

Advanced Control Systems

- 1) Introduction , system representation
- 2) Control-loop requirements & mapping
- 3) Recap linear algebra / system norms
- 4) Analysis of MIMO Systems: Gain, Direction, RGA, controllability , observability
poles and zeros
- 5) _____ : Internal Stability, Youla parametrization
- 6) _____ : Small gain theorem
- 7) Performance Limitations in SISO systems
- 8) Uncertainty & Robustness : stability & performance of SISO systems
- 9) _____ : MIMO systems

④ Something about the history:

- Classical (40's - 50's) : frequency domain methods - for SISO
 - ⊕ can yield insights (phase margin, gain margin, root locus...)
 - ⊕ address uncertainty
 - ⊖ only applicable to SISO system
 - MIMO (60's - 70's) : state-space, optimal control
Kalman, etc.
 - ⊕ could address MIMO systems
 - ⊕ could pose control problem as optimization problem
 - ⊖ no clear links to classical methods
 - ⊖ could not address uncertainty explicitly
 - Modern (80's - 90's) : robust control ..
 - ⊕ frequency domain based method
 - ⊕ could handle uncertainty explicitly
- thus try to combine with the classical methods →

Advanced Control System

Exercise

- ✓ 1) - Differential equation \Rightarrow linearize \Rightarrow state space model
 - ⊗ - Transfer function matrix \Rightarrow state space form
 - System scaling
- 2) - Closed Loop performance - MATLAB
 - ? - Classical loop shaping
- 3) - ✓ Moore - Penrose Pseudoinverse
 - ✓ Jordan canonical form
 - ? Signal norms
- ⊗ 4) - System norms
 - ⊗ - Gain & directions
 - * - Relative gain array
 - Minimal realisation
- 5) - Minimal realisation - MATLAB only
 - Poles and zeros of of MIMO
 - ⊗ [Rosenbrock matrix
 - Mac Farlane & Karcianas
 - Smith form
 - Smith - McMillan form

$$C = [B \quad AB \quad \dots \quad A^{n-1}B]$$

$$D = [C \quad CA \quad \dots \quad CA^{n-1}]^T$$

$$P(s) = \begin{bmatrix} sI - A & B \\ C & D \end{bmatrix}$$

6) Internal Stability

⊗ Coprime factorization

Nyquist criterion for MIMO (MATLAB)

7) Root locus & stability MATLAB

⊗ Bode Sensitivity integral

Poisson

8, ⊗ Modelling uncertainty

Robust stability

9, MIMO Robust stability

LFT

10, ⊗ Optimal State - feedback

⊗ Linear Quadratic Regulator (MATLAB)

Kalman Filter (MATLAB)

11) LQR margins and H_2 -control

LQR margins (MATLAB)

H_2 -control design (LQG is a special case of H_2 -optimal control)
(MATLAB)

12) Hamiltonians and AREs

H_∞ control

H_2 and H_∞ control (MATLAB)

13) Linear Fractional Transformation

H_∞ loop shaping design (MATLAB)

Fans anti-windup approach (MATLAB)

14, μ - analysis

Calculation of μ

Robust stability

Robust performance

④ Consider $\dot{x} = Ax$

Solution is: $x(t) = e^{At} \cdot x(0)$

$$\text{with } e^{At} = I + At + \frac{A^2 t^2}{2!} + \frac{A^3 t^3}{3!} + \dots$$

Expand A to eigen values & vector. $A\vec{s} = \lambda \vec{s}$:

$$\Rightarrow T = [\vec{s}_1 \dots \vec{s}_{n_1}] \text{ eigen vectors}$$

$$D = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} \text{ eigen value}$$

$$\Rightarrow AT = TD \Rightarrow T^{-1}AT = D$$

$$\begin{aligned} - \text{Let } z \text{ that } x = Tz &\Rightarrow \dot{x} = T\dot{z} = Ax = ATz \\ &\Rightarrow \dot{z} = T^{-1}ATz = Dz \\ &\Rightarrow \dot{z} = Dz \\ &z(t) = e^{Dt} z(0) \end{aligned}$$

$$\text{Also } e^{At} = T e^{Dt} T^{-1}$$

$$\Rightarrow x(t) = e^{At} x(0) = T \cdot e^{Dt} \underbrace{T^{-1} x(0)}_{z(0)} = T \cdot \underbrace{e^{Dt} z(0)}_{z(t)} = T \cdot z(t)$$

Just like SISO, the eigen value $(\lambda_i \text{ of } D)$ has to be < 0 to stable

④ $\dot{x} = Ax + Bu$ is controllable if we can choose $u = -Cx$
and put the eigen value of A anywhere we want
steer x anywhere I want

In practice, we are given fixed A and B

$$\textcircled{S} \quad \dot{x} = Ax + Bu \quad x \in \mathbb{R}^n \quad A \in \mathbb{R}^{n \times n}$$

$$y = Cx \quad u \in \mathbb{R}^q \quad B \in \mathbb{R}^{n \times q}$$

$$y \in \mathbb{R}^p \quad C \in \mathbb{R}^{p \times n}$$

\dagger Static gain: assume system in steady-state condition

$$\frac{dx}{dt} = 0$$

$$G(0) = \lim_{s \rightarrow 0} G(s) \quad \Leftrightarrow G(j\omega) \text{ when } \omega \rightarrow 0$$

\textcircled{S} , Controllability and Gramians:

$$\dot{x} = Ax + Bu \quad x \in \mathbb{R}^n$$

$$G = [B \quad AB \quad A^2B \quad \dots \quad A^{n-1}B] \quad \text{controllability matrix}$$

$$x(t) = e^{At}x(0) + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau$$

Gramian (controllability):

$$W_t = \int_0^t e^{A\tau} B B^T e^{A^T \tau} d\tau \quad \in \mathbb{R}^{n \times n}$$

$$W_t \xi = \lambda \xi \quad \Rightarrow \quad W_t \approx C C^T$$

$[U, \Sigma, V] = \text{svd}(G, \text{'econ'})$ in controllability, there are levels of controllability

there are some directions that are easy to go in
which we can get out from SVD: U

④ Popov - Belevitch - Hautus (PBH) test for controllability:

$$(A, B) \text{ is ctrb iff } \text{rank}[(A - \lambda I) B] = n \quad \forall \lambda \in \mathbb{C}$$

1, Rank $(A - \lambda I) = n$ except for eigenvalues λ

\Rightarrow Only need to test at eigenvalues λ_i

2, B needs to have some component in each eigenvector direction

3, If A has λ_i of power k .

At λ_i , we lost k dof for $(A - \lambda I)$, thus B need at least k columns

But also when we have close values of eigenvalues, we need extra columns in B to prevent short degeneration matrix

④ Cayley - Hamilton: $e^{At} = \phi_0(t) \cdot I + \phi_1(t) \cdot A + \dots + \phi_{n-1}(t) \cdot A^{n-1}$

$$G = [B \ AB \ A^2B \ \dots \ A^{n-1}B]$$

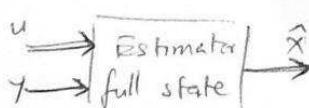
$$\xi = \int_0^t e^{A(t-\tau)} B u(\tau) d\tau = \dots$$

$$= [B \ AB \ \dots \ A^{n-1}B] \begin{bmatrix} \vdots \\ \vdots \end{bmatrix}$$

④ Observability:

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases}$$

Estimator:



$$\frac{d}{dt} \hat{x} = A\hat{x} + Bu + K_f(y - \hat{y})$$

$$\hat{y} = C\hat{x}$$

$$\Rightarrow \frac{d}{dt} \hat{x} = (A - K_f C) \hat{x} + [B \ K_f] \begin{bmatrix} u \\ y \end{bmatrix}$$

$$\text{Set } \varepsilon = x - \hat{x}$$

$$\frac{d}{dt} \varepsilon = (A - K_f C) \varepsilon \dots$$

Design K_f in presence of disturbance & noise

- Phase margin PM: how robust we are to system delay
(cause there might be extra delay in control, in system model..
with these noise, uncertainty.. we still want to assure stability)
- Gain margin GM: how robust we are to extra gain
from system model, controller, .. that we still assure stability or

- Integrator $\frac{K}{s}$

$|G|$ vs ω

$\angle G$ vs ω

pole

Derivative Ks

$|G|$ vs ω

$\angle G$ vs ω

zero

lead $\Rightarrow 1+T_1 s \Rightarrow$ zero \Rightarrow add phase

$$\frac{s + w_z}{s + w_p}$$

compensator

lag $\Rightarrow \frac{1}{1+T_2 s} \Rightarrow$ pole \Rightarrow subtract phase

$w_z < w_p \Rightarrow$

$|G|$ vs ω

$\angle G$ vs ω

$w_z > w_p \Rightarrow$

$|G|$ vs ω

$\angle G$ vs ω

4,

- Regulator problem: attenuate effect of d on y
- Servo problem: make y follow r

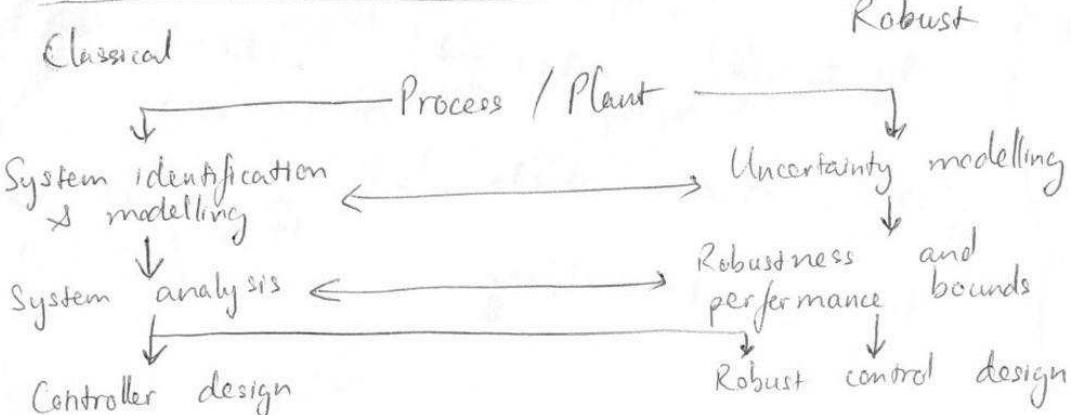
+ Price & limitations of feedback control:

- Loop might still be unstable

- Noise from measurement

- Control performance depends on both system & controller

+ Classical / Robust Control Design Process



+ Robust control design methodology:

$$G_p = G_{\text{nominal mode}} + \Delta_{\text{uncertainty / perturbation}}$$

(NP) Nominal Performance

System satisfies perf. specifications
for nominal model

(RP) Robust performance

System satisfies ..
under uncertainty

(NS) Nominal Stability

System is stable for nominal
model

(RS) Robust Stability

System is stable
under uncertainty

- Linear system: $f(a_1 u_1 + a_2 u_2) = a_1 \cdot f(u_1) + a_2 \cdot f(u_2)$

- Nonlinear system:

$$\frac{d}{dt} x(t) = f(x(t), u(t))$$

$$y(t) = g(x(t), u(t)), \quad u \in \mathbb{R}^m, y \in \mathbb{R}^p, x \in \mathbb{R}^n$$

- Linearization around equilibrium point x_{eq} :

$$f(x_{\text{eq}}, u_{\text{eq}}) = 0, \quad g(x_{\text{eq}}, u_{\text{eq}}) = y_{\text{eq}}$$

$$\Delta x = x - x_{\text{eq}}$$

$$\Rightarrow \begin{cases} \frac{d}{dt} \Delta x \approx \left. \frac{\partial f}{\partial x} \right|_{x_{\text{eq}}, u_{\text{eq}}} \cdot \Delta x + \left. \frac{\partial f}{\partial u} \right|_{x_{\text{eq}}, u_{\text{eq}}} \cdot \Delta u \\ \Delta y \approx \left. \frac{\partial g}{\partial x} \right|_{x_{\text{eq}}, u_{\text{eq}}} \cdot \Delta x + \left. \frac{\partial g}{\partial u} \right|_{x_{\text{eq}}, u_{\text{eq}}} \cdot \Delta u \end{cases}$$

$$\Rightarrow \begin{cases} \frac{d}{dt} \Delta x = A \cdot \Delta x + B \cdot \Delta u \\ \Delta y = C \cdot \Delta x + D \cdot \Delta u \end{cases}$$

$$G \stackrel{s}{=} \begin{bmatrix} A & B \\ C & D \end{bmatrix}$$

+ Transfer function:

$$Y(s) = (C(sI - A)^{-1} B + D) U(s) \in \mathbb{C}^{p \times m}$$

$$G_{1,1}(s) = \frac{b_{n_n} s^{n_n} + b_{n_n-1} s^{n_n-1} + \dots + b_0 s^0}{a_{n_d} s^{n_d} + a_{n_d-1} s^{n_d-1} + \dots + a_0 s^0}$$

- n_n : order of numerator

n_d : order of denominator

$n_d - n_n$: pole excess or relative degree

- Strictly proper: $n_d - n_n > 0$

$$\lim_{s \rightarrow \infty} G(s) = 0 \quad \text{physical system}$$

System is semi proper: $n_d - n_n = 0$

$$= 0 \neq 0$$

improper: $n_d - n_n < 0$

$$\rightarrow \infty$$

not exists
physical system
not causal

+ Irrational transfer function:

$$G(s) = \begin{bmatrix} G_{1,1}(s) \cdot e^{-\theta_{1,1}s} & G_{1,2}(s) \cdot e^{-\theta_{1,2}s} & \dots \\ G_{2,1}(s) \cdot e^{-\theta_{2,1}s} & \dots & \dots \\ \vdots & \ddots & \ddots \end{bmatrix}$$

due to
time delay

- causal if $\theta \geq 0$
- infinite dimensional system (sometimes)
→ will not be representable by rational TFs
- Approximation by Padé series

+ Polynomial model:

left $G(s) = D_L^{-1}(s) \cdot N_L(s)$
 right $= N_R(s) \cdot D_R^{-1}(s)$

+ System conversion:

Coprime factorisation
in RH as

$$\{N_R(s), M_R(s)\}$$

$$\{N_L(s), M_L(s)\}$$

State space

$$\{A, B, C, D\}$$

TF to SS: more complex
may not be minimal

SS → TF: relative easy
minimal realisation

Coprime polynomial
Matrix

$$\{N_R(s), M_R(s)\}$$

$$\{N_L(s), M_L(s)\}$$

Transfer function

$$G(s)$$

+ System Scaling

- unscaled system $\hat{y} = \hat{G}\hat{u} + \hat{G}_d\hat{d}$, $\hat{e} = \hat{r} - \hat{y}$

$$d_i = \frac{\hat{d}_i}{\hat{d}_{i,\max}}, u_i = \frac{\hat{u}_i}{\hat{u}_{i,\max}}, y_i = \frac{\hat{y}_i}{\hat{y}_{i,\max}}, r_i = \frac{\hat{r}_i}{\hat{r}_{i,\max}}, e_i = \frac{\hat{e}_i}{\hat{e}_{i,\max}}$$

- Diagonal scaling matrices D_e, D_u, D_d, D_r

$$\text{Ex: } D_e = \text{diag}(\hat{d}_{e,\max})$$

→ scaled variables:

$$\oplus \quad d = \hat{D}_d^{-1}\hat{d}, u = \hat{D}_u^{-1}\hat{u}, y = \hat{D}_e^{-1}\hat{y}, r = \hat{D}_r^{-1}\hat{r}, e = \hat{D}_e^{-1}\hat{e}$$

→ Replace back to unscaled system:

$$D_e y = \hat{G} D_u u + \hat{G}_d D_d d; \quad D_e e = D_e y - D_e r$$

$$\Rightarrow y = D_e^{-1} \hat{G} D_u u + D_e^{-1} \hat{G}_d D_d d \quad |u, d, e| \in [0, 1]$$

$$\oplus \quad \begin{cases} G = D_e^{-1} \hat{G} D_u \\ \hat{G} D_d = D_e^{-1} \hat{G}_d D_d \end{cases} \Rightarrow y = Gu + G_d d$$

$$- \text{Also introduce: } \tilde{r} = \frac{\hat{r}}{\hat{r}_{\max}} = D_r^{-1} \hat{r} \quad |\tilde{r}(t)| \leq 1$$

$$\Rightarrow r = R \cdot \tilde{r}; \quad R \triangleq D_r^{-1} D_r = \frac{\hat{r}_{\max}}{\hat{e}_{\max}}$$

$$\Rightarrow e = y - r = Gu + G_d d - R \tilde{r}$$

To simplify the process of control design

engineers must make judgements on required performance
expected noise & disturbances

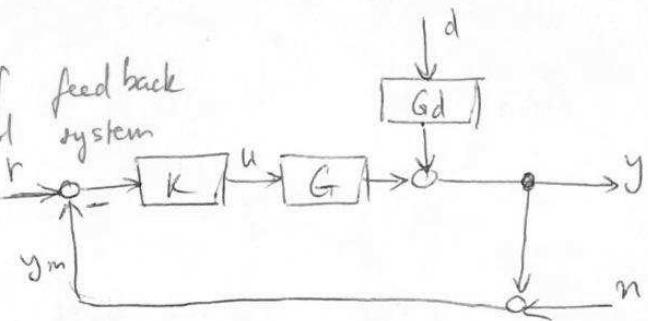
⇒ system scaling

+) Feedback Control

$$u = K(r - y_m) = K(r - y - n)$$

$$e = \underline{y} - \underline{r} \neq \hat{e} = r - y - n$$

+ 1 dof control feed back system



$$\Rightarrow \underline{y} = \underline{G} \underline{u} + \underline{G}_d \cdot \underline{d}$$

$$\Rightarrow \underline{y} = \underbrace{(I+GK)^{-1} GK r}_{T \Rightarrow \text{want } T \text{ high for low freq}} + \underbrace{(I+GK)^{-1} G_d d}_{S \Rightarrow \text{want } S \text{ small, slow for low freq}} - \underbrace{(I+GK)^{-1} GKn}_{T \Rightarrow \text{cause noise is usually high freq}} \\ = Tr + SG_d d - Tn$$

$$\text{Since } T - I = -S : \quad \text{or} \quad S + T = I$$

\Rightarrow we want T small for low freq

$$\Rightarrow e = \underline{y} - \underline{r} = -S\underline{R} + SG_d d - Tn$$

$$\text{and } u = KSR - KS G_d d - KSn$$

- (*) - Loop transfer function:
Sensitivity function:
Complementary sensitivity function:

$$L = GK$$

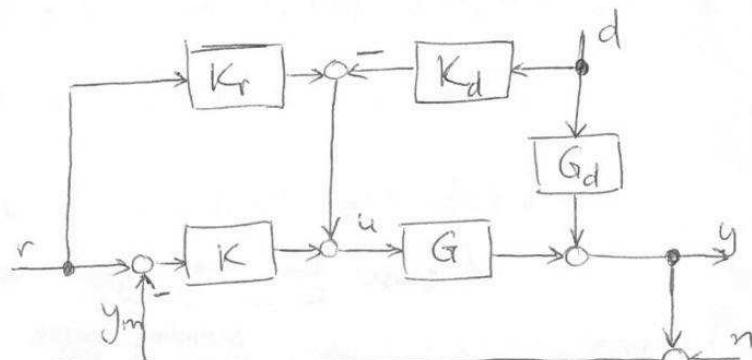
$$S = (I+GK)^{-1} = (I+L)^{-1}$$

$$T = (I+GK)^{-1} G K = (I+L)^{-1} L$$

$$R = KS$$

+) 2 dof controller

$$u = \underbrace{K(r - y - n)}_{\text{feedback}} + \underbrace{K_r r - K_d d}_{\text{feed forward}}$$



$$\Rightarrow y = (I+GK)^{-1} [G(K+K_r)r - GKn + (G_d - GK)d]$$

$$\Rightarrow e = S[-S_r r - GKn + S_d G_d d]$$

$$\text{with } S = (I+GK)^{-1}$$

$$S_r = I - GK_r$$

$$S_d = I - G K_d G_d^{-1}$$

} can be interpreted as feed-forward sensitivity function

L2)

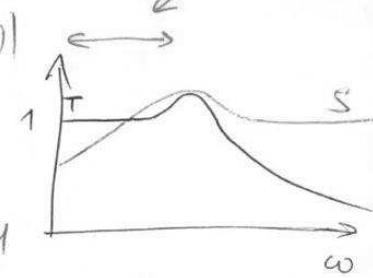
+ Band width & system damping

- Fast response time $\Leftrightarrow |T(j\omega)| \approx 1$ for large freq range
- Maximum magnitude of sens. & comp. sens. functions:

$$M_S = \max_{\omega \in \mathbb{R}} |S(j\omega)| ; M_T = \max_{\omega \in \mathbb{R}} |T(j\omega)|$$

$$M_S = \|S\|_\infty , M_T = \|T\|_\infty$$

$$S + T = 1 \text{ thus } \|S - T\| \leq |S + T| = 1$$



- For specific M_S, M_T , we can derive gain & phase margins:

$$GM \geq \frac{M_S}{M_S - 1} ; PM \geq 2\arcsin\left(\frac{1}{2M_S}\right) \geq \frac{1}{M_S} \text{ (rad)}$$

$$GM \geq 1 + \frac{1}{M_T} ; PM \geq 2\arcsin\left(\frac{1}{2M_T}\right) \geq \frac{1}{M_T} \text{ (rad)}$$

- ④ The closed-loop band-width, ω_B , is the freq. where $|S(j\omega)|$ first crosses $1/\sqrt{2}$ ($\approx -3 \text{ dB}$) from below

[High $\omega_B \Rightarrow$ faster rise time (response time); sensitive to noise params variation
Low $\omega_B \Rightarrow$ slow response time, more robust to noise (cause high freq signals are easily passed to output)
including noise]

$\omega_{B,T}$: highest freq at which $|T(j\omega)|$ crosses $1/\sqrt{2}$ from above

ω_c : $|L(j\omega_c)| = 1 \Leftrightarrow |S(j\omega_c)| = |T(j\omega_c)| = 1$

bandwidth
in term of T

the gain
crossover
freq

- Good performance:

$$\begin{cases} |S| \approx 0 \\ |T| \approx 1 \\ \varphi_T \text{ not too negative} \end{cases}$$

need
2 conditions

Cause $e = S(G_d \cdot d - r)$
 \Rightarrow we want $|S| < 1$
With integral, there will be
 $|S| \approx 0$

Typically require that $M_S < 2(6 \text{ dB})$
 $M_T < 1,25 (2 \text{ dB})$

⊖ Loop-shaping: shaping $L = GK$ to get desired perf.

$$e = - \underbrace{(I+L)^{-1} r}_{S} + \underbrace{(I+L)^{-1} G_d d}_{S} - \underbrace{(I+L)^{-1} L_{in}}_T$$

- Assume scaled circuit $|d(j\omega)| \leq 1 \forall \omega$
 and we want $|e(j\omega)| \leq 1$

- Consider worst case $|d(j\omega)| = 1$, we need $|S \cdot G_d| < 1 \forall \omega$
 $\Leftrightarrow |(I+L)^{-1} G_d| < 1 \Leftrightarrow |I+L| > |G_d|$
 At range ω that $|G_d| > 1 \Rightarrow |L| > |G_d|$

⇒ 1st step $|L_{min}| = |G_d| \Leftrightarrow K_{min} \approx |G^{-1} G_d|$

⇒ 2nd step: add integral to deal with disturbance:
 $K = k \cdot \frac{s + w_I}{s}$ $k \frac{1 + T_I s}{T_I s}$

$\frac{s + w_I}{s} = \begin{cases} \text{meaningful value} \Rightarrow \text{active at small freq} \\ 1 \quad \omega > w_I \Rightarrow \text{want } w_I \text{ high} \\ \text{but if } w_I \text{ too high, can't maintain acceptable PM} \end{cases}$

⇒ choose $w_I = 0,2 w_C$

⇒ 3rd step: High freq correction. to increase PM ..

lead-lag term $\frac{k_{D_I} \cdot s + 1}{k_{D_{II}} \cdot s + 1} = \begin{cases} 1/k_{D_I} < \frac{1}{k_{D_I}} \\ \text{meaningful value} \Rightarrow \text{only active after } \omega > \frac{1}{k_{D_I}} \end{cases}$

$k_{D_I} > k_{D_{II}}$ ⇒ effective over $\frac{k_{D_I}}{10 \cdot k_{D_{II}}}$ decade, starting at $\omega = \frac{1}{k_{D_I}}$ rad/s

+ 2 dof - design

- Let call desired tf. for ref. tracking: T_{ref}
- Design K_y first, for disturbance rejection

$$T = L(I+L)^{-1} ; \quad L = G K_y$$

Then $T K_r = T_{ref}$

$$\Rightarrow K_r = T^{-1} T_{ref}$$

Usually $K_r(s) = \frac{\tau_{lead} s + 1}{\tau_{lag} s + 1}$

$\tau_{lead} > \tau_{lag}$ if we want speed up
 $\tau_{lead} < \tau_{lag}$ if we want slow down

+ H_∞ and H_2

- H_∞ norm: the peak value

$$\|f(s)\|_\infty \triangleq \max_{\omega} |f(j\omega)| = \lim_{p \rightarrow \infty} \left(\int_{-\infty}^{\infty} |f(j\omega)|^p d\omega \right)^{1/p}$$

- H_∞ : Hardy space = set of tf. with bounded ∞ -norm
 \Rightarrow set of stable & proper tf.

- H_2 norm:

$$\|f(s)\|_2 \triangleq \left(\frac{1}{2\pi} \int_{-\infty}^{\infty} |f(j\omega)|^2 d\omega \right)^{1/2}$$

- Semiproper tf: H_2 norm = ∞

H_∞ norm is finite

Example: S is semi-proper

Linear Algebra

Signal & System norms

1. Definitions

- Vector space
- Sub spaces
- Linear dependence
 - & independence
- Basis & dimension
 - Orthogonal vs orthonormal basis
- Null space: $\text{Ker}(A) = \mathcal{N}(A) = \{x \in \mathbb{F}^n : Ax = 0\}$

Image: $\text{Im}(A) = \mathcal{R}(A) = \{y \in \mathbb{F}^m : y = Ax, x \in \mathbb{F}^n\}$

- Eigen values & eigen vectors: $Ax_i = \lambda_i x_i ; x_i \in \mathbb{C}$

$$AT = T\Lambda \quad (\text{T is called Modal matrix})$$

- Jordan normal form (Jordan canonical form)

$$J = T^{-1}AT \quad (\text{or } \Lambda)$$

$$J_k(\lambda) \in \mathbb{C}^{k \times k}; J_k(\lambda) = \begin{bmatrix} \lambda & 1 & \cdots & 0 \\ 0 & \ddots & \ddots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \lambda \end{bmatrix} \Rightarrow J = \begin{bmatrix} J_{k_1}(\lambda_1) & & & 0 \\ \vdots & \ddots & & \vdots \\ 0 & \cdots & J_{k_m}(\lambda_m) & \end{bmatrix}$$

- Singular value decomposition:

$$A = U \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} V^H$$

$$\text{Moore-Penrose inverse: } A^+ \triangleq V \begin{bmatrix} \Sigma^{-1} & 0 \\ 0 & 0 \end{bmatrix} U^H$$

3 Invariant Subspaces:

- Subspace S is called $\begin{cases} A\text{-invariant} \\ \text{invariant to transformation } A \end{cases}$ if $Ax \in S \forall x \in S$
- Generally A has eigenvalues: $\lambda_1 = \lambda_2 = \dots = \lambda_l$
eigen vectors: x_i

generalized eigenvectors: $\begin{cases} (A - \lambda_1 I)x_1 = 0 \\ (A - \lambda_1 I)x_2 = x_1 \\ \vdots \\ (A - \lambda_1 I)x_l = x_{l-1} \end{cases} \Leftrightarrow (A - \lambda_1 I)^l x_l = 0$

\Rightarrow Subspace S with $x_t \in S$ for some $t \leq l$ is A -invariant
iff all $\begin{cases} \text{lower rank eigenvectors of } x_t \in S \\ \text{generalized eigenvectors} \end{cases}$

- ~~$S \subset F^n$~~ $S \subset F^n$ is stable invariant subspace
if all eigenvalues of A has negative real parts

- Singular Value Decomposition:

$$A = U \cdot \Sigma \cdot V^H$$

$$\Rightarrow A^+ = V \cdot \Sigma^{-1} \cdot U^H \quad (\text{Moore-Penrose inverse})$$

- + Norm: $\begin{cases} \text{non-negative: } \|e\| \geq 0 \\ \text{positive: } \|e\|=0 \Leftrightarrow e=0 \\ \text{homogeneous: } \|\alpha \cdot e\| = |\alpha| \cdot \|e\| \text{ all complex scalar } \alpha \\ \text{triangle inequality: } \|e_1 + e_2\| \leq \|e_1\| + \|e_2\| \end{cases}$

+ Conjugate Transpose - Hermitean transpose

$$M = \begin{bmatrix} 2+3i & i & 6-9i \\ 2 & 2-3i & -i \end{bmatrix} \rightarrow M^H = M^* = \begin{bmatrix} 2-3i & 7 \\ -i & 2+3i \\ 6+9i & i \end{bmatrix}$$

\Rightarrow + Hermitian matrix: $M^H = M$

+ Orthogonal (real) \iff

columns form orthonormal basis

$$A^T = A^{-1}$$

$$A \cdot A^T = I \quad \text{But } A \cdot A^T \neq I$$

unitary (complex)

columns form orthonormal vectors

$$U^H = U^{-1}$$

$$U \cdot U^H = I$$

Vector norms: $\|a\|_p = \left(\sum_i |a_i|^p \right)^{1/p}$

- Vector 1-norm (sum norm)

$$\|a\|_1 \triangleq \sum_i |a_i|$$

$$\text{Ex: } d = \begin{bmatrix} 1 \\ 3 \\ -5 \end{bmatrix} \Rightarrow \|d\|_1 = 9$$

- Vector 2-norm (Euclidean norm)

$$\|a\|_2 \triangleq \sqrt{\sum_i |a_i|^2}$$

$$\|d\|_2 = \sqrt{35}$$

- Vector ∞ -norm (max norm)

$$\|a\|_\infty \triangleq \|a\|_{\max} \triangleq \max_i |a_i| \quad \|d\|_{\max} = 5 = |-5|$$

+ Matrix norms:

$$A = \begin{bmatrix} 1 & 2 \\ -3 & 4 \end{bmatrix}$$

- Multiplicative property: $\|A \cdot B\| \leq \|A\| \cdot \|B\|$

- Sum matrix norm

$$\|A\|_{\text{sum}} = \sum_{ij} |a_{ij}| \quad \|A\|_{\text{sum}} = 10$$

- Frobenius matrix norm:

$$\|A\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2} = \sqrt{\text{tr}(A \cdot A^H)} \quad \|A\|_F = \sqrt{30}$$

- Induced matrix norms

$$\|A\|_{ip} \triangleq \max_{w \neq 0} \frac{\|Aw\|_p}{\|w\|_p}$$

$$\|A\|_1 = \max_j \left(\sum_i |a_{ij}| \right) \quad \text{max column sum}$$

$$\|A\|_2 = \max_{1 \leq i \leq n} \sqrt{\lambda_i(A^T A)} = \bar{\sigma}(A) = \sqrt{\rho(A^H A)} \quad \text{singular value / spectral norm}$$

$$\|A\|_\infty = \max_i \left(\sum_j |a_{ij}| \right) \quad \text{max row sum}$$

+ Signal norms : $e(t)$

$$l_p \text{ norm: } (\|e(t)\|_p)^p = \int_{-\infty}^{\infty} \underbrace{\sum_i |e_i(\tau)|^p d\tau}_{\|e(\tau)\|_p^p}$$

- 1-norm in time

$$\|e(t)\|_1 = \int_{-\infty}^{\infty} \sum_i |e_i(\tau)| d\tau$$

- 2-norm in time : "energy" of signal

$$\|e(t)\|_2 = \sqrt{\int_{-\infty}^{\infty} \sum_i |e_i(\tau)|^2 d\tau}$$

- ∞ norm in time: peak value in time

$$\|e(t)\|_\infty = \max_{\tau} \left(\max_i |e_i(\tau)| \right)$$

- minimizing $\|e\|_\infty$ norm \Leftrightarrow minimizing peak of largest singular value (worst direction, worst freq)

- minimizing $\|e\|_2$ norm \Leftrightarrow minimize average direction, average freq

+ System norms

$$e = Gd$$

- H_∞ norm:

$$\|G(s)\|_\infty = \max_{d(t)} \frac{\|e(t)\|_2}{\|d(t)\|_2}$$

- l_1 - norm: $\|g(t)\|_1 = \max_{d(t)} \frac{\|e(t)\|_\infty}{\|d(t)\|_\infty}$

- \mathcal{F}_2 - norm: $\|G(s)\|_2 \triangleq \sqrt{\frac{1}{2\pi} \int_{-\infty}^{\infty} \text{tr}((G(j\omega)^H G(j\omega)) d\omega)}$ As if we use unit impulse $\delta_i(t)$ to each input δ_i

$$= \|g(t)\|_2 = \sqrt{\int_0^\infty \text{tr}(g(\omega)^T g(\omega)) d\omega}$$

Analysis of MIMO system

L9)

1) Gain & directions of MIMO System

- Gain of a matrix $G \in \mathbb{R}^{P \times m}$

$$y = G \cdot u$$

Apply SVD: $G = U \cdot \Sigma \cdot V^T$
 $= \sigma_1 u_1 v_1^T + \dots + \sigma_r u_r v_r^T$

$$U \in \mathbb{R}^{P \times P}$$

$$V \in \mathbb{R}^{m \times m}$$

$$\bar{\sigma} = \max_i \sigma_i ; \quad \underline{\sigma} = \min_i \sigma_i$$

with input direction $v_i \Rightarrow$ output dir. u_i
 and gain σ_i

\Rightarrow Interpretation: U, V as unitary matrix \Rightarrow rotation only, not scaling
 Σ is scaling with σ_i

$\Rightarrow \bar{\sigma}$ is max gain, $\underline{\sigma}$ is min gain

- Condition number of a matrix: $\gamma(G) = \frac{\bar{\sigma}(G)}{\underline{\sigma}(G)}$

Need lots of
change in u
to compensate
small change in A

If cond. number is large \Rightarrow difficult to control

(Ill-conditioned matrix: small change in $A \rightarrow$ large changes in C or X)

\Rightarrow Frequency response matrix:

$$G(j\omega) = U(j\omega) \Sigma(\omega) V(j\omega)^H$$

freq dependent gain

\Rightarrow Relative gain array: (RGA)

gain when open loop
others

$$\left. \frac{y_1(s)}{u_1(s)} \right|_{\text{others}} \triangleq \lambda_{1,1}(s)$$

gain when close loop

$$\left. \frac{y_1(s)}{u_2(s)} \right|_u$$

- we desire $\lambda_{ij} = 1$
desirable pairing because
it is not affected by others loop

- if $\lambda_{ij} = 0 \Rightarrow$ avoid pairing

For general non-singular square complex matrix.

$$RGA(G(s)) = \Delta(s) \triangleq G(s) \times \underbrace{(G^{-1}(s))^T}_{\text{element multiplication}}$$

$$RGA = G \cdot \text{pinv}(G)^T$$

- Usage of RGA: for MIMO system, we want to pair which output is controlled by which input.
- And we decide this by the RGA: $\Delta(G)$
- Good pairing: close to 1
- If RGA is great \rightarrow bad for control

+ Note: for 2×2 matrix $G(s)$

$$\Delta(G) = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 1-\lambda_{11} \\ 1-\lambda_{21} & \lambda_{22} \end{bmatrix} \quad \text{with } \lambda_{11} = \frac{1}{1 - \frac{g_{12}g_{21}}{g_{11}g_{22}}}$$

2) State controllability and observability:

$$\begin{bmatrix} \lambda_i I - A \\ C \end{bmatrix} t_i = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

\Rightarrow System is observable if rank $\begin{bmatrix} \lambda I - A \\ C \end{bmatrix} = n \quad \forall \lambda$ Hautus test
 controllable if rank $\begin{bmatrix} \lambda I - A \mid B \end{bmatrix} = n \quad \forall \lambda$

- When transferring from transfer function model \Rightarrow State space might not lead to minimal realisation (deleting all uncontrollable &/or unobservable states)
- Uncontrollable states do not need to be considered if not unstable

$$O(A, C) = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix}$$

Observability matrix

$$C(A, B) = [B \ AB \ \dots \ A^{n-1}B]$$

controllability matrix

5) +, Minimal realisation given A, B, C

i) Compute $C(A, B)$ & $O(A, C)$

2, Calculate SVD of $C(A, B)$

$$C(A, B) = [U_c \ U_{\bar{c}}] \begin{bmatrix} \Sigma_c & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_c^T \\ V_{\bar{c}}^T \end{bmatrix} = U_c \Sigma_c V_c^T$$

3, Get rank: $r_c = \text{rank } C(A, B) = \dim \Sigma_c$

4, Calculate SVD of:

$$O(A, C) U_c \Sigma_c^{1/2} = [U_{co} \ U_{\bar{co}}] \begin{bmatrix} \Sigma_{co} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_{co}^T \\ V_{\bar{co}}^T \end{bmatrix} = U_{co} \Sigma_{co} V_{co}^T$$

5, For which the rank is given by

$$r_{co} = \text{rank } O(A, C) U_c \Sigma_c^{1/2} = \dim \Sigma_{co}$$

6, And the transformation matrices:

$$R_1 = U_c \Sigma_c^{1/2} V_{co} \Sigma_{co}^{1/2} \quad T_1 = U_c \Sigma_c^{1/2} V_{co} \Sigma_{co}^{-1/2}$$

$$\Rightarrow (\bar{A}, \bar{B}, \bar{C}) = [R_1^T A T_1, R_1^T B, R_1^T C T_1]$$

3, Poles and zeros in MIMO systems

- Non-minimal system will leads to poles (eigenvalues) that correspond to uncontrollable / unobservable states..

+), How to find poles & zeros of MIMO :

- MacFarlane and Karczmaras

Matrix minor Determinant of smaller matrix (by removing 1 or more col, rows)

\Rightarrow Pole polynomial $\phi(s)$: least common denominator of all non-identically-zero minors of all orders of $G(s)$

and Zero polynomial $z(s)$: greatest common divisor of all numerators of all order- r minors of $G(s)$, $r = \text{normal rank of } G(s)$

+)Zeros from state-space realizations:

- Rosenbrock matrix:

$$P(s) = \begin{bmatrix} sI - A & -B \\ C & D \end{bmatrix}$$

Zeros all $=$ such: $s=0 \Rightarrow P(s)$ loose rank

+)TF2SS

SIMO \Rightarrow controllable canonical form
MISO \Rightarrow observable canonical form

+)Gilbert's realisation: to find poles & zeros

$$G(s) = D + \sum_{i=1}^r \frac{w_i}{s-\lambda_i}$$

Ex. Given TF matrix:

$$G(s) = \frac{1}{(s+1)(s+2)} \begin{bmatrix} 2s+1 & s \\ s+1 & 1 \end{bmatrix} = D + \frac{1}{s+2} \begin{bmatrix} 3 & 2 \\ 1 & -1 \end{bmatrix} + \frac{1}{s+1} \begin{bmatrix} -1 & -1 \\ 0 & 1 \end{bmatrix}$$

$$\Rightarrow SS: G(s) = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \dots$$

to find poles & zeros

+)Smith form

- Given polynomial matrix $P(s)$, find $S(s)$ such

$$S(s) = \begin{bmatrix} f_1'(s) & & & \\ & f_2'(s) & & \\ & & \ddots & \\ & & & f_r'(s) \\ & & & 0 \end{bmatrix} = U(s) \cdot P(s) \cdot V(s)$$

- Step Find minor of $P(s)$

Find greatest common divisor (gcd) & $D_0(s), D_1(s), D_2(s), \dots$

$$\text{Then } f_i'(s) = \frac{D_i(s)}{D_{i-1}(s)} \quad (f_1'(s) = \frac{D_1(s)}{D_0(s)}, f_2'(s) = \frac{D_2(s)}{D_1(s)})$$

+ Smith - McMillan form also just to find poles & zeros

$$\underline{M(s)} = \frac{1}{d(s)} S(s)$$

$$\text{with } d(s) \text{ from } G(s) = \frac{D(s)}{d(s)}$$

- Poles : determine stability

I/O system behavior

Location to be influenced by feedback

- Zeros: stability of feedback

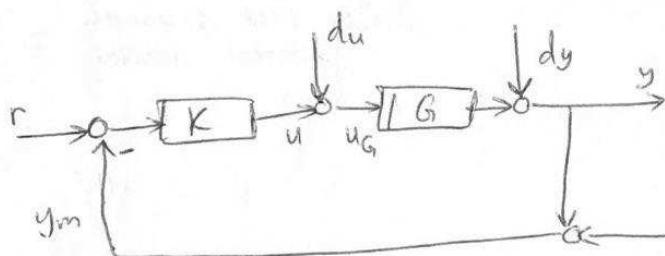
I/O system behavior

location not manipulable by feedback

L6) Analysis of MIMO system

1) Internal Stability

- When K & G are stable, doesn't ensure that feedback is realisable



\Rightarrow also want to check if $M(s)$ is stable

$$\begin{bmatrix} u \\ y \end{bmatrix} = M(s) \begin{bmatrix} du \\ dy \end{bmatrix}; \quad M(s) = \begin{bmatrix} I & K \\ -G & I \end{bmatrix}^{-1}$$

$$\Leftrightarrow \begin{cases} u = (I + GK)^{-1} du - K(I + GK)^{-1} dy \\ y = G(I + GK)^{-1} du + (I + GK)^{-1} dy \end{cases} \text{ Internally stable iff } \underline{\text{both}} \text{ are stable}$$

2) We have: $K(I + GK)^{-1} = Q$

$$(I + GK)^{-1} = I - GQ$$

$$(I + GK)^{-1} = I - GQ$$

$$G(I + GK)^{-1} = G(I - GQ)$$

If G & G are stable \Rightarrow all are (internally) stable

- Q is stable if: $K = Q(I - GG)^{-1}$ with a proper Q
(Youla parametrisation)

+ Coprime factorisation

- Given tf $G(s)$, find $G(s) = \frac{N(s)}{M(s)}$

such that \exists ~~$U(s)$~~ & $V(s)$ that

$$U(s)N(s) + V(s)M(s) = 1 \quad (\text{Bezout's identity})$$

- Step: - Given $G(s)$

$$\text{Replace } s = \frac{1-\lambda}{\lambda} \Rightarrow \tilde{G}(\lambda) = \frac{n(\lambda)}{m(\lambda)}$$

- Find quotient & remainder: q_i & r_i

$$n = m \cdot q_1 + r_1$$

$$m = r_1 q_2 + r_2$$

$$r_1 = r_2 q_3 + r_3$$

∴ \rightarrow Choose controller $K = \frac{X(s)}{Y(s)}$ f $M(s)V(s) + N(s)U(s) = 1$ a controller that guarantee internal stability

3) Nyquist criterion for NMIC systems

- Plot Nyquist graph of $\det(I + L(s)) = F(s)$

- The closed-loop control circuit is asymptotically stable if the plot contour makes $\Delta\varphi(F) = 2m_0\pi$ counter-clockwise encirclements of the point $(0,0)$ & does not pass through the point $m_0 = \# \text{No of open-loop RHP-poles}$

4) Small gain theorem (basically closed-loop stability condition)

- Spectral radius: $\rho(L(j\omega)) = \max_i |\lambda_i(L(j\omega))|$ maximum eigenvalue

\Rightarrow Spectral radius stability condition: Closed loop system is stable if $\rho(L(j\omega)) < 1$ th In most case, this is too much (^{+ L is stable}conservative), since we only need for $\omega = -\pi \pm k2\pi$

- Small gain theorem: L is stable, closed $\|L(j\omega)\| < 1$ th any induced norm (not H_2), also applied for non linear systems independent of sign for feedback, more conservative than spectral rad. stab.

Performance Limitations

AOB

1) SISO systems

1) Phase-gain relation

- As feedback gain K increase $\rightarrow \infty$, closed loop poles go to open-loop zeros
- \Rightarrow If there is RHP zeros, implies high-gain instability

2) Bode's sensitivity integral

- Open loop tf $L(s)$ is rational & at least 2 more poles than zeros
 $L(s)$ has N_p RHP poles at p_i
 $\Rightarrow \int_0^\infty \ln |S(j\omega)| d\omega = \pi \sum_{i=1}^{N_p} \operatorname{Re}(p_i)$
- If plant is stable \Rightarrow no RHP poles ($= 0$)
 $\Rightarrow \int_0^\infty \ln |S(j\omega)| d\omega = \int_0^\infty \ln \left| \frac{1}{1 + G(j\omega)K(j\omega)} \right| d\omega = 0$
- In practice, we try to limit to a certain freq range
 $\int_0^{\omega_c} \ln |S(j\omega)| d\omega = 0$

2

3) Poisson's sensitivity integral

- $G(s)$ has N_z RHP zeros $\Rightarrow N_p - N_z \geq 1$
 N_p RHP poles p_i

$$\int_0^\infty \ln |S(j\omega)| w(\omega, z_k) d\omega = \pi \ln \prod_{i=1}^{N_p} \left| \frac{p_i + z_k}{p_i - z_k} \right|$$

- Real zero: $w(\omega, z_k) = \frac{2z_k}{z_k^2 + \omega^2}$

- Complex zero: $w(\omega, z_k) = \frac{x}{x^2 + (y-\omega)^2} + \frac{x}{x^2 + (y+\omega)^2}$

- Weighting func: $d\theta(\omega, z_k) = \frac{d}{d\omega} \arctan \left[\frac{\omega-y}{x} \right] d\omega$

4) Bounds on peaks

- S is primarily limited by RHP zeros

T is primarily limited by RHP poles

- Stability: no RHP poles,
 $\|w_s S\|_\infty \geq |w_s(z)|$

no RHP zeros & delay
 $\|w_T T\|_\infty \geq |w_T(p)|$

- For closed loop stability,

for each RHP zeros of $G(s)$

$$\|w_s S\|_\infty \geq |w_s(z)| \cdot \prod_{i=1}^{N_p} \left| \frac{z + p_i}{z - p_i} \right|$$

for RHP poles of $G(s)$

$$\|w_T T\|_\infty \geq |w_T(p)| \cdot \prod_{j=1}^{N_z} \frac{|z_j + p|}{|z_j - p|} e^{kp\theta}$$

- With out weight w_s

w_T

$$\Rightarrow \|S\|_\infty = M_s \geq \prod_{i=1}^{N_p} \frac{|z + p_i|}{|z - p_i|}$$

$$\|T\|_\infty \geq M_T \geq \prod_{j=1}^{N_z} \frac{|z_j + p|}{|z_j - p|} \cdot e^{kp\theta}$$

Uncertainty & Robustness

L8,

RP: Robust performance

- RS: Robust stability

Π - set of possible perturbed models

$G(s) \in \Pi$ - a nominal plant model (no uncertainty)

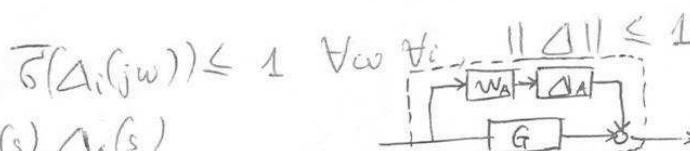
$G_p(s) \in \Pi$ - a particular perturbed plant model

Uncertainty

- Parametric uncertainty
 - model structure is known
 - some params are unknown
- Dynamic uncertainty
 - missing or neglected dynamic
 - frequency dependent

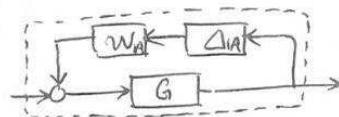
Additive Uncertainty

$$\Pi_A: G_p(s) = G(s) + w_A(s) \cdot \Delta_A(s)$$



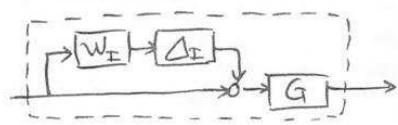
Additive Inverse Uncertainty

$$\Pi_{iA}: G_p(s) = G(s) [I - w_{iA}(s) \cdot \Delta_{iA}(s)]^{-1} G(s)$$



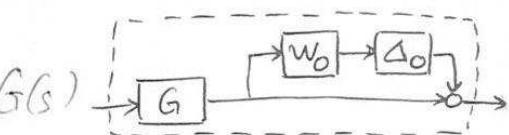
Multiplicative Input Uncertainty

$$\Pi_I: G_p(s) = G(s) (I + w_I(s) \cdot \Delta_I(s))$$



Multiplicative Output Uncertainty

$$\Pi_O: G_p(s) = G(s) (I + w_O(s) \cdot \Delta_O(s)) \cdot G(s)$$



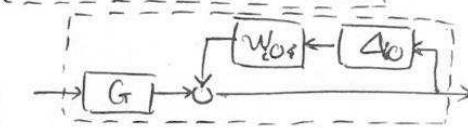
Multiplicative inverse input uncertainty

$$\Pi_{iI}: G_p(s) = G(s) [I - w_{iI}(s) \Delta_{iI}(s)]^{-1}$$



Multiplicative inverse output uncertainty

$$\Pi_{iO}: G_p(s) = [I - w_{iO}(s) \Delta_{iO}(s)]^{-1} G(s)$$



- Scalar uncertainty weight:

$$\Pi_o : G_p(s) = (I + w_o(s) \cdot \Delta_o(s)) \cdot G(s)$$

where $\ell_o(\omega) = \max_{G_p(j\omega) \in \Pi} \overline{\sigma}[(G_p(j\omega) - G(j\omega)) G^{-1}(j\omega)]$
 with $|w_o(j\omega)| \geq \ell_o(j\omega) \quad \forall \omega$

or $G_p(s) = G(s)[I + w_I(s) \cdot \Delta_I(s)], \|\Delta_I(s)\|_\infty \leq 1$

where $\ell_I(\omega) = \max_{G_p(j\omega) \in \Pi} \overline{\sigma}[G^{-1}(j\omega)(G_p(j\omega) - G(j\omega))], |w_I(j\omega)| \geq \ell_I(j\omega) \quad \forall \omega$

→ Lumping uncertainty into a single perturbation

2) SISO Robust Stability

+ For multiplicative uncertainty:

$$L_p(s) = GK(1 + w_I \Delta_I) = L + w_I \cdot L \Delta_I, |\Delta_I(j\omega)| \leq 1 \quad \forall \omega$$

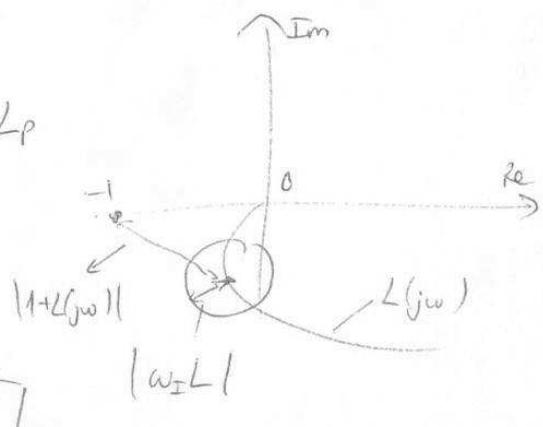
RS ⇔ System stable with $\forall L_p$

⇒ L_p should not encircle $-1 \quad \forall L_p$

$$\Leftrightarrow |w_I L| < |1+L| \quad \forall \omega$$

$$\Leftrightarrow \left| \frac{w_I L}{1+L} \right| < 1 \quad \forall \omega$$

$$\Leftrightarrow |w_I T| < 1 \quad \forall \omega \Leftrightarrow \|w_I T\|_\infty < 1$$



+ For inverse multiplicative uncertainty $|w_I^{-1} S| < 1 \quad \forall \omega$

⊗ Nominal performance:

- Weighting func: $w_p(s)$

$$\Leftrightarrow |w_p(s) \cdot S(s)| < 1 \quad \forall \omega \Leftrightarrow |w_p(s)| < |1 + L(s)| \quad \forall \omega$$

3) Robust performance:

$$RP \stackrel{\text{def}}{\Leftrightarrow} |w_p S_p| < 1 \quad \forall \omega$$

$$\Leftrightarrow |w_p| < |1 + L_p| \quad \forall \omega$$

And if we consider multiplicative uncertainty $\Rightarrow L_p = L + \omega_L L \Delta_L$

$$\Leftrightarrow RP \Leftrightarrow |w_p| + |w_L L| < |1 + L| \quad \forall \omega$$

$$\Leftrightarrow \max_{\omega} (|w_p S_p| + |w_L T|) < 1$$

$$\text{also } \Leftrightarrow \max_{S_p} |w_p S_p| < 1 \quad \forall \omega$$

④ Comparison:

$$NP \Leftrightarrow |w_p S| < 1 \quad \forall \omega$$

$$RS \Leftrightarrow |w_L T| < 1 \quad \forall \omega$$

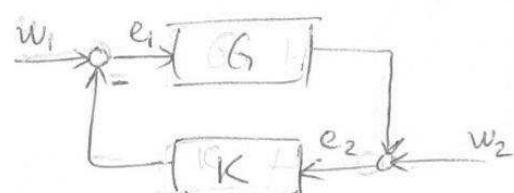
$$RP \Leftrightarrow |w_p S| + |w_L T| < 1 \quad \forall \omega$$

2g) Robust Stability & Performance

1) MIMO Robust Stability

→ Form control loop for considering internal stability

$$\begin{bmatrix} I & K \\ -G & I \end{bmatrix} \cdot \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$



→ Sensitivity & complementary sensitivity funcs regarding I/O direction

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

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

→ Closed loop is well-posed and internally stable if $\begin{bmatrix} I & K \\ -G & I \end{bmatrix} = \dots \in RFL_s$

→ Small Gain Theorem extension for perturbed system:

Assume $M(s) \in RF_{\text{loc}}$ and $\gamma > 0$. The system is well-posed and internally stable for $\forall \Delta(s) \in RF_{\text{loc}}$ if

$$\|\Delta(s)\|_{\infty} \leq \frac{1}{\gamma} \quad \text{if } \|M(s)\|_{\infty} < \gamma$$

$$\text{or } \|\Delta(s)\|_{\infty} < \frac{1}{\gamma} \quad \text{if } \|M(s)\|_{\infty} \leq \gamma$$

→ Using Small gain theorem extension, we then can derive Robust stability condition for each type of dynamic uncertainties and also coprime factorisation:

Example:

$$- G_p = (I + W_1 \Delta W_2) G \quad (\text{Multiplicative uncertainty}) \Rightarrow RS: \|W_2 T_0 W_1\|_{\infty} \leq 1$$

$$- G_p = G + W_1 \Delta W_2 \quad (\text{Additive uncertainty}) \Rightarrow RS: \|W_2 K S_0 W_1\|_{\infty} \leq 1$$

$$- G(s) = M_i(s), N_i(s)$$

$$G_p(s) = (M_i(s) + \Delta M(s))^{-1} (N_i(s) + \Delta N(s))$$

$$\Rightarrow RS: \|\Delta M(s), \Delta N(s)\| \leq \varepsilon$$

...

3 Robust performance: MIMO

⊗ Keep the tf from \tilde{d} to e small:

$$\sup_{\|\tilde{d}\|_2 \leq 1} \|e\|_2 \leq \varepsilon$$

$$+ TF: T_{ed} = W_e (I + G_p K)^{-1} W_d$$

$$\Rightarrow RP: \begin{array}{l} RS \\ \text{conditions} \end{array} \quad \& \|T_{ed}\|_{\infty} \leq 1$$

Linear Quadratic Regulator / Gaussian LQR / LQG

407

1) Formulation:

$$J = \int_0^T [x^T Q x(t) + u^T(t) R u(t)] dt + x^T(T) Q_T x(T)$$

$$\begin{cases} x(0) = x_0 \\ \frac{dx}{dt} = Ax + Bu \\ y = Cx + Du \end{cases}$$

$$2) \text{ LQR: } T \rightarrow \infty \quad \lim_{T \rightarrow \infty} x(T) = 0$$

$$\Rightarrow J = \int_0^\infty [x^T(t) Q x(t) + u^T(t) R u(t)] dt$$

Q is non-negative definite (semi-definite)

R is positive definite

+) Optimal control:

$$u(t) = -K x(t), \quad K = R^{-1} B^T P$$

with P is the unique positive definite solution to the matrix Algebraic Riccati Equation

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

	stable systems	unstable systems
+, LQR GM	∞	6 dB
PM	$\geq 60^\circ$	$\geq 60^\circ$

3) LQG: is LQR with Gaussian noise

→ combine optimal state estimation & optimal state feedback

$$+\dot{x} = Ax + Bu + \underline{v}$$
$$y = Cx + \underline{w}$$

→ $v(t)$ & $w(t)$ as white Gaussian noise, independent

$$\mathbb{E}[v(t)] = 0, \quad \mathbb{E}[w(t)] = 0, \quad \mathbb{E}[v^T(t)w(t)] = 0$$

$$\rightarrow \mathbb{E}[v(t)v^T(t)] = \underline{V}, \quad \mathbb{E}[w(t)w^T(t)] = \underline{W}$$

→ Assume also $A, C, V^{1/2}$ is observable (need to check)
 $A, B, Q^{1/2}$ is stabilisable

$$\rightarrow J_e = \mathbb{E}[(\{x(t) - \hat{x}\})^T \cdot (\{x(t) - \hat{x}\})] = 0 \quad \text{Kalman filter problem}$$

$$\rightarrow \dot{\hat{x}} = Ax + Bu + K_e(y - C\hat{x}), \quad \hat{x}(0) = \hat{x}_0$$

$$\rightarrow \text{Optimal } K_e = P_e \cdot C^T W^{-1}$$

With P_e as positive definite solution of the ARE

$$P_e A^T + A \cdot P_e - P_e C^T W^{-1} C P_e + V = 0$$

→ Usually W & V as design parameters

$$\text{E.g. } W = B \cdot B^T, \quad V = m \cdot I$$

1) H_2 optimal control:

- Find a stabilizing controller K which minimizes

$$\|F(s)\|_2 = \sqrt{\frac{1}{2\pi} \int_{-\infty}^{\infty} F(j\omega) F(j\omega)^T d\omega}, \quad F = F_\ell(P, K)$$

- LQG = a special case of H_2 optimal controller

2) H_∞ optimal control:

- Find all stabilizing controllers K which minimize:

$$\|F_\ell(P, K)\|_\infty = \max_\omega \bar{\sigma}(F_\ell(P, K)(j\omega))$$

$\Rightarrow H_\infty$ sub optimal control, $\|\bar{F}_\ell(P, K)\|_\infty < \gamma$

⊗ - H_2 norm is not an induced norm

- Induced norm will satisfy multiplicative properties

$$\|AB\| \leq \|A\| \cdot \|B\|$$

which later on $\|z\| \leq \|P\| \cdot \|w\|$

+) μ as structured singular value

$$\mu \text{ synthesis} = F\infty - \text{synthesis} + \mu - \text{analysis}$$

④ Linear Fractional Transformation:

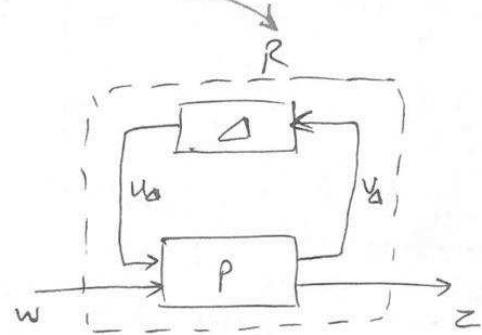
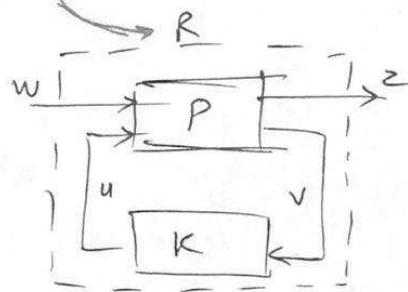
- Consider P of dimension $(n_1+n_2) \times (m_1+m_2)$ and partition as:

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

Let $\Delta \in \mathbb{R}^{m_1 \times n_1}$ and $K \in \mathbb{C}^{m_2 \times n_2}$

\Rightarrow Lower and upper LFT.

$$\begin{aligned} F_L(P, K) &\triangleq P_{11} + P_{12} K (I - P_{22} K)^{-1} P_{21} \\ F_U(P, \Delta) &\triangleq P_{22} + P_{21} \Delta (I - P_{11} K)^{-1} P_{12} \end{aligned}$$



$$z = P_{11}w + P_{12}u$$

$$v = P_{21}w + P_{22}u$$

$$u = Kv$$

$$\begin{aligned} \Rightarrow z &= R w \\ &= [P_{11} + P_{12} K (I - P_{22} K)^{-1} P_{21}] w \end{aligned}$$

\Rightarrow Relation between F_L and F_U

$$R = F_L(M, K) \Rightarrow F_U(\tilde{M}, K) = F_L(M, K)$$

with $\tilde{M} = \begin{bmatrix} 0 & I \\ I & 0 \end{bmatrix} \cdot M \begin{bmatrix} 0 & I \\ I & 0 \end{bmatrix}$

\Rightarrow Inverse of LFT: assumption all relevant inverses exist

$$(F_L(M, K))^{-1} = F_L(\tilde{M}, K)$$

$$\text{where } \tilde{M} = \begin{bmatrix} M_{11}^{-1} & -M_{11}^{-1} M_{12} \\ M_{21} M_{11}^{-1} & M_{22} - M_{21} M_{11}^{-1} M_{12} \end{bmatrix}$$

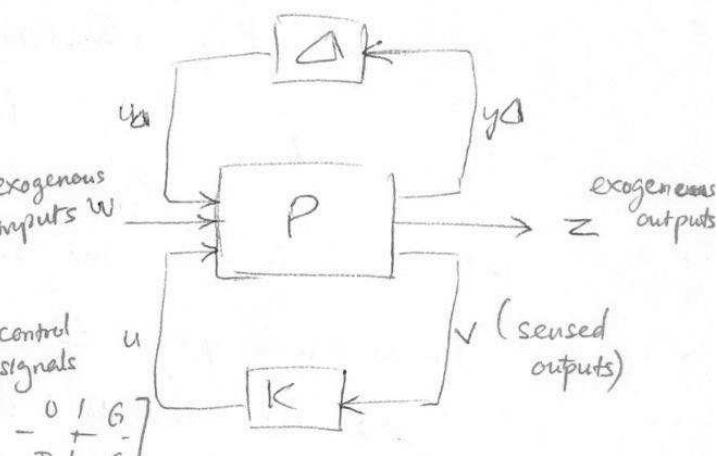
④ The 3 structure formulation:

1) "Pull out" the controller K

P is the generalized plant

⇒ useful for controller synthesis

$$w = \begin{bmatrix} d \\ r \\ n \end{bmatrix}; z = e = y - r; P = \begin{bmatrix} I & I & 0 & G \\ -I & I & I & -G \end{bmatrix}$$



2) Δ structure: if the controller is given

⇒ useful when we want to analyze the uncertain system

$$- \boxed{N = F_\ell(P, K)} = P_{11} + P_{12} K (I - P_{22} K)^{-1} P_{21} \quad (N \text{ as lower LFT of } P+K)$$

- The uncertain closed loop transfer function from w to z :

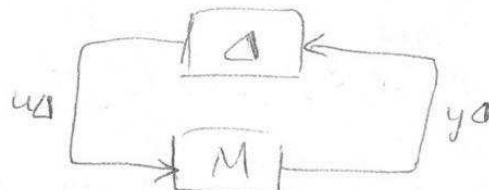
$$z = F(\Delta) w$$

$$\boxed{F = F_u(N, \Delta)} = N_{22} + N_{21} \Delta (I - N_{11} \Delta)^{-1} N_{12} \quad (F \text{ as upper LFT of } N \Delta)$$

3) $M\Delta$ structure:

⇒ when we only need to analyze robust stability of F

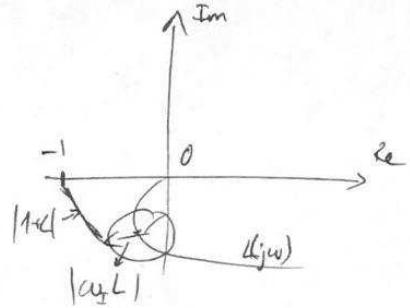
$$\boxed{M = N_{11}}$$



↑ All of these relate to Linear Fractional Transformations (LFT)

SISO. \Rightarrow RS $\Leftrightarrow \|w_I T\|_\infty < 1$

$$\left(\left\| \frac{w_I L}{1+L} \right\|_\infty < 1 + \omega \right)$$



(Multiplicative uncertainty)

$$\Rightarrow NP: |w_p(s)| < |1+L(s)| \quad \forall \omega \Leftrightarrow |w_p S| < 1$$

$$\Rightarrow RP: |w_p S| + |w_I T| < 1 \quad \forall \omega$$

For: $L_p(s) = GK (1+w_I \Delta_I) = L + w_I L \Delta_I$ (multiplicative uncertainty)

w_p is a upper bound for the performance of S

$$|w_p S_p| < 1 \quad \forall S_p \forall \omega$$

$$\Leftrightarrow |w_p| < |1+L_p| \quad \forall L_p \forall \omega$$

MIMO: \Rightarrow RS: first: LFT $\Rightarrow P \Rightarrow N \rightarrow M$

$$RS \Leftrightarrow \|M(s)\|_\infty < \gamma \quad \text{with } M(s) \in RF_{\text{loc}} \text{ and } \gamma > 0$$

Use small gain theorem extension for each type of dynamic uncertainty

$$\Rightarrow RR = RS + \|T_{ed}\|_\infty \leq 1$$