FRTN10 Multivariable Control, Lecture 2

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Course Outline

- L1-L5 Specifications, models and loop-shaping by hand
  1. Introduction
  2. Stability and robustness
  3. Specifications and disturbance models
  4. Control synthesis in frequency domain
  5. Case study
- L6-L8 Limitations on achievable performance
- L9-L11 Controller optimization: Analytic approach
- L12-L14 Controller optimization: Numerical approach

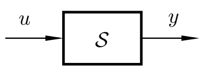
Lecture 2: Stability and Robustness

- Stability
- Robustness and sensitivity
- Small gain theorem

Stability is crucial

- bicycle
- JAS 39 Gripen
- Mercedes A-class
- ABS brakes

Input–output stability



A system is called **input–output stable** (or "$\mathcal{L}_2$-stable" or just "stable") if its $\mathcal{L}_2$-gain is finite:

$$\|\mathcal{S}\| = \sup_u \frac{\|\mathcal{S}(u)\|_2}{\|u\|_2} < \infty$$

Input–output stability of LTI systems

For an LTI system $\mathcal{S}$ with impulse response $g(t)$ and transfer function $G(s)$, the following stability conditions are equivalent:

- $\|\mathcal{S}\|$ is bounded
- $g(t)$ decays exponentially
- $\int_0^\infty |g(t)| dt$ is bounded
- All poles of $G(s)$ have negative real part (G(s) is Hurwitz stable)

Internal stability

The autonomous LTI system

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

is called **exponentially stable** if the following equivalent conditions hold:

- There exist constants $\alpha, \beta > 0$ such that

$$|x(t)| \leq \alpha e^{-\beta t}|x(0)| \qquad \text{for } t \geq 0$$

- All eigenvalues of A have negative real part

(Exponential stability is a stronger form of asymptotic stability. For LTI systems, they are equivalent.)

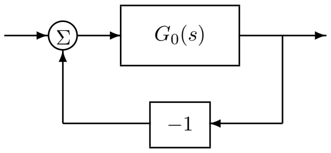
Internal vs input–output stability

If $\dot{x} = Ax$ is exponentially stable, then $G(s) = C(sI - A)^{-1}B + D$ is input–output stable.

Warning: The opposite is not always true! There may be unstable pole-zero cancellations (that also render the system uncontrollable and/or unobservable), and these may not be seen in the transfer function!

Stability of feedback loops

Assume scalar open-loop system $G_0(s)$



The closed-loop system is input–output stable if and only if all solutions to the equation

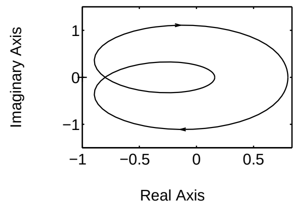
$$1 + G_0(s) = 0$$

are in the left half plane (i.e., have negative real part).

The Nyquist criterion

If $G_0(s)$ is stable, then the closed-loop system $[1 + G_0(s)]^{-1}$ is stable if and only if the Nyquist curve does not encircle -1.

More generally, the difference between the number of unstable poles in $[1 + G_0(s)]^{-1}$ and the number of unstable poles in $G_0(s)$ is equal to the number of times the point -1 is encircled by the Nyquist plot in the clockwise direction.



(Note: Matlab gives a Nyquist plot for both positive and negative frequencies!)

Sensitivity and robustness

- How sensitive is the closed-loop system to model errors?
- How do we measure the "distance to instability"?
- Is it possible to guarantee stability for all systems within some distance from the ideal model?

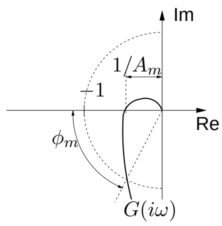
Amplitude and phase margin

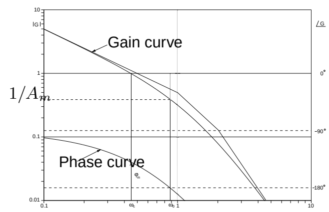
Amplitude margin A_m:

$$\arg G(i\omega_0) = -180^\circ, \quad |G(i\omega_0)| = \frac{1}{A_m}$$

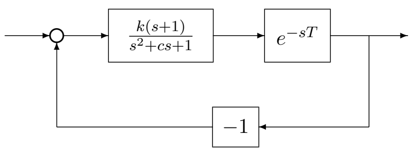
Phase margin ϕ_m:

$$|G(i\omega_c)| = 1, \quad \arg G(i\omega_c) = \phi_m - 180^\circ$$

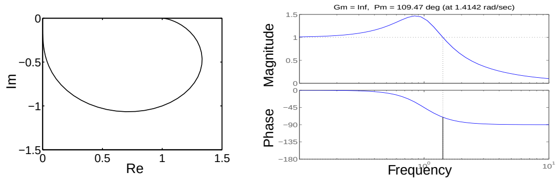




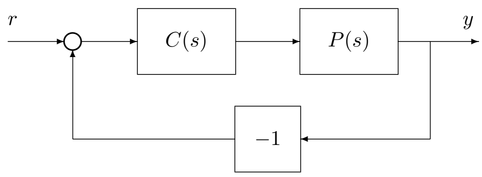
Mini-problem



Nominally $k = 1$, $c = 1$ and $T = 0$. How much margin is there in each of the parameters before the system becomes unstable?



How sensitive is T to changes in P?



$$Y(s) = \underbrace{\frac{P(s)C(s)}{1 + P(s)C(s)}}_{T(s)} R(s)$$

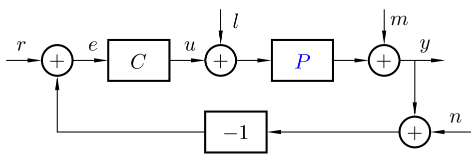
$$\frac{dT}{dP} = \frac{d}{dP}\left(1 - \frac{1}{1+PC}\right) = \frac{C}{(1+PC)^2} = \frac{T}{P(1+PC)}$$

Define the **sensitivity function**, S:

$$S := \frac{d(\log T)}{d(\log P)} = \frac{dT/T}{dP/P} = \frac{1}{1+PC}$$

and the **complementary sensitivity function** T:

$$T := 1 - S = \frac{PC}{1+PC}$$



Note that the

- complementary sensitivity function T is the transfer function $G_{r\to y}$
- sensitivity function S is the transfer function $G_{m\to y}$

$$S + T = 1$$

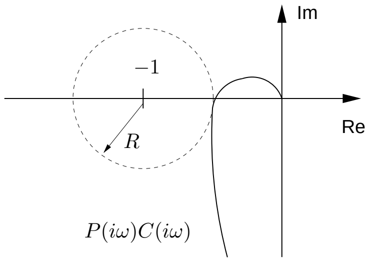
Note: there are four different transfer functions for this closed-loop system and all have to be stable for the system to be stable!

It may be OK to use an unstable controller C

Nyquist plot illustration

The sensitivity function measures the distance between the Nyquist plot and the point -1:

$$R^{-1} = \sup_{\omega} \left| \frac{1}{1+P(i\omega)C(i\omega)} \right| = M_s$$

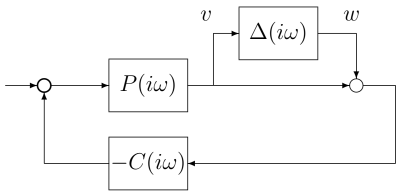


Lecture 2

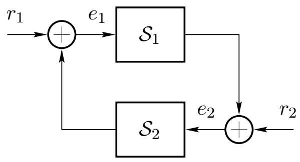
- Stability
- Robustness and sensitivity
- **Small gain theorem**

Robustness analysis

Example: How large perturbations $\Delta(i\omega)$ can be tolerated without risking instability?



The Small Gain Theorem



Assume that $\mathcal{S}_1$ and $\mathcal{S}_2$ are input-output stable. If $\|\mathcal{S}_1\| \cdot \|\mathcal{S}_2\| < 1$, then the gain from (r_1, r_2) to (e_1, e_2) in the closed loop system is finite.

- Note 1: The theorem applies also to nonlinear, time-varying, and multivariable systems
- Note 2: The stability condition is sufficient but not necessary, so the results may be conservative

Proof

Define $\|y\|_T = \sqrt{\int_0^T |y(t)|^2 dt}$. Then $\|\mathcal{S}(y)\|_T \leq \|\mathcal{S}\| \cdot \|y\|_T$.

$$e_1 = r_1 + \mathcal{S}_2(r_2 + \mathcal{S}_1(e_1))$$

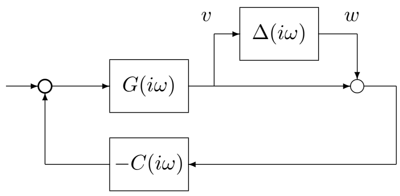
$$\|e_1\|_T \leq \|r_1\|_T + \|\mathcal{S}_2\| \Big(\|r_2\|_T + \|\mathcal{S}_1\| \cdot \|e_1\|_T \Big)$$

$$\|e_1\|_T \leq \frac{\|r_1\|_T + \|\mathcal{S}_2\| \cdot \|r_2\|_T}{1 - \|\mathcal{S}_1\| \cdot \|\mathcal{S}_2\|}$$

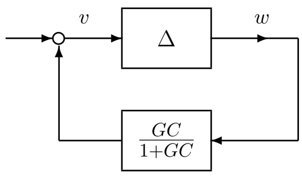
This shows bounded gain from (r_1, r_2) to e_1.

The gain to e_2 is bounded in the same way.

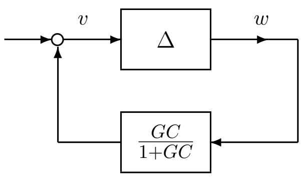
Application to robustness analysis



The diagram can be redrawn as



Application to robustness analysis



The small gain theorem guarantees stability if

$$\|\Delta\|_\infty \cdot \left\| \frac{GC}{1+GC} \right\|_\infty < 1$$

Gain of multivariable LTI systems

Recall from Lecture 1 that

$$||\mathcal{S}|| = \sup_{\omega} |G(i\omega)| = ||G||_\infty$$

for a stable LTI system $\mathcal{S}$.

How to calculate $|G(i\omega)|$ for a multivariable system?

Vector norm and matrix gain

For a vector $x \in \mathbf{C}^n$, we use the 2-norm

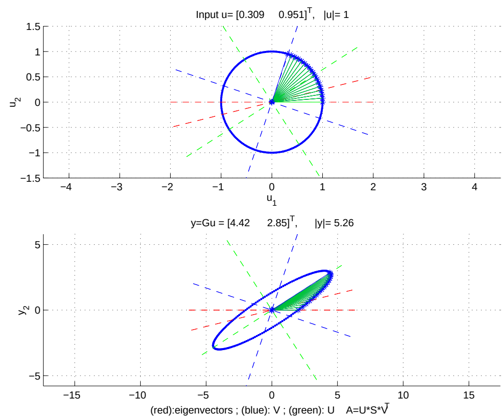
$$|x| = \sqrt{x^*x} = \sqrt{|x_1|^2 + \cdots + |x_n|^2}$$

For a matrix $M \in \mathbf{C}^{n\times n}$, we use the L_2-induced norm

$$\|M\| := \sup_x \frac{|Mx|}{|x|} = \sup_x \sqrt{\frac{x^*M^*Mx}{x^*x}} = \sqrt{\bar{\lambda}(M^*M)}$$

Here $\bar{\lambda}(M^*M)$ denotes the largest eigenvalue of M^*M. The ratio $|Mx|/|x|$ is maximized when x is a corresponding eigenvector.

Example: Different gains in different directions: $\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 2 & 4 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$



Example: matlab-demo

Singular Values

For a matrix M, its singular values σ_i are defined as

$$\sigma_i = \sqrt{\lambda_i}$$

where λ_i are the eigenvalues of M^*M.

Let $\bar{\sigma}(M)$ denote the largest singular value and $\underline{\sigma}(M)$ the smallest singular value.

For a linear map $y = Mu$, it holds that

$$\underline{\sigma}(M) \le \frac{|y|}{|u|} \le \bar{\sigma}(M)$$

The singular values are typically computed using singular value decomposition (SVD):

$$M = U\Sigma V^*$$

SVD example

Matlab code for singular value decomposition of the matrix

$$A = \begin{bmatrix} 2 & 4 \\ 0 & 3 \end{bmatrix}$$

SVD:

$$A = U \cdot S \cdot V^*$$

where both the matrices U and V are unitary (i.e. have orthonormal columns s.t. $V^* \cdot V = I$) and S is the diagonal matrix with (sorted decreasing) singular values σ_i. Multiplying A with a input vector along the first column in V gives

$$A \cdot V_{(:,1)} = USV^* \cdot V_{(:,1)} =$$
$$= US \begin{bmatrix} 1 \\ 0 \end{bmatrix} = U_{(:,1)} \cdot \sigma_1$$

That is, we get maximal gain σ_1 in the output direction $U_{(:,1)}$ if we use an input in direction $V_{(:,1)}$ (and minimal gain $\sigma_n = \sigma_2$ if we use the last column $V_{(:,n)} = V_{(:,2)}$).

```
>> A=[2 4 ; 0 3]
A =
     2     4
     0     3
>> [U,S,V]=svd(A)
U =
    0.8416   -0.5401
    0.5401    0.8416
S =
    5.2631         0
         0    1.1400
V =
    0.3198   -0.9475
    0.9475    0.3198

>> A*V(:,1)
ans =
    4.4296
    2.8424

>> U(:,1)*S(1,1)
ans =
    4.4296
    2.8424
```

Example: Gain of multivariable system

Consider the transfer function matrix

$$G(s) = \begin{bmatrix} \dfrac{2}{s+1} & \dfrac{4}{2s+1} \\ \dfrac{s}{s^2+0.1s+1} & \dfrac{3}{s+1} \end{bmatrix}$$

```
>> s=tf('s')
>> G=[ 2/(s+1) 4/(2*s+1); s/(s^2+0.1*s+1) 3/(s+1)];
>> sigma(G) % plot sigma values of G  wrt fq
>> grid on
>> norm(G,inf)  % infinity norm = system gain
   ans =
       10.3577
```

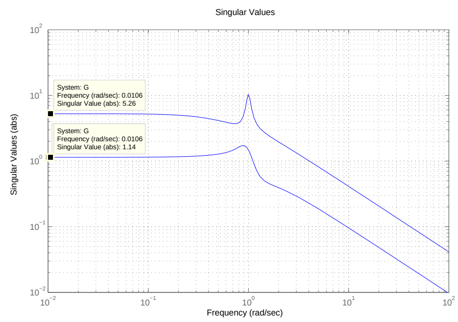


Figure: The singular values of the tranfer function matrix (prev slide). Note that G(0)=[2,4 ; 0 3] which corresponds to M in the SVD-example above. $\|G\|_\infty = 10.3577$.

Summary of today's most important concepts

- Input–output stability: $\|\mathcal{S}\| < \infty$
- Sensitivity function: $S := \frac{dT/T}{dP/P} = \frac{1}{1+PC}$
- Complementary sensitivity function: $T = 1 - S$
- Small Gain Theorem: The feedback interconnection of $\mathcal{S}_1$ and $\mathcal{S}_2$ is stable **if** $\|\mathcal{S}_1\| \cdot \|\mathcal{S}_2\| < 1$
- The gain of a multivariable system $G(s)$ is given by $\sup_\omega \bar{\sigma}(G(i\omega))$, where $\bar{\sigma}$ is the largest singular value

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