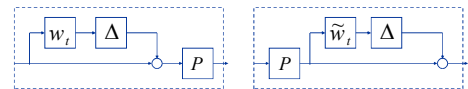
The Role of Condition Number

- Covering Uncertainty:

$$\Pi_1 := \{P(I + w\Delta) : \Delta \in RH_\infty, \|\Delta\|_\infty < 1\}, \quad \Pi_2 := \{(I + \tilde{w}\tilde{\Delta})P : \Delta \in RH_\infty, \|\Delta\|_\infty < 1\}.$$

$$\Pi_2 \supseteq \Pi_1 \text{ if } |\tilde{w}| \geq |w| \kappa(P) \quad \forall \omega$$

since $P(I + w\Delta) = (I + \tilde{w}\tilde{\Delta})P$.



$$P(s) = \begin{bmatrix} -0.2 & 0.1 & 1 & 0 & 1 \\ -0.05 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & -1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} = \frac{1}{a(s)} \begin{bmatrix} s & (s+1)(s+0.07) \\ -0.05 & 0.7(s+1)(s+0.13) \end{bmatrix}$$

$$P(s) = \begin{bmatrix} -0.2 & 0.1 & 1 & 0 & 1 \\ -0.05 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & -1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} = \frac{1}{a(s)} \begin{bmatrix} s & (s+1)(s+0.07) \\ -0.05 & 0.7(s+1)(s+0.13) \end{bmatrix}$$

where $a(s) = (s+1)(s+0.1707)(s+0.02929)$.

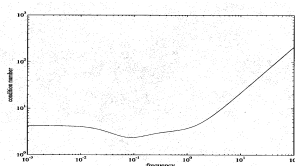


Figure 8.16: Condition number $\kappa(\omega) = \bar{\sigma}(P(j\omega)) / \underline{\sigma}(P(j\omega))$

Example: SISO vs MIMO

- Spinning body with constant velocity in the z direction.

$$\begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} = \begin{bmatrix} 0 & a \\ -a & 0 \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$y = \begin{bmatrix} 1 & a \\ -a & 1 \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}$$

$$P(s) = \frac{1}{s^2 + a^2} \begin{bmatrix} s - a^2 & a(s+1) \\ -a(s+1) & s - a^2 \end{bmatrix}$$

$$S = (I + P)^{-1} = \frac{1}{s+1} \begin{bmatrix} s & -a \\ a & s \end{bmatrix}$$

$$T = P(I + P)^{-1} = \frac{1}{s+1} \begin{bmatrix} 1 & a \\ -a & 1 \end{bmatrix}$$

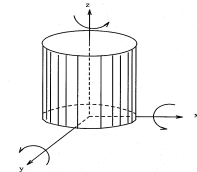
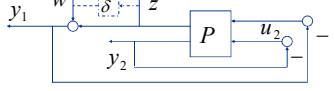


Figure 8.17: Spinning body

❖ Each loop has the open-loop transfer function as $1/s$ so each loop has phase margin $\phi_{\max} = \phi_{\min} = 90^\circ$ and gain margin $k_{\max} = 0, k_{\min} = \infty$



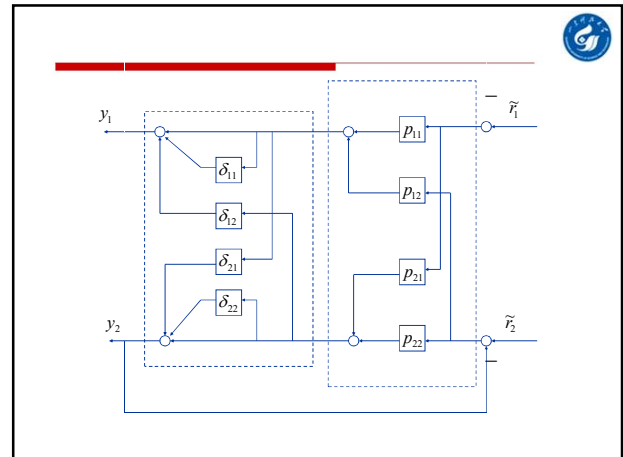
❖ Suppose one loop transfer function is perturbed

Denote $z(s)/w(s) = T_{11}(s) = -1/(s+1)$. Then the maximum allowable perturbation is $\|\delta\|_\infty < 1/\|T_{11}(s)\|_\infty = 1$, which is independent of a .

❖ However, if both loops are perturbed at the same time, then the maximum allowable perturbation is much smaller, as shown below

$$P_A = (I + \Delta)P, \quad \Delta = \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \end{bmatrix} \in RH_\infty, \quad \|\Delta\|_\infty < \gamma$$

The system is robustly stable for every such Δ iff

$$\gamma \leq \frac{1}{\|T\|_\infty} = \frac{1}{\sqrt{1+a^2}} \quad (< 1 \text{ if } a \gg 1).$$


❖ In particular, consider

$$\Delta = \Delta_d = \begin{bmatrix} \delta_{11} & \\ & \delta_{22} \end{bmatrix} \in \mathbb{R}^{2 \times 2}.$$

Then the closed-loop system is stable for every such Δ iff

$$\det(I + T\Delta_d) = \frac{(s^2 + (2 + \delta_{11} + \delta_{22})s + 1 + \delta_{11} + \delta_{22} + (1 + a^2)\delta_{11}\delta_{22})}{(s+1)^2}$$

has no zero in the closed right-half plane.

Hence the stability region is given by

$$2 + \delta_{11} + \delta_{22} > 0,$$

$$1 + \delta_{11} + \delta_{22} + (1 + a^2)\delta_{11}\delta_{22} > 0$$

The system is unstable with

$$\delta_{11} = \delta_{22} = (1 + a^2)^{-1/2}$$
