Theory of Robust Control

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Contents

1 Introduction to Basic Concepts

1.1 Systems and Signals

In these notes we intend to develop the theory of robust control for linear time invariant finite-dimensional systems that are briefly called LTI-systems. Recall that such systems are described in the state-space as

$$\begin{aligned} \dot{x} &= Ax + Bu, \quad x(0) = x_0 \\ y &= Cx + Du \end{aligned} \tag{1}$$

with input u, output y, state x, and matrices A, B, C, D of suitable size.

Here u, y, x are signals. Signals are functions of time $t \in [0, \infty)$ that are piece-wise continuous. (On finite intervals, such signals have only finitely many jumps as discontinuities.) They can either take their values in $\mathbb{R}$, or they can have k components such that they take their values in $\mathbb{R}^k$. To clearly identify e.g. x as a signal, we sometimes write $x(.)$ to stress this point.

Remark. Note that $x(.)$ denotes the signal as a whole, whereas $x(t)$ denotes the value of the signal at time-instant t.

The system responds to the input $u(.)$ with the output $y(.)$ which can be computed according to the relation

$$y(t) = Ce^{At}x_0 + \int_0^t Ce^{A(t-\tau)}Bu(\tau)\,d\tau + Du(t)$$

for $t \geq 0$.

We do not repeat the basic notions of controllability of the system or of the pair (A, B), and of observability of the system or of (A, C). Nevertheless we recall the following very basic facts:

- The system (1) or (A, B) is said to be **stabilizable** if there exists a feedback matrix F such that $A + BF$ has all its eigenvalues in the open left-half plane $\mathbb{C}^-$.

  Recall the **Hautus test for stabilizability**: (A, B) is stabilizable if and only if the matrix
  $$\begin{pmatrix} A - \lambda I & B \end{pmatrix}$$
  has full row rank for all $\lambda \in \mathbb{C}^0 \cup \mathbb{C}^+$.

- The system (1) or (A, C) is said to be **detectable** if there exists an L such that $A + LC$ has all its eigenvalues in the open left-half plane $\mathbb{C}^-$.

  Recall the **Hautus test for detectability**: (A, C) is detectable if and only if the matrix
  $$\begin{pmatrix} A - \lambda I \\ C \end{pmatrix}$$
  has full column rank for all $\lambda \in \mathbb{C}^0 \cup \mathbb{C}^+$.

The **transfer matrix** $G(s)$ of the system (1) is defined as

$$G(s) = C(sI - A)^{-1}B + D$$

and is a matrix whose elements consist of real-rational and proper functions.

Why does the transfer matrix pop up? Suppose the input signal $u(.)$ has the Laplace-transform

$$\hat{u}(s) = \int_0^\infty e^{-st}u(t)\,dt.$$

Then the output $y(.)$ of (1) does also have a Laplace transform that can be calculated as

$$\hat{y}(s) = C(sI - A)^{-1}x_0 + [C(sI - A)^{-1}B + D]\hat{u}(s).$$

For $x_0 = 0$ (such that the system starts at time 0 at rest), the relation between the Laplace transform of the input and the output signals is hence given by the transfer matrix as follows:

$$\hat{y}(s) = G(s)\hat{u}(s).$$

The 'complicated' convolution integral is transformed into a 'simpler' multiplication operation.

We have briefly addressed two different ways of representing a system: One representation in the state-space defined with specific constant matrices A, B, C, D, and one in the frequency domain defined via a real-rational proper transfer matrix $G(s)$.

Remark. It is important to view a system as a device that processes signals; hence a system is nothing but a mapping that maps the input signal $u(.)$ into the output signal $y(.)$ (for a certain initial condition). One should distinguish the system (the mapping) from its representations, such as the one in the state-space via A, B, C, D, or that in the frequency domain via $G(s)$. System properties should be formulated in terms of how signals are processed, and system representations are used to formulate algorithms how certain system properties can be verified.

The fundamental relation between the state-space and frequency domain representation is investigated in the so-called realization theory.

Going from the state-space to the frequency domain just requires to calculate the transfer matrix $G(s)$.

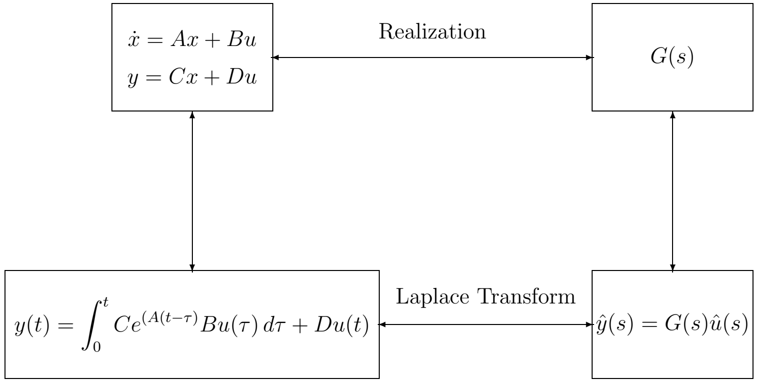
Conversely, suppose $H(s)$ is an arbitrary matrix whose elements are real-rational proper functions. Then there **always** exist matrices A_H, B_H, C_H, D_H such that

$$H(s) = C_H(sI - A_H)^{-1}B_H + D_H$$

holds true. This representation of the transfer matrix is called a **realization**. Realizations are not unique. Even more importantly, the size of the matrix A_H can vary for various realizations. However, there are realizations where A_H is of minimal size, the so-called minimal realization. There is a simple answer to the question of whether a realization is minimal: This happens if and only if (A_H, B_H) is controllable and (A_H, C_H) is observable.

Task. Recapitulate how you can compute a minimal realization of an arbitrary real rational proper transfer matrix H.

Pictorially, this discussion about the system representations in the time- and frequency-domain and the interpretation as a mapping of signals can be summarized as follows:



We use the symbol

$$\left[\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right]$$

both for the system mapping $u \to y$ as defined via the differential equation with initial condition 0, and for the corresponding transfer matrix G.

1.2 Stability of LTI Systems

Recall that any matrix $H(s)$ whose elements are real rational functions is **stable** if

- $H(s)$ is proper (there is no pole at infinity) and
- $H(s)$ has only poles in the open left-half $\mathbb{C}^-$ plane (there is no pole in the closed right half plane $\mathbb{C} \setminus \mathbb{C}^-$).

For the set of real rational proper and stable matrices of dimension $k \times l$ we use the special symbol

$$RH_\infty^{k\times l}$$

and if the dimension is understood from the context we simply write RH_∞. Recall that the three most important operations performed on stable transfer matrices do not leave out of this set: A scalar multiple of one stable transfer matrix as well as the sum and the product of stable transfer matrices (of compatible dimension) are stable.

On the other hand, the system (1) is said to be **stable** if A has all its eigenvalues in the open left-half plane $\mathbb{C}^-$. We will denote the set of eigenvalues of A by $\lambda(A)$, the spectrum of A. Then stability of (1) is simply expressed as

$$\lambda(A) \subset \mathbb{C}^-.$$

We say as well that the *matrix* A is stable if it has this property.

We recall the following relation between the stability of the system (1) and the stability of the corresponding transfer matrix $G(s) = C(sI - A)^{-1}B + D$:

- If (1) (or A) is stable, then $G(s)$ is stable.
- Conversely, if $G(s)$ is stable, if (A, B) is stabilizable, and if (A, C) is detectable, then (1) (or A) is stable.

Note that all these definitions are given in terms of properties of the representation. Nevertheless, these concepts are closely related - at least for LTI systems - to the so-called bounded-input bounded-output stability properties.

A vector valued signal $u(.)$ is bounded if the **maximal amplitude** or **peak**

$$\|u\|_\infty = \sup_{t\geq 0} \|u(t)\| \text{ is finite.}$$

Note that $\|u(t)\|$ just equals the Euclidean norm $\sqrt{u(t)^T u(t)}$ of the vector $u(t)$. The symbol $\|u\|_\infty$ for the peak indicates that the peak is, in fact, a norm on the vector space of all bounded signals; it is called the L_∞-norm.

The system (1) is said to be bounded-input bounded-output (BIBO) stable if it maps an arbitrary bounded input $u(.)$ into an output that is bounded as well. In short, $\|u\|_\infty < \infty$ implies $\|y\|_\infty < \infty$.

It is an interesting fact that, for LTI systems, BIBO stability is equivalent to the stability of the corresponding transfer matrix as defined earlier.

Theorem 1 *The system (1) maps bounded inputs $u(.)$ into bounded outputs $y(.)$ if and only if the corresponding transfer matrix $C(sI - A)^{-1}B + D$ is stable.*

To summarize, for a stabilizable and detectable realization $\left[\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right]$ of an LTI system, the following notions are equivalent: stability of the system (1), stability of the corresponding transfer matrix $C(sI - A)^{-1}B + D$, and BIBO stability of the system (1) viewed as an input output mapping.

Stability is a qualitative property. Another important fact is to quantify in how far signals are amplified or quenched by a system. If we look at one input $u(.)$, and if we take $\|u\|_\infty$ and $\|y\|_\infty$ as a measure of size for the input and the output of the system (1), the amplification for this specific input signal is nothing but

$$\frac{\|y\|_\infty}{\|u\|_\infty}.$$

The worst possible amplification is obtained by finding the largest of these quotients if varying $u(.)$ over **all** bounded signals:

$$\gamma_{\text{peak}} = \sup_{0<\|u\|_\infty<\infty} \frac{\|y\|_\infty}{\|u\|_\infty}. \tag{2}$$

This is the so-called **peak-to-peak gain** of the system (1). Then it just follows from the definition that

$$\|y\|_\infty \leq \gamma_{\text{peak}}\|u\|_\infty$$

holds for all bounded input signals $u(.)$: Hence γ_{peak} quantifies how the amplitudes of the bounded input signals are amplified or quenched by the system. Since γ_{peak} is, in fact, the smallest number such that this inequality is satisfied, there does exist an input signal such that the peak amplification is actually arbitrarily close to γ_{peak}. (The supremum in (2) is not necessarily attained by some input signal. Hence we cannot say that γ_{peak} is attained, but we can come arbitrarily close.)

Besides the peak, we could as well work with the energy of a signal $x(.)$, defined as

$$\|x\|_2 = \sqrt{\int_0^\infty \|x(t)\|^2\, dt},$$

to measure its size. Note that a signal with a large energy can have a small peak and vice versa (think of examples!) Hence we are really talking about different physical motivations if deciding for $\|.\|_\infty$ or for $\|.\|_2$ as a measure of size.

Now the question arises when a system maps any signal of finite energy again into a signal of finite energy; in short:

$$\|u\|_2 < \infty \ \text{ implies } \ \|y\|_2 < \infty.$$

It is somewhat surprising that, for the system (1), this property is again equivalent to the stability of the corresponding transfer matrix $C(sI - A)^{-1}B + D$. Hence the qualitative property of BIBO stability does not depend on whether one chooses the peak $\|.\|_\infty$ or the energy $\|.\|_2$ to characterize boundedness of a signal.

Remark. Note that this is a fundamental property of LTI system that is by no means valid for other type of systems, even if they admit a state-space realization such as non-linear system defined via differential equations.

Although the qualitative property of stability does not depend on the chosen measure of size for the signals, the quantitative measure for the system amplification, the system gain, is highly dependent on the chosen norm. The **energy gain** of (1) is analogously defined as for the peak-to-peak gain defined by

$$\gamma_{\text{energy}} = \sup_{0<\|u\|_2<\infty} \frac{\|y\|_2}{\|u\|_2}.$$

Contrary to the peak-to-peak gain, one can nicely relate the energy gain of the system (1) to the transfer matrix of the system. In fact, one can prove that γ_{energy} is equal to the maximal value that is taken by

$$\sigma_{\max}(G(i\omega)) = \|G(i\omega)\|$$

over the frequency $\omega \in \mathbb{R}$. Let us hence introduce the abbreviation

$$\|G\|_\infty := \sup_{\omega\in\mathbb{R}} \sigma_{\max}(G(i\omega)) = \sup_{\omega\in\mathbb{R}} \|G(i\omega)\|.$$

As indicated by the symbol, this formula defines a norm on the vector space of all real-rational proper and stable matrices $RH_\infty^{k\times l}$; it is called the H_∞-norm for mathematical reasons that are not important to us.

We can conclude that the energy gain of the stable LTI system (1) is just equal to the H_∞-norm of the corresponding transfer matrix:

$$\gamma_{\text{energy}} = \|G\|_\infty.$$

1.3 Stable Inverses

For any real-rational *matrix* $G(s)$, we can compute the real rational *function* $\det(G(s))$. It is well-known that $G(s)$ has a real-rational inverse if and only if $\det(G(s))$ is not the zero function (does not vanish identically). If $G(s)$ is proper, it is easy to verify that it has a *proper inverse* if and only if $\det(G(\infty))$ (which is well-defined since $G(\infty)$ is just a real matrix) does not vanish.

The goal is to derive a similar condition for the proper and stable $G(s)$ to have a proper and stable inverse. Here is the desired characterization.

Lemma 2 *The proper and stable matrix $G(s)$ has a proper and stable inverse if and only if the matrix $G(\infty)$ is non-singular, and the rational function $\det(G(s))$ does not have any zeros in the closed right-half plane.*

Proof. Assume that $G(s)$ has the proper and stable inverse $H(s)$. From $G(s)H(s) = I$ we infer $\det(G(s))\det(H(s)) = 1$ or

$$\det(G(s)) = \frac{1}{\det(H(s))}.$$

Since $H(s)$ is stable, $\det(H(s))$ has no poles in $\mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}$. Therefore, the reciprocal rational function and hence $\det(G(s))$ does not have zeros in this set.

Conversely, let us assume that $\det(G(s))$ has no zeros in $\mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}$. This certainly implies that

$$\frac{1}{\det(G(s))} \text{ is proper and stable.}$$

Now recall that the inverse of $G(s)$ is given by the formula

$$G(s)^{-1} = \frac{1}{\det(G(s))}\text{adj}(G(s))$$

where $\text{adj}(G(s))$ denotes the adjoint of $G(s)$. Adjoints are computed by taking products and sums/differences of the elements of $G(s)$; since $G(s)$ is stable, the adjoint of $G(s)$ is, therefore, a stable matrix. Then the explicit formula for $G(s)^{-1}$ reveals that this inverse must actually be stable as well.

■

Remark. It is important to apply this result to stable $G(s)$ only. For example, the proper unstable matrix

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

satisfies $\det(G(s)) = 1$ for all s. Hence, its determinant has no zeros in the closed right-half plane and at infinity; nevertheless, it has no stable inverse!

Let us now assume that the proper G has a realization

$$G = \left[\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right].$$

Recall that G has a proper inverse iff $D = G(\infty)$ is invertible. If D has an inverse, the proper inverse of G admits the realization

$$G^{-1} = \left[\begin{array}{c|c} A - BD^{-1}C & BD^{-1} \\ \hline -D^{-1}C & D^{-1} \end{array}\right].$$

Why? A signal based arguments leads directly to the answer:

$$\dot{x} = Ax + Bw, \quad z = Cx + Dw \tag{3}$$

is equivalent to

$$\dot{x} = Ax + Bw, \quad w = -D^{-1}Cx + D^{-1}z$$

and hence to

$$\dot{x} = (A - BD^{-1}C)x + BD^{-1}z, \quad w = -D^{-1}Cx + D^{-1}z. \tag{4}$$

This leads to a test of whether the stable G has a proper and stable inverse directly in terms of the matrices A, B, C, D of some realization.

Lemma 3 *Let $G(s)$ be stable and let $G(s) = \left[\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right]$ be a stabilizable and detectable realization. Then $G(s)$ has a proper and stable inverse if and only if D is non-singular and $A - BD^{-1}C$ is stable.*

Proof. Suppose G has the proper and stable inverse H. Then $G(\infty) = D$ is non-singular. We can hence define the system (4); since the realization (3) is stabilizable and detectable, one can easily verify (with the Hautus test) that the same is true for the realization (4). We have argued above that (4) is a realization of H; since H is stable, we can conclude that $A - BD^{-1}C$ must be stable.

The converse is easier to see: If D is non-singular and $A - BD^{-1}C$ is stable, (4) defines the stable transfer ymatrix H. As seen above, H is the inverse of G what reveals that G admits a proper and stable inverse.

■

1.4 Linear Fractional Transformations

Suppose P and K are given transfer matrices. Then the so-called **lower linear fractional transformation** $S(P, K)$ of P and K is defined as follows: Partition

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

such that $P_{22}K$ is *square*, check whether the rational matrix $I - P_{22}K$ has a rational inverse, and set

$$S(P, K) := P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21}.$$

In the literature, the expression $\mathcal{F}_l(P, K)$ is often used instead of $S(P, K)$. Since a lower linear fractional transformation is a particular form of a more general operation that carries the name **s**tar-product, we prefer the symbol $S(P, K)$.

Similarly, the **upper linear fractional transformation** $S(\Delta, P)$ of the rational matrices Δ and P is defined as follows: Choose a partition

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

such that $P_{11}\Delta$ is square, check whether the rational matrix $I - P_{11}\Delta$ has a rational inverse, and set

$$S(\Delta, P) := P_{22} + P_{21}\Delta(I - P_{11}\Delta)^{-1}P_{12}.$$

One often finds the notation $\mathcal{F}_u(P, \Delta)$ in the literature where one has to note that, unfortunately, the matrices Δ and P appear in reverse order.

At this point, $S(P,K)$ and $S(\Delta,P)$ should be just viewed as abbreviations for the formulas given above. The discussion to follow will reveal their system theoretic relevance.

Exercises

1) Suppose that $G(s)$ is a real-rational proper matrix. Explain in general how you can compute a state-space realization of $G(s)$ with the command `sysic` of the μ-tools, and discuss how to obtain a minimal realization.

   (Matlab) Compute in this way a realization of

$$G(s) = \begin{pmatrix} 1/s & 1/(s+1)^2 & s/(s+1) \\ (s^2-3s+5)/(2s^3+4s+1) & 1/s & 1/(s+1) \end{pmatrix}.$$

2) Suppose that $u(.)$ has finite energy, let $y(.)$ be the output of (1), and denote the Laplace transforms of both signals by $\hat{u}(.)$ and $\hat{y}(.)$ respectively. Show that

$$\int_{-\infty}^{\infty} \hat{y}(i\omega)^* \hat{y}(i\omega)\, d\omega \leq \|G\|_\infty^2 \int_{-\infty}^{\infty} \hat{u}(i\omega)^* \hat{u}(i\omega)\, d\omega.$$

   Argue that this implies $\|y\|_2 \leq \|G\|_\infty \|u\|_2$, and that this reveals that the energy gain is not larger than $\|G\|_\infty$.

   Can you find a sequence $u_j(.)$ of signals with finite energy such that

$$\lim_{j\to\infty} \frac{\|Gu_j\|_2}{\|u_j\|_2} = \|G\|_\infty ?$$

3) Look at the system $\dot{x} = ax + u,\ y = x$. Compute the peak-to-gain of this system. Determine a worst input u, i.e., an input for which the peak of the corresponding output equals the peak-to-peak gain of the system.

4) For any discrete-time real-valued signal $x = (x_0, x_1, \ldots)$ let us define the peak as

$$\|x\|_\infty := \sup_{k\geq 0} |x_k|.$$

   Consider the SISO discrete-time system

$$x_{k+1} = Ax_k + Bu_k, \quad y_k = Cx_k + Du_k, \quad x_0 = 0, \quad k \geq 0$$

   where all eigenvalues of A have absolute value smaller than 1 (discrete-time stability). As in continuous-time, the peak-to-peak gain of this system is defined as

$$\sup_{0<\|u\|_\infty<\infty} \frac{\|y\|_\infty}{\|u\|_\infty}.$$

   Derive a formula for the the peak-to-peak gain of the system!

   Hint: If setting $u^m := (u_0 \ \cdots \ u_m)^T$, $y^m := (y_0 \ \cdots \ y_m)^T$, determine a matrix M_m such that $y^m = M_m u^m$. How are the peak-to-peak gain of the system and the norm of M_m induced by the vector norm $\|.\|_\infty$ related?

2 Stabilizing Controllers for System Interconnections

In the previous section we have discussed the stability of one system. In practice, however, one encounters *interconnections* of systems. In the most simple case, typical components of such an interconnection are a model of a considered physical plant and a to-be-designed feedback controller.

2.1 A Specific Tracking Interconnection

To be concrete, let us look at the typical one-degree of freedom control configuration in Figure 1. Here G is the plant model, K is the to-be-designed controller, r is the reference input signal, d is a disturbance at the plant's output, n is measurement noise, e is the tracking error, u is the control input, and y is the measured output.

It is important to note that we have explicitly specified those signals that are of interest to us:

- Signals that affect the interconnection and cannot be influenced by the controller: r, d, n.
- Signals with which we characterize whether the controller achieves the desired goal: e should be kept as small as possible for all inputs r, d, n in a certain class.
- Signals via which the plant can be controlled: u.
- Signals that are available for control: y.

The interconnection does not only comprise the system compoments (G, K) and how the signals that are processed by these components are related to each other, but it also specifies those signals (e and r, d, n) that are related to the targeted task of the controller.

The corresponding *open-loop interconnection* is simply obtained by disconnecting the controller as shown in Figure 2.

It is straightforward to arrive, without any computation, at the following input-output description of the open-loop interconnection:

$$\begin{pmatrix} e \\ \hline y \end{pmatrix} = \left(\begin{array}{ccc|c} I & 0 & -I & G \\ \hline -I & -I & I & -G \end{array}\right) \begin{pmatrix} d \\ n \\ r \\ \hline u \end{pmatrix}.$$

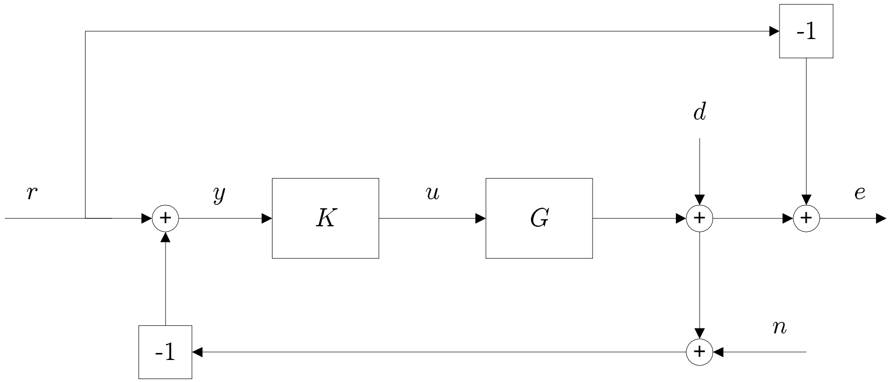


Figure 1: Closed-loop interconnection

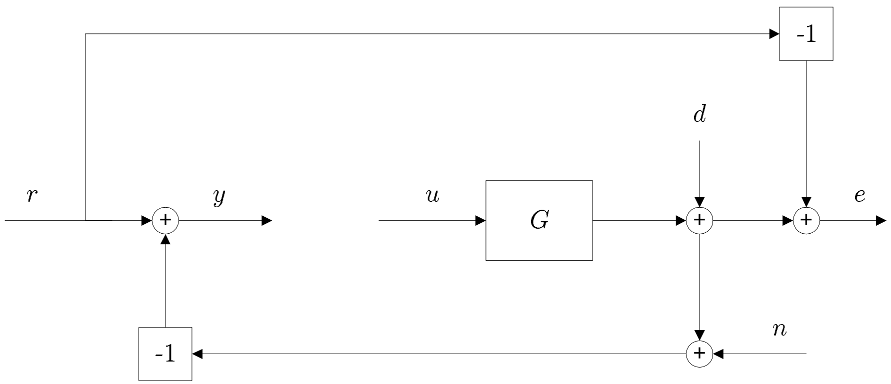


Figure 2: Open-loop interconnection that corresponds to Figure 1

The input-output description of the closed-loop interconnection is then obtained by closing the loop as

$$u = Ky.$$

A simple calculation reveals that

$$e = \left[\begin{pmatrix} I & 0 & -I \end{pmatrix} + GK(I-(-G)K)^{-1}\begin{pmatrix} -I & -I & I \end{pmatrix}\right]\begin{pmatrix} d \\ n \\ r \end{pmatrix}$$

what can be simplified to

$$e = \begin{pmatrix} (I+GK)^{-1} & -GK(I+GK)^{-1} & -(I+GK)^{-1} \end{pmatrix}\begin{pmatrix} d \\ n \\ r \end{pmatrix}.$$

As expected for this specific interconnection, we arrive at

$$e = \begin{pmatrix} S & -T & -S \end{pmatrix}\begin{pmatrix} d \\ n \\ r \end{pmatrix}$$

with sensitivity $S = (I+GK)^{-1}$ and complementary sensitivity $T = GK(I+GK)^{-1}$.

Let us now extract a general scheme out of this specific example.

2.2 The General Framework

In an arbitrary closed-loop interconnection structure, let

- w denote the signal that affects the system and cannot be influence by the controller. w is called **generalized disturbance**. (In our example, $w = \begin{pmatrix} d \\ n \\ r \end{pmatrix}$.)
- z denote the signal that allows to characterize whether a controller has certain desired properties. z is called **controlled variable**. (In our example, $z = e$.)
- u denote the output signal of the controller, the so-called **control input**. (In our example it's just u.)
- y denote the signal that enters the controller, the so-called **measurement output**. (In our example it's just y.)

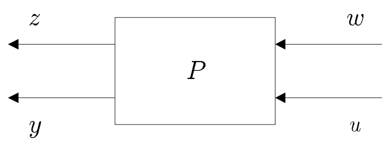


Figure 3: General Open-loop interconnection

Any open-loop interconnection can then be generally described by (Figure 3)

$$\begin{pmatrix} z \\ y \end{pmatrix} = P \begin{pmatrix} w \\ u \end{pmatrix} = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \begin{pmatrix} w \\ u \end{pmatrix} \tag{5}$$

where the system P comprises the subsystems that are involved in the interconnection and the manner how these subsystems are connected with each other.

Even if we start with an interconnection of SISO systems, the resulting open-loop interconnection will generally be described by a MIMO system since one has to stack several signals with only one component to vector valued signals.

In these whole notes we start from the fundamental hypothesis that P is an LTI system. We denote the corresponding transfer matrix with the same symbol as

$$P(s) = \begin{pmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \end{pmatrix}.$$

Let

$$\begin{aligned} \dot{x} &= Ax + B_1 w + B_2 u \\ z &= C_1 x + D_{11} w + D_{12} u \\ y &= C_2 x + D_{21} w + D_{22} u \end{aligned} \tag{6}$$

denote a stabilizable and detectable state-space realization of P.

A controller (Figure 4) is any LTI system

$$y_K = K u_K. \tag{7}$$

It can be described in the frequency domain by specifying its transfer matrix

$$K(s)$$

or via the stabilizable and detectable state-space realization

$$\begin{aligned} \dot{x}_K &= A_K x_K + B_K u_K \\ y_K &= C_K x_K + D_K u_K. \end{aligned} \tag{8}$$

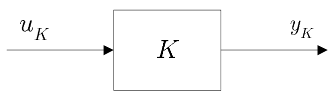


Figure 4: Controller

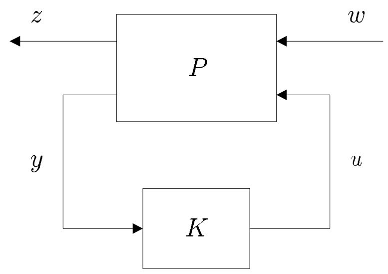


Figure 5: General closed-loop interconnection

The interconnection of the controller and the open-loop system as

$$u_K = y \quad \text{and} \quad u = y_K$$

leads to the closed-loop interconnection as depicted in Figure 5.

Remark. To have a minimal dimensions of the matrices and, hence, reduce the effort for all subsequent computations, one should rather work with *minimal* (controllable and observable) realizations for P and K. One can take these stronger hypothesis as the basis for the discussion throughout these notes without the need for any modification.

2.3 Stabilizing Controllers - State-Space Descriptions

Let us now first compute a realization of the interconnection as

$$\begin{pmatrix} u \\ u_K \end{pmatrix} = \begin{pmatrix} y_K \\ y \end{pmatrix} \tag{9}$$

of the system (6) and the controller (8).

For that purpose it is advantageous to merge the descriptions of (6) and (8) as

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline z \\ \hline y_K \\ y \end{pmatrix} = \left(\begin{array}{cc|c|cc} A & 0 & B_1 & B_2 & 0 \\ 0 & A_K & 0 & 0 & B_K \\ \hline C_1 & 0 & D_{11} & D_{12} & 0 \\ \hline 0 & C_K & 0 & 0 & D_K \\ C_2 & 0 & D_{21} & D_{22} & 0 \end{array}\right) \begin{pmatrix} x \\ x_K \\ \hline w \\ \hline u \\ u_K \end{pmatrix}.$$

To simplify the calculations notationally, let us introduce the abbreviation

$$\begin{pmatrix} \boldsymbol{A} & \boldsymbol{B}_1 & \boldsymbol{B}_2 \\ \boldsymbol{C}_1 & \boldsymbol{D}_{11} & \boldsymbol{D}_{12} \\ \boldsymbol{C}_2 & \boldsymbol{D}_{21} & \boldsymbol{D}_{22} \end{pmatrix} := \left(\begin{array}{cc|c|cc} A & 0 & B_1 & B_2 & 0 \\ 0 & A_K & 0 & 0 & B_K \\ \hline C_1 & 0 & D_{11} & D_{12} & 0 \\ \hline 0 & C_K & 0 & 0 & D_K \\ C_2 & 0 & D_{21} & D_{22} & 0 \end{array}\right). \tag{10}$$

The interconnection (9) leads to

$$\begin{pmatrix} y_K \\ y \end{pmatrix} = \left(\boldsymbol{C}_2 \middle| \boldsymbol{D}_{21} \right) \begin{pmatrix} x \\ x_K \\ \hline w \end{pmatrix} + \boldsymbol{D}_{22} \begin{pmatrix} y_K \\ y \end{pmatrix}$$

or

$$[I - \boldsymbol{D}_{22}] \begin{pmatrix} y_K \\ y \end{pmatrix} = \left(\boldsymbol{C}_2 \middle| \boldsymbol{D}_{21} \right) \begin{pmatrix} x \\ x_K \\ \hline w \end{pmatrix}.$$

If $I - \boldsymbol{D}_{22}$ is non-singular, we arrive at

$$\begin{pmatrix} y_K \\ y \end{pmatrix} = [I - \boldsymbol{D}_{22}]^{-1} \left(\boldsymbol{C}_2 \middle| \boldsymbol{D}_{21} \right) \begin{pmatrix} x \\ x_K \\ \hline w \end{pmatrix}$$

what finally leads to

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline z \end{pmatrix} = \left(\begin{pmatrix} \boldsymbol{A} & \boldsymbol{B}_1 \\ \boldsymbol{C}_1 & \boldsymbol{D}_{11} \end{pmatrix} + \begin{pmatrix} \boldsymbol{B}_2 \\ \boldsymbol{D}_{12} \end{pmatrix} [I - \boldsymbol{D}_{22}]^{-1} \begin{pmatrix} \boldsymbol{C}_2 & \boldsymbol{D}_{21} \end{pmatrix} \right) \begin{pmatrix} x \\ x_K \\ \hline w \end{pmatrix}$$

or

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline z \end{pmatrix} = \left(\begin{array}{c|c} \boldsymbol{A} + \boldsymbol{B}_2[I - \boldsymbol{D}_{22}]^{-1}\boldsymbol{C}_2 & \boldsymbol{B}_1 + \boldsymbol{B}_2[I - \boldsymbol{D}_{22}]^{-1}\boldsymbol{D}_{21} \\ \hline \boldsymbol{C}_1 + \boldsymbol{D}_{12}[I - \boldsymbol{D}_{22}]^{-1}\boldsymbol{C}_2 & \boldsymbol{D}_1 + \boldsymbol{D}_{12}[I - \boldsymbol{D}_{22}]^{-1}\boldsymbol{D}_{21} \end{array} \right) \begin{pmatrix} x \\ x_K \\ \hline w \end{pmatrix}. \tag{11}$$

This is an explicit formula for a state-space representation of the closed-loop interconnection.

On our way to derive this formula we assumed that $I - \boldsymbol{D}_{22}$ is non-singular. This is a condition to ensure that we could indeed close the loop; this is the reason why it is often called a well-posedness condition for the interconnection.

Any controller should at least be chosen such that the interconnection is well-posed. In addition, we require that the controller stabilizes the interconnection. This will just amount to requiring that the matrix $\boldsymbol{A} + \boldsymbol{B}_2[I - \boldsymbol{D}_{22}]^{-1}\boldsymbol{C}_2$ which defines the dynamics of the interconnection is stable.

We arrive at the following fundamental definition of when the controller (8) stabilizes the open-loop system (6).

Definition 4 *The controller (8)* **stabilizes** *the system (6) if*

$$\begin{pmatrix} I & -D_K \\ -D_{22} & I \end{pmatrix} \quad \textit{is non-singular} \tag{12}$$

and if

$$\begin{pmatrix} A & 0 \\ 0 & A_K \end{pmatrix} + \begin{pmatrix} B_2 & 0 \\ 0 & B_K \end{pmatrix} \begin{pmatrix} I & -D_K \\ -D_{22} & I \end{pmatrix}^{-1} \begin{pmatrix} 0 & C_K \\ C_2 & 0 \end{pmatrix} \tag{13}$$

has all its eigenvalues in the open left-half plane $\mathbb{C}^-$.

Remarks.

- Verifying whether K stabilizes P is very simple: First check whether the realizations of both P and K are stabilizable and detectable, then check (12), and finally verify whether (13) is stable.
- Note that the definition only involves the matrices

  $$\begin{pmatrix} A & B_2 \\ C_2 & D_{22} \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} A_K & B_K \\ C_K & D_K \end{pmatrix}.$$

  The matrices B_1 and C_1 only play a role in requiring that $\left(A, \begin{pmatrix} B_1 & B_2 \end{pmatrix}\right)$ is stabilizable and $\left(A, \begin{pmatrix} C_1 \\ C_2 \end{pmatrix}\right)$ is detectable.
- The same definition is in effect if the channel $w \to z$ is void and the system (6) just reads as

  $$\begin{pmatrix} \dot{x} \\ y \end{pmatrix} = \begin{pmatrix} A & B_2 \\ C_2 & D_{22} \end{pmatrix} \begin{pmatrix} x \\ u \end{pmatrix}.$$

Note that the formulas (11) for the closed-loop interconnection simplify considerably if either D_{22} or D_K vanish. Let us look at the case when

$$D_{22} = 0.$$

Then (12) is always true. Due to

$$\begin{pmatrix} I & -D_K \\ 0 & I \end{pmatrix}^{-1} = \begin{pmatrix} I & D_K \\ 0 & I \end{pmatrix},$$

a straightforward calculation reveals that (11) now reads as

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline z \end{pmatrix} = \left(\begin{array}{cc|c} A + B_2 D_K C_2 & B_2 C_K & B_1 + B_2 D_K D_{21} \\ C_2 B_K & A_K & B_K D_{21} \\ \hline C_1 + D_{12} D_K C_2 & D_{12} C_K & D_{11} + D_{12} D_K D_{21} \end{array}\right) \begin{pmatrix} x \\ x_K \\ \hline w \end{pmatrix}.$$

Then the matrix (13) just equals

$$\begin{pmatrix} A + B_2 D_K C_2 & B_2 C_K \\ C_2 B_K & A_K \end{pmatrix}.$$

2.4 Stabilizing Controllers - Input-Output Descriptions

Let us first see how to determine an input-ouput description of the closed-loop interconnection as in Figure 5. For that purpose we only need to eliminate the signals u, y in

$$z = P_{11} w + P_{12} u, \quad y = P_{21} w + P_{22} u, \quad u = K y.$$

The last two relations lead to $y = P_{21} w + P_{22} K y$ or $(I - P_{22} K) y = P_{21} w$. If $I - P_{22} K$ does have a proper inverse, we obtain $y = (I - P_{22} K)^{-1} P_{21}$ and, finally,

$$z = [P_{11} + P_{12} K (I - P_{22} K)^{-1} P_{21}] w. \tag{14}$$

This is a general formula how to obtain, from the input-ouput description P and from that of the controller K, the corresponding input-output description of the closed-loop interconnection. If we recall the definitions in Section 1.4, we observe that the closed-loop input-output description by performing the lower linear fractional transformation of P with K which has been denoted as $S(P, K)$:

$$z = S(P, K) w.$$

This is the mere reason why these fractional transformations play such an important role in these notes and, in general, in robust control.

Note that (14) gives the transfer matrix that is defined by (11) and, conversely, (11) is a state-space realization of (14).

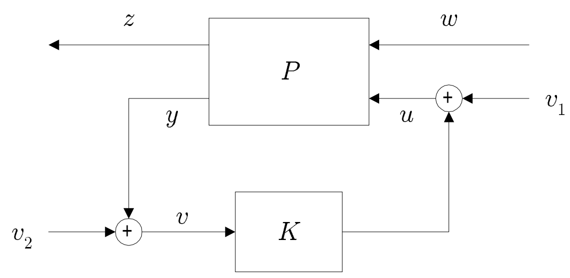


Figure 6: Interconnection to Test Stabiltity

Let us now observe that $I - P_{22} K$ has a proper inverse if and only if $I - P_{22}(\infty) K(\infty)$ is non-singular. If we look back to the realizations (6) and (8), this just means that $I - D_{22} D_K$ is non-singular, what is in turn equivalent to (12).

Unfortunately, the relation for stability is not as straightforward. In general, if (11) is stable, the transfer matrix defined through (14) is stable as well. However, the realization (11) is not necessarily stabilizable or detectable. Therefore, even if (14) defines a stable transfer matrix, the system (11) is not necessarily stable. For checking whether K stabilizes P, it hence *does not suffice* to simply verify whether $P_{11} + P_{12} K (I - P_{22} K)^{-1} P_{21}$ defines a stable transfer matrix.

This indicates that we have to check more transfer matrices in the loop in Figure 5 than just the one explicitly displayed by the channel $w \to z$ in order to guarantee that K stabilizes P. It turns out that Figure 6 gives a suitable setup to define all the relevant transfer matrices that have to be tested.

Theorem 5 *K stabilizes P if and only if the interconnection as depicted in Figure 6 and defined through the relations*

$$\begin{pmatrix} z \\ y \end{pmatrix} = P \begin{pmatrix} w \\ u \end{pmatrix}, \quad u = K v + v_1, \quad v = y + v_2$$

or, equivalently, by

$$\begin{pmatrix} z \\ \hline v_1 \\ v_2 \end{pmatrix} = \left(\begin{array}{c|cc} P_{11} & P_{12} & 0 \\ \hline 0 & I & -K \\ -P_{21} & -P_{22} & I \end{array}\right) \begin{pmatrix} w \\ \hline u \\ v \end{pmatrix} \tag{15}$$

defines a proper transfer matrix

$$\begin{pmatrix} w \\ v_1 \\ v_2 \end{pmatrix} \to \begin{pmatrix} z \\ u \\ v \end{pmatrix} \tag{16}$$

that is stable.

With this result we can test directly on the basis of the transfer matrices whether K stabilizes P: One has to check whether the relations (15) define a proper and stable transfer matrix (16).

Let us first clarify what this means exactly. Clearly, (15) can be rewritten as

$$\begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = \begin{pmatrix} 0 \\ -P_{21} \end{pmatrix} w + \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix}, \quad z = P_{11} w + \begin{pmatrix} P_{12} & 0 \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix}. \tag{17}$$

These relations define a proper transfer matrix (16) if and only if

$$\begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix} \text{ has a proper inverse.}$$

As well-known, this is true if and only if

$$\begin{pmatrix} I & -K(\infty) \\ -P_{22}(\infty) & I \end{pmatrix} \text{ is non-singular.}$$

Indeed, under this hypothesis, the first relation in (17) is equivalent to

$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ P_{21} \end{pmatrix} w + \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix}.$$

Hence (17) is nothing but

$$\begin{pmatrix} z \\ \hline u \\ v \end{pmatrix} = \left(\begin{array}{c|c} P_{11} + \begin{pmatrix} P_{12} & 0 \end{pmatrix} \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ P_{21} \end{pmatrix} & \begin{pmatrix} P_{12} & 0 \end{pmatrix} \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} \\ \hline \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ P_{21} \end{pmatrix} & \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} \end{array} \right) \begin{pmatrix} w \\ \hline v_1 \\ v_2 \end{pmatrix}.$$

If we recall the formula

$$\begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} = \begin{pmatrix} (I - KP_{22})^{-1} & K(I - P_{22}K)^{-1} \\ (I - P_{22}K)^{-1} P_{22} & (I - P_{22}K)^{-1} \end{pmatrix},$$

this can be rewritten to

$$\begin{pmatrix} z \\ \hline u \\ v \end{pmatrix} = \left(\begin{array}{c|cc} P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21} & P_{12}(I - KP_{22})^{-1} & P_{12}K(I - P_{22}K)^{-1} \\ \hline K(I - P_{22}K)^{-1}P_{21} & (I - KP_{22})^{-1} & K(I - P_{22}K)^{-1} \\ (I - P_{22}K)^{-1}P_{21} & (I - P_{22}K)^{-1}P_{22} & (I - P_{22}K)^{-1} \end{array} \right) \begin{pmatrix} w \\ \hline v_1 \\ v_2 \end{pmatrix}. \tag{18}$$

We have arrived at a more explicit reformulation of Theorem 5.

Corollary 6 *K stabilizes P if and only if $I - P_{22}K$ has a proper inverse and all nine transfer matrices in (18) are stable.*

Remark. If the channel $w \to z$ is absent, the characterizing conditions in Theorem 5 or Corollary 6 read as follows: The transfer matrix

$$\begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}$$

has a proper and stable inverse. Since K and P_{22} are, in general, not stable, it does not suffice to simply verify whether the determinant of this matrix is stable; Lemma (2) does not apply!

Proof of Theorem 5. We have already clarified that (15) defines a proper transfer matrix (16) if and only if (12) is true. Let us hence assume the validity of (12).

Then we observe that (15) admits the state-space realization

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline z \\ \hline v_1 \\ v_2 \end{pmatrix} = \left(\begin{array}{cc|c|cc} A & 0 & B_1 & B_2 & 0 \\ 0 & A_K & 0 & 0 & B_K \\ \hline C_1 & 0 & D_{11} & D_{12} & 0 \\ \hline 0 & -C_K & 0 & I & -D_K \\ -C_2 & 0 & -D_{21} & -D_{22} & I \end{array} \right) \begin{pmatrix} x \\ x_K \\ \hline w \\ \hline u \\ v \end{pmatrix}. \tag{19}$$

Using the abbreviation (10), this is nothing but

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline z \\ \hline v_1 \\ v_2 \end{pmatrix} = \left(\begin{array}{c|c|c} \boldsymbol{A} & \boldsymbol{B}_1 & \boldsymbol{B}_2 \\ \hline \boldsymbol{C}_1 & \boldsymbol{D}_{11} & \boldsymbol{D}_{12} \\ \hline -\boldsymbol{C}_2 & -\boldsymbol{D}_{21} & I - \boldsymbol{D}_{22} \end{array} \right) \begin{pmatrix} x \\ x_K \\ \hline w \\ \hline u \\ v \end{pmatrix}.$$

By (12), $\tilde{\boldsymbol{D}}_{22} := I - \boldsymbol{D}_{22}$ is non-singular. The same calculation as performed earlier leads to a state-space realization of (16):

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline z \\ \hline u \\ v \end{pmatrix} = \left(\begin{array}{c|c|c} \boldsymbol{A} + \boldsymbol{B}_2 \tilde{\boldsymbol{D}}_{22}^{-1} \boldsymbol{C}_2 & \boldsymbol{B}_1 + \boldsymbol{B}_2 \tilde{\boldsymbol{D}}_{22}^{-1} \boldsymbol{D}_{21} & \boldsymbol{B}_2 \tilde{\boldsymbol{D}}_{22}^{-1} \\ \hline \boldsymbol{C}_1 + \boldsymbol{D}_{12} \tilde{\boldsymbol{D}}_{22}^{-1} \boldsymbol{C}_2 & \boldsymbol{D}_1 + \boldsymbol{D}_{12} \tilde{\boldsymbol{D}}_{22}^{-1} \boldsymbol{D}_{21} & \boldsymbol{D}_{12} \tilde{\boldsymbol{D}}_{22}^{-1} \\ \hline \tilde{\boldsymbol{D}}_{22}^{-1} \boldsymbol{C}_2 & \tilde{\boldsymbol{D}}_{22}^{-1} \boldsymbol{D}_{21} & \tilde{\boldsymbol{D}}_{22}^{-1} \end{array} \right) \begin{pmatrix} x \\ x_K \\ \hline w \\ \hline v_1 \\ v_2 \end{pmatrix}. \tag{20}$$

Here is the crux of the proof: Since (6) and (8) are stabilizable/detectable realizations, one can easily verify with the Hautus test that (19) has the same property. This implies that the the realization (20) is stabilizable and detectable as well.

Therefore we can conclude: The transfer matrix of (20) is stable *if and only if* the system (20) is stable *if and only if* $\boldsymbol{A}+\boldsymbol{B}_2\tilde{\boldsymbol{D}}_{22}^{-1}\boldsymbol{C}_2 = \boldsymbol{A}+\boldsymbol{B}_2(I-\boldsymbol{D}_{22})^{-1}\boldsymbol{C}_2$ has all its eigenvalues in $\mathbb{C}^-$. Since we have guaranteed the validity of (12), this property is (by Definition 4) nothing but the fact that K stabilizes P.

∎

2.5 Generalized Plants

Contrary to what one might expect, it is not possible to find a stabilizing controller K for any P.

Example. Let us consider (5) with

$$P(s) = \begin{pmatrix} 1 & 1/s \\ 1 & 1/(s+1) \end{pmatrix}.$$

We claim that there is no $K(s)$ that stabilizes $P(s)$. Reason: Suppose we found a $K(s)$ that stabilizes $P(s)$. Then the two transfer functions

$$P_{12}(s)(I-K(s)P_{22}(s))^{-1} = \frac{1}{s}\frac{1}{1-\frac{K(s)}{s+1}}$$
$$P_{12}(s)(I-K(s)P_{22}(s))^{-1}K(s) = \frac{K(s)}{s-\frac{s}{s+1}K(s)} = \frac{1}{s}\frac{1}{\frac{1}{K(s)}-\frac{1}{s+1}}$$

are stable. But this cannot be true. To show that, we distinguish two cases:

- Suppose $K(s)$ has no pole in 0. Then the denominator of $\frac{1}{1-\frac{K(s)}{s+1}}$ is finite in $s=0$ such that this function cannot have a zero in $s=0$. This implies that the first of the above two transfer functions has a pole in 0, i.e., it is unstable.
- Suppose $K(s)$ does have a pole in 0. Then $\frac{1}{K(s)}$ vanishes in $s=0$ such that $\frac{1}{\frac{1}{K(s)}-\frac{1}{s+1}}$ takes the value -1 in $s=0$. Hence, the second of the above two transfer functions has a pole in 0 and is, thus, unstable.

We arrive at the contradiction that at least one of the above two transfer functions is always unstable. Roughly speaking, the pole $s=0$ of the transfer function $P_{12}(s)=\frac{1}{s}$ cannot be stabilized via feeding y back to u since this is not a pole of $P_{22}(s)$ as well.

Our theory will be based on the hypothesis that P does in fact admit a stabilizing controller. For such open-loop interconnections we introduce a particular name.

Definition 7 *If there exists at least one controller K that stabilizes the open-loop interconnection P, we call P a* **generalized plant**.

Fortunately, one can very easily check whether a given P is a generalized plant or not. We first formulate a test for the state-space description of P.

Theorem 8 *P with the stabilizable/detectable realization (6) is a generalized plant if and only if (A, B_2) is stabilizable and (A, C_2) is detectable.*

Since the realization (6) is stabilizable, we know that $\left(A, \begin{pmatrix} B_1 & B_2 \end{pmatrix}\right)$ is stabilizable. This does clearly not imply, in general, that the pair (A, B_2) defining a system with fewer inputs is stabilizable. A similar remark holds for detectability.

Let us now assume that (A, B_2) is stabilizable and (A, C_2) is detectable. Then we can explicitly construct a controller that stabilizes P. In fact, stabilizability of (A, B_2) and detectability of (A, C_2) imply that there exist F and L such that $A+B_2F$ and $A+LC_2$ are stable. Let us now take the controller K that is defined through

$$\dot{x}_K = (A+B_2F+LC_2+LD_{22}F)x_K - Ly, \quad u = Fx_K.$$

Note that this is nothing but the standard observer-based controller which one would design for the system

$$\dot{x} = Ax + B_2u, \quad y = C_2x + D_{22}u.$$

It is simple to check that K indeed stabilizes P. First, K is strictly proper ($D_K = 0$) such that (12) is obviously true. Second, let us look at

$$\begin{aligned}
&\begin{pmatrix} A & 0 \\ 0 & A_K \end{pmatrix} + \begin{pmatrix} B_2 & 0 \\ 0 & B_K \end{pmatrix}\begin{pmatrix} I & 0 \\ -D_{22} & I \end{pmatrix}^{-1}\begin{pmatrix} 0 & C_K \\ C_2 & 0 \end{pmatrix} = \\
&= \begin{pmatrix} A & 0 \\ 0 & A+B_2F+LC_2+LD_{22}F \end{pmatrix} + \begin{pmatrix} B_2 & 0 \\ 0 & -L \end{pmatrix}\begin{pmatrix} I & 0 \\ D_{22} & I \end{pmatrix}\begin{pmatrix} 0 & F \\ C_2 & 0 \end{pmatrix} = \\
&= \begin{pmatrix} A & 0 \\ 0 & A+B_2F+LC_2+LD_{22}F \end{pmatrix} + \begin{pmatrix} B_2 & 0 \\ 0 & -L \end{pmatrix}\begin{pmatrix} 0 & F \\ C_2 & D_{22}F \end{pmatrix} = \\
&= \begin{pmatrix} A & B_2F \\ -LC_2 & A+B_2F+LC_2 \end{pmatrix}.
\end{aligned}$$

We claim that this matrix is stable. This should be known from classical theory. However, it can be verified by performing the similarity transformation (error dynamics!)

$$\begin{pmatrix} I & 0 \\ I & -I \end{pmatrix}\begin{pmatrix} A & B_2F \\ -LC_2 & A+B_2F+LC_2 \end{pmatrix}\begin{pmatrix} I & 0 \\ I & -I \end{pmatrix}^{-1}$$

to arrive at

$$\begin{pmatrix} A+B_2F & B_2F \\ 0 & A+LC_2 \end{pmatrix}$$

which is, obviously, stable since the diagonal blocks are.

This was the proof of the if-part in Theorem 8 with an explicit construction of a stabilizing controller.

Proof of only if. To finish the proof, we have to show: If there exists a K that stabilizes P, then (A, B_2) is stabilizable and (A, C_2) is detectable. If K stabilizes P, we know by definition that

$$\mathcal{A} := \begin{pmatrix} A & 0 \\ 0 & A_K \end{pmatrix} + \begin{pmatrix} B_2 & 0 \\ 0 & B_K \end{pmatrix} \begin{pmatrix} I & -D_K \\ -D_{22} & I \end{pmatrix}^{-1} \begin{pmatrix} 0 & C_K \\ C_2 & 0 \end{pmatrix}$$

is stable. This implies that (A, C_2) is detectable. Let us prove this fact with the Hautus test: Suppose $Ax = \lambda x$, $x \neq 0$, and $C_2 x = 0$. Then we observe that

$$\mathcal{A} \begin{pmatrix} x \\ 0 \end{pmatrix} = \begin{pmatrix} Ax \\ 0 \end{pmatrix} = \lambda \begin{pmatrix} x \\ 0 \end{pmatrix}.$$

Hence $\begin{pmatrix} x \\ 0 \end{pmatrix}$ is an eigenvector of $\mathcal{A}$ with eigenvalue λ. Since $\mathcal{A}$ is stable, we infer $\mathrm{Re}(\lambda) < 0$. This proves that (A, C_2) is detectable.

Task. Show in a similar fashion that (A, B_2) is stabilizable what finishes the proof.

■

Remark. If the channel $w \to z$ is absent, then (A, B_2) and (A, C_2) are obviously stabilizable and detectable. (The matrices B_1, C_2, D_{11}, D_{12}, D_{21} in (6) are void.) Then there *always* exists a controller K that stabilizes P.

This last remark reveals that we can always find a $u = Ky$ that stabilizes $y = P_{22}u$. This leads us to a input-output test of whether P is a generalized plant or not.

Theorem 9 *Let $u = Ky$ be any controller that stabilizes $y = P_{22}u$. Then P is a generalized plant if and only if this controller K stabilizes the open-loop interconnection P.*

Again, this test is easy to perform: Find an (always existing) K that stabilizes P_{22}, and verify that this K renders all the nine transfer matrices in (18) stable. If yes, P is a generalized plant, if no, P is not.

Proof. Let K stabilize P_{22}.

If K also stabilizes P, we infer that there exists a stabilizing controller and, hence, P is a generalized plant.

Conversely, let P be a generalized plant. We intend to show that K not only stabilizes P_{22} but even P. We proceed with state-space arguments. Recall that $\begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix}$ admits the state-space realization

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline v_1 \\ v_2 \end{pmatrix} = \left(\begin{array}{cc|cc} A & 0 & B_2 & 0 \\ 0 & A_K & 0 & B_K \\ \hline 0 & -C_K & I & -D_K \\ -C_2 & 0 & -D_{22} & I \end{array}\right) \begin{pmatrix} x \\ x_K \\ \hline u \\ v \end{pmatrix}. \tag{21}$$

Using the abbreviation (10), this is nothing but

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline v_1 \\ v_2 \end{pmatrix} = \left(\begin{array}{c|c} \boldsymbol{A} & \boldsymbol{B}_2 \\ \hline -\boldsymbol{C}_2 & I - \boldsymbol{D}_{22} \end{array}\right) \begin{pmatrix} x \\ x_K \\ \hline u \\ v \end{pmatrix}.$$

By (12), $I - \boldsymbol{D}_{22}$ is non-singular. Again, the same calculation as earlier leads to a state-space realization of $\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}^{-1} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix}$ given by

$$\begin{pmatrix} \dot{x} \\ \dot{x}_K \\ \hline u \\ v \end{pmatrix} = \left(\begin{array}{c|c} \boldsymbol{A} + \boldsymbol{B}_2(I - \boldsymbol{D}_{22})^{-1}\boldsymbol{C}_2 & \boldsymbol{B}_2(I - \boldsymbol{D}_{22})^{-1} \\ \hline (I - \boldsymbol{D}_{22})^{-1}\boldsymbol{C}_2 & (I - \boldsymbol{D}_{22})^{-1} \end{array}\right) \begin{pmatrix} x \\ x_K \\ \hline v_1 \\ v_2 \end{pmatrix}. \tag{22}$$

Since P is a generalized plant, (A, B_2) is stabilizable and (A, C_2) is detectable. Therefore, the same is true for (21) and, similarly as in the proof of Theorem 5, also for (22). Since K stabilizes P_{22}, the transfer matrix defined through (22) is stable. Since this realization is stabilizable and detectable, we can conclude that $\boldsymbol{A} + \boldsymbol{B}_2(I - \boldsymbol{D}_{22})^{-1}\boldsymbol{C}_2$ is actually stable. Hence K stabilizes also P by definition.

■

2.6 Summary

For a specific control task, extract the open-loop interconnection (5).

Then test whether this open-loop interconnection defines a generalized plant by applying either one of the following procedures:

- Find a state-space realization (6) of P for which $\left(A, \begin{pmatrix} B_1 & B_2 \end{pmatrix}\right)$ is stabilizable (or even controllable) and $\left(A, \begin{pmatrix} C_1 \\ C_2 \end{pmatrix}\right)$ is detectable (or even observable), and check whether (A, B_2) is stabilizable and (A, C_2) is detectable. If yes, P is a generalized plant, if no, P is not.

- Find any K such that $\begin{pmatrix} I & -K \\ -P_{22} & I \end{pmatrix}$ does have a proper and stable inverse. Then verify whether this K renders all transfer matrices in (18) stable. If yes, P is a generalized plant, if no, P is not.

If P turns out to be no generalized plant, the interconnection under consideration is not suitable for the theory to be developed in these notes.

Suppose K stabilizes P. Then the closed-loop interconnection is described as

$$z = (P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21})w = S(P, K)w$$

In the state-space, the closed-loop system admits the realization (11) with the abbreviations (10).

2.7 Back to the Tracking Interconnection

Let us come back to the specific tracking interconnection in Figure 1 for which we have obtained

$$P = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} = \left(\begin{array}{ccc|c} I & 0 & -I & G \\ \hline -I & -I & I & -G \end{array}\right).$$

We claim that this is a generalized plant.

Input-output test: Let K stabilize $P_{22} = -G$. This means that that

$$\begin{pmatrix} (I - KP_{22})^{-1} & K(I - P_{22}K)^{-1} \\ (I - P_{22}K)^{-1}P_{22} & (I - P_{22}K)^{-1} \end{pmatrix} = \begin{pmatrix} (I + KG)^{-1} & K(I + GK)^{-1} \\ -(I + GK)^{-1}G & (I + GK)^{-1} \end{pmatrix}$$

is well-defined and stable. Let us now look at (18). Since $P_{21}(s) = \begin{pmatrix} -I & -I & I \end{pmatrix}$ is stable, the same is true of $K(I - P_{22}K)^{-1}P_{21}$ and $K(I - P_{22}K)^{-1}P_{21}$. Since $P_{12} = G$, we infer

$$P_{12}(I - KP_{22})^{-1} = G(I + KG)^{-1} = (I + GK)^{-1}G$$

and

$$P_{12}K(I - KP_{22})^{-1} = KG(I + KG)^{-1} = I - (I + KG)^{-1}$$

that are both stable. Hence it remains to check stability of

$$S(P, K) = P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21} :$$

We have just seen that $P_{12}K(I - KP_{22})^{-1}$ is stable. Since the same is true for $P_{11} = \begin{pmatrix} I & 0 & -I \end{pmatrix}$ and P_{21}, we can indeed conclude that $S(P, K)$ is stable. This reveals that all nine transfer matrices in (18) are stable. By Theorem 9, P is a generalized plant.

State-space test: Let us assume that

$$G(s) = C_G(sI - A_G)^{-1}B_G + D_G$$

is a minimal realization. Then we observe that

$$P(s) = \begin{pmatrix} C_G \\ -C_G \end{pmatrix} (sI - A_G)^{-1} \left(\begin{array}{ccc|c} 0 & 0 & 0 & B_G \end{array}\right) + \left(\begin{array}{ccc|c} I & 0 & -I & D_G \\ \hline -I & -I & I & -D_G \end{array}\right)$$

and hence $P(s)$ admits a minimal realization with the matrix

$$\begin{pmatrix} A & B_1 & B_2 \\ C_1 & D_{11} & D_{12} \\ C_2 & D_{21} & D_{22} \end{pmatrix} = \left(\begin{array}{c|ccc|c} A_G & 0 & 0 & 0 & B_G \\ \hline C_G & I & 0 & -I & D_G \\ \hline -C_G & -I & -I & I & -D_G \end{array}\right).$$

Since $(A, B_2) = (A_G, B_G)$ is controllable and $(A, C_2) = (A_G, C_G)$ is observable, Theorem 8 implies that P is a generalized plant.

Note that all these tests are very simple, mainly due to the simplicity of the feedback interconnection in Figure 1 under scrutiny. In practical circumstances one might encounter a much more complicated configuration where the tests have to be performed numerically. The μ-tools have a very powerful command that allows to easily obtain a state-space realization even for complicated interconnections.

Exercises

1) Let P be a stable stable LTI system.

   a) Show that K stabilizes P if and only if $I - P_{22}K$ has a proper inverse and $K(I - P_{22}K)^{-1}$ is stable. (It suffices to check *one* instead of *nine* transfer matrices.)

      Is the same statement true if we replace $K(I - P_{22}K)^{-1}$ with $(I - P_{22}K)^{-1}$?

   b) Show that the set of closed-loop transfer matrices $S(P, K)$ where K varies over all controllers that stabilize P is given by the set of all

      $$P_{11} + P_{12}QP_{21}$$

      where Q is a free parameter in RH_∞. What is the relation between K and Q?

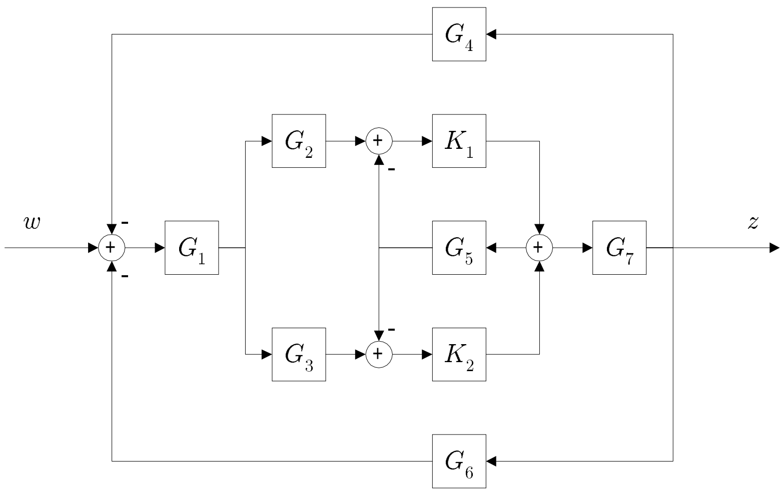


Figure 7: An interconnection

(This is the so-called Youla parameterization. Note that K enters in $S(P,K)$ in a non-linear fashion, whereas Q enters $P_{11} + P_{12}QP_{21}$ in an affine fashion. Hence the change of parameters $K \to Q$ leads to an affine dependence of the closed-loop system on the so-called Youla-parameter. All this can be extended to general systems P that are not necessarily stable.)

2) Which of the following transfer matrices $P(s)$ define a generalized plant:

$$\begin{pmatrix} 1/(s+1) & 1/(s+2) \\ 1/(s+3) & 1/s \end{pmatrix}, \quad \begin{pmatrix} 1/(s^2+s) & 1/(s+2) \\ 1/(s+3) & 1/s \end{pmatrix}$$
$$\begin{pmatrix} 1/(s+1) & 1/(s^2+2s) \\ 1/(s+3) & 1/s \end{pmatrix}, \quad \begin{pmatrix} 1/(s+1) & 1/(s+2) \\ 1/(s+3) & 1/s^2 \end{pmatrix}?$$

It is assumed that all signals in $\begin{pmatrix} z \\ y \end{pmatrix} = P \begin{pmatrix} w \\ u \end{pmatrix}$ have one component.

3) Suppose you have given the interconnection in Figure 7. We view G_j, $j = 1,2,3,4,5,6,7$ as possibly MIMO system components, and K_j, $j = 1,2$, are possibly MIMO controller blocks.

a) Compute the description P of the open-loop interconnection in terms of G_j. Mind the fact that all components can have multiple inputs and outputs.

b) Find two examples with simple SISO components G_j such that the resulting two open-loop interconnections P_1, P_2 have the following properties:

P_1 is no generalized plant. There exists a controller K that renders $S(P_2, K)$ stable but that does not stabilize P_2.

Is it possible to take $P_1 = P_2$?

c) (Matlab) Choose

$$G_1(s) = 1,\ G_2(s) = \frac{1}{s-1},\ G_3(s) = \frac{s+1}{s^2+1},\ G_4(s) = 0,$$
$$G_5(s) = \frac{1}{s},\ G_6(s) = 1,\ G_7(s) = \frac{s+2}{(s+3)(s-2)}.$$

Show that P is a generalized plant. Design a controller K that stabilizes P. Explain how you obtain K, and how you check whether K indeed stabilizes P. Draw a Bode magnitude plot of the resulting closed loop system $S(P,K)$.

3 Robust Stability Analysis

All mathematical models of a physical system suffer from inaccuracies that result from non-exact measurements or from the general inability to capture all phenomena that are involved in the dynamics of the considered system. Even if it is possible to accurately model a system, the resulting descriptions are often too complex to allow for a subsequent analysis, not to speak of the design of a controller. Hence one rather chooses for a simple model and takes a certain error between the simplified and the more complex model into account.

Therefore, there is always a mismatch between the model and the system to be investigated. A control engineer calls this mismatch *uncertainty*. Note that this is an abuse of notation since neither the system nor the model are uncertain; it is rather our knowledge about the actual physical system that we could call uncertain.

The main goal of robust control techniques is to take these uncertainties in a systematic fashion into account when analyzing a control system or when designing a controller for it.

In order to do so, one has to arrive at a mathematical description of the uncertainties. Sometimes it is pretty obvious what to call an uncertainty (such as parameter variations in a good physical model), but sometimes one just has to postulate a certain structure of the uncertainty. Instead of being general, we shall first turn again to the specific interconnection in Figure 1 and anticipate, on some examples, the general paradigm and tools that are available in robust control.

3.1 Uncertainties in the Tracking Configuration - Examples

3.1.1 A Classical SISO Example

Let us be concrete and assume that the model $G(s)$ in Figure 1 is given as

$$G(s) = \frac{200}{10s+1}\frac{1}{(0.05s+1)^2}. \tag{23}$$

Suppose the controller is chosen as

$$K(s) = \frac{0.1s+1}{(0.65s+1)(0.03s+1)}. \tag{24}$$

The code

```
G=nd2sys( [200],conv([10 1],conv([0.05 1],[0.05 1])) );
K=nd2sys( [0.1 1], conv([0.65 1],[0.03 1]) );
```



```
systemnames='G';
inputvar='[d;n;r;u]';
outputvar='[G+d-r;r-n-d-G]';
input_to_G='[u]';
sysoutname='P';
cleanupsysic='yes';
sysic
S=starp(P,K);
[A,B,C,D]=unpck(S);
eig(A)
```

actually computes realizations of the open-loop interconnection P, of the controller K, and of the closed-loop interconnection $S(P, K)$ denoted as (A, B, C, D). It turns out that A is stable such that K stabilizes P.

Suppose that we know (for example from frequency domain experiments) that the frequency response $H(i\omega)$ of the actual stable plant $H(s)$ does not coincide with that of the model $G(i\omega)$. Let us assume that we can even quantify this mismatch as

$$|H(i\omega) - G(i\omega)| < 1 \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}. \tag{25}$$

Here is the fundamental question we would like to ask: If we replace G by H, does the controller still stabilize the feedback interconnection?

If we knew H, we could just plug in H and test this property in the same way as we did for G. Unfortunately, however, H could be any element of the *set* of all stable systems H that satisfy (25). Hence, in principle, we would have to test infinitely many transfer functions H what is not possible.

This motivates to look for alternative verifiable tests. Let us introduce the notation

$$\Delta(s) := H(s) - G(s)$$

for the plant-model mismatch. Then the actual plant is given as

$$H(s) = G(s) + \Delta(s)$$

with some stable $\Delta(s)$ that satisfies

$$|\Delta(i\omega)| < 1 \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}. \tag{26}$$

Therefore, our main question can be formulated as follows: Does the closed-loop interconnections as depicted in Figure 8 remain stable if Δ is any stable transfer function that satisfies (26)?

We could also ask instead: Does there exists a stable $\Delta(s)$ with (26) that *destabilizes* the closed-loop interconnection?

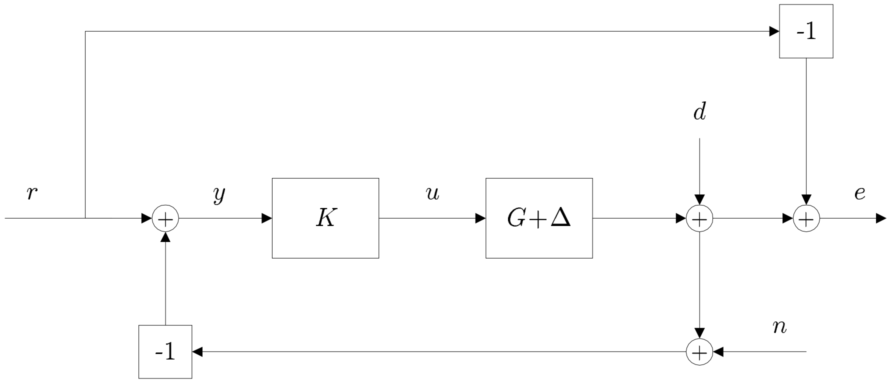


Figure 8: Uncertain closed-loop interconnection

Roughly speaking, the answer is obtained by looking at the influence which the uncertainty can exert on the interconnection. For that purpose we calculate the transfer function that is 'seen' by Δ: Just rewrite the loop as in Figure 9 in which we have just introduced notations for the input signal z_Δ and the output signal w_Δ of Δ. After this step we disconnect Δ to arrive at the interconnection in Figure 10. The transfer function seen by Δ is nothing but the transfer function $w_\Delta \to z_\Delta$.

For this specific interconnection, a straightforward calculation reveals that this transer function is given as

$$M = -(I + KG)^{-1}K.$$

As a fundamental result, we will reveal that the loop remains stable for a specific Δ if $I - M\Delta$ does have a proper and stable inverse.

Let us motivate this result by putting the interconnection in Figure 9 into the the general structure as in Figure 11 by setting $z = e$ and collecting again all the signals d, n, r into the vector-valued signal $w = \begin{pmatrix} d \\ n \\ r \end{pmatrix}$ as we did previously. Then Figure 10 corresponds to Figure 12.

Mathematically, the system in Figure 12 with disconnected uncertainty is described as

$$\begin{pmatrix} z_\Delta \\ z \end{pmatrix} = N \begin{pmatrix} w_\Delta \\ w \end{pmatrix} = \begin{pmatrix} N_{11} & N_{12} \\ N_{21} & N_{22} \end{pmatrix} \begin{pmatrix} w_\Delta \\ w \end{pmatrix} = \begin{pmatrix} M & N_{12} \\ N_{21} & N_{22} \end{pmatrix} \begin{pmatrix} w_\Delta \\ w \end{pmatrix}$$

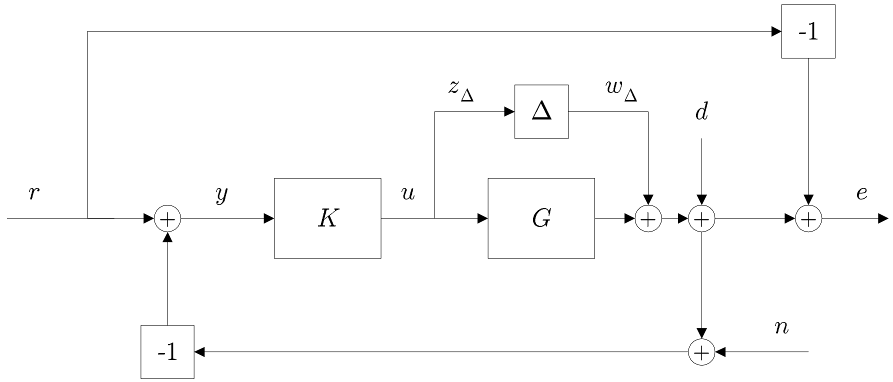


Figure 9: Rewritten uncertain closed-loop interconnection

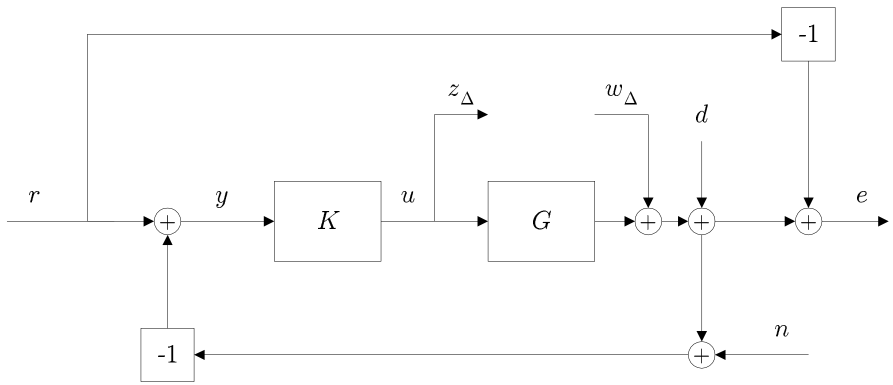


Figure 10: Closed-loop interconnection with disconnected uncertainty

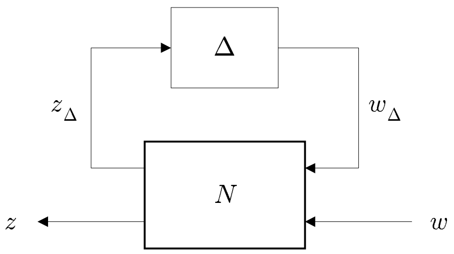


Figure 11: Uncertain closed-loop interconnection

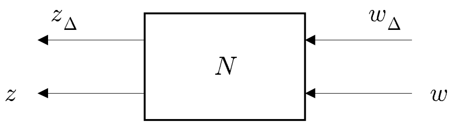


Figure 12: Uncertain closed-loop interconnection

where N is partitioned according to the (possibly vector valued) signals w_Δ, w and z_Δ, z. Then the transfer matrix seen by Δ is nothing but $N_{11} = M$.

If we reconnect the uncertainty as

$$w_\Delta = \Delta z_\Delta,$$

we arrive at

$$z = [N_{22} + N_{21}\Delta(I - M\Delta)^{-1}N_{12}]w.$$

This easily clarifies the above statement: Since the controller is stabilizing, all $N_{11} = M$, N_{12}, N_{21}, N_{22} are proper and stable. Only through the inverse $(I - M\Delta)^{-1}$, improperness or instability might occur in the loop. Therefore, if $I - M\Delta$ does have a proper and stable inverse, the loop remains stable.

Note that these arguments are not sound: We did not proved stability of the interconnection as defined in Definition 4. We will provide rigorous arguments in Section 3.7.

What have we achieved for our specific interconnection? We have seen that we need to verify whether

$$I - M\Delta = I + (I + KG)^{-1}K\Delta$$

does have a proper stable inverse for all stable Δ with (26). Let us apply the Nyquist criterion: Since both $M = -(I + KG)^{-1}K$ and Δ are stable, this is true if the Nyquist

curve

$$\omega \to -M(i\omega)\Delta(i\omega) = (I + K(i\omega)G(i\omega))^{-1}K(i\omega)\Delta(i\omega)$$

does not encircle the point -1. This is certainly true if

$$|M(i\omega)\Delta(i\omega)| = |(I + K(i\omega)G(i\omega))^{-1}K(i\omega)\Delta(i\omega)| < 1 \text{ for all } \omega \in \mathbb{R} \cup \{\infty\}. \quad (27)$$

Due to (26), this is in turn implied by the condition

$$|M(i\omega)| = |(I + K(i\omega)G(i\omega))^{-1}K(i\omega)| \leq 1 \text{ for all } \omega \in \mathbb{R} \cup \{\infty\}. \quad (28)$$

We conclude: If (28) is valid, the transfer function $I - M\Delta = I + (I + KG)^{-1}K\Delta$ does have a proper and stable inverse for all stable Δ with (26), and hence none of these uncertainties can destabilize the loop.

To continue with the example, the code

```
G=nd2sys( [200],conv([10 1],conv([0.05 1],[0.05 1])) );
K=nd2sys( [0.1 1], conv([0.65 1],[0.03 1]) );
systemnames='G';
inputvar='[w;d;n;r;u]';
outputvar='[u;w+G+d-r;w+r-n-d-G]';
input_to_G='[u]';
sysoutname='P';
cleanupsysic='yes';
sysic
N=starp(P,K);
[A,B,C,D]=unpck(N);
eig(A)
M=sel(N,1,1);
om=logspace(-2,4);
Mom=frsp(M,om);
vplot('liv,lm',Mom);
grid on
```

determines the transfer matrix N, it picks out the left upper block M, the transfer function seen by the uncertainty, and plots the magnitude of M over frequency; the result is shown in Figure 13. Since the magnitude exceeds one at some frequencies, we see that we *cannot guarantee robust stability* against all stable Δ that satisfy (26).

Although this is a negative answer, the plot provides us with a lot of additional insight.

Let us first *construct* an uncertainty that destabilizes the loop. This is expected to happen for a Δ for which $(I - M\Delta)^{-1}$ has an unstable pole, i.e., for which $I - M\Delta$ has an unstable zero. Let us look specifically for a zero $i\omega_0$ on the imaginary axis; then we need to have

$$M(i\omega_0)\Delta(i\omega_0) = 1.$$

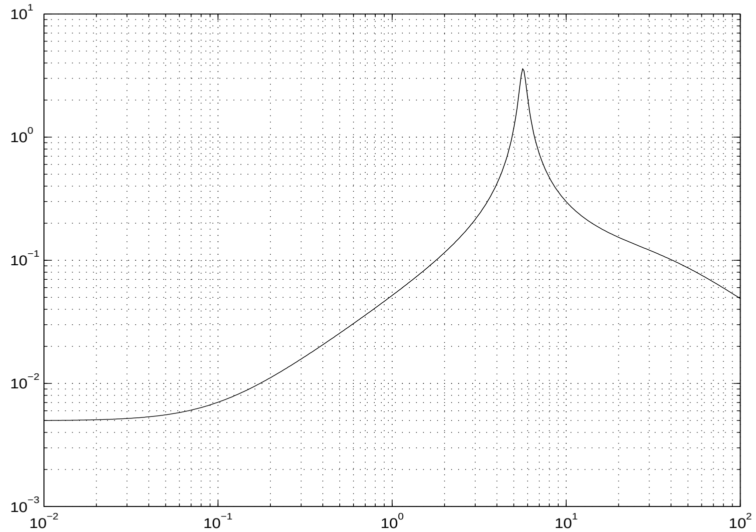


Figure 13: Magnitude plot of M

Let us pick ω_0 such that $|M(i\omega_0)| > 1$. As the magnitude plot shows, such a frequency indeed exists. Then the *complex number*

$$\Delta_0 := \frac{1}{M(i\omega_0)}$$

indeed renders $M(i\omega_0)\Delta_0 = 1$ satisfied. In our example, we chose $\omega_0 = 5$. If we calculate Δ_0 and replace G by $G + \Delta_0$, a state-space realization of the close-loop interconnection as calculated earlier will have an eigenvalue $5i$ and is, hence, unstable. We have constructed a complex number Δ_0 that destabilizes the interconnection. Note, however, that complex number are not in our uncertainty class that consisted of real rational proper transfer functions only. The following Lemma helps to find such destabilizing perturbation from Δ_0.

Lemma 10 *Let $\omega_0 \geq 0$ and $\Delta_0 \in \mathbb{C}$ be given. Set*

$$\alpha = \pm|\Delta_0|, \quad \beta = i\omega_0\,\frac{\alpha - \Delta_0}{\alpha + \Delta_0}.$$

Then the function

$$\Delta(s) = \alpha\frac{s - \beta}{s + \beta}$$

is proper, real rational, and satisfies

$$\Delta(i\omega_0) = \Delta_0 \;\; \text{and} \;\; |\Delta(i\omega)| = |\Delta_0| \;\; \text{for all} \;\; \omega \in \mathbb{R} \cup \{\infty\}.$$

Either for $\alpha = |\Delta_0|$ or for $\alpha = -|\Delta_0|$, Δ is stable.

Proof. One can prove $\Delta_0 = \Delta(i\omega_0)$ by direct calculations. Since $|\alpha| = |\Delta_0|$, the vectors that correspond to the complex numbers $\alpha + \Delta_0$ and $\alpha - \Delta_0$ are perpendicular. (Draw a picture to see this.) Hence $\frac{\alpha-\Delta_0}{\alpha+\Delta_0}$ is purely imaginary. This implies that β is real. Therefore, the distances of $i\omega$ to β and to $-\beta$ are identical such that $|i\omega - \beta| = |i\omega + \beta|$ what implies $|\Delta(i\omega)| = |\alpha| = |\Delta_0|$. Moreover, a change of sign of α leads to the reciprocal of $\frac{\alpha-\Delta_0}{\alpha+\Delta_0}$ which is, again due to the fact that this number is purely imaginary, just $-\frac{\alpha-\Delta_0}{\alpha+\Delta_0}$. Hence we can adjust the sign of α to render β non-negative. Then Δ is stable. (Note that β might vanish what causes no problem!)

■

This little lemma solves our problem. In fact, it says that we can construct a real-rational proper and stable $\Delta(s)$ satisfying

$$\Delta(i\omega_0) = \Delta_0, \quad |\Delta(i\omega)| = |\Delta_0| < 1 \;\; \text{for all} \;\; \omega \in \mathbb{R} \cup \{\infty\}.$$

In our case the construction leads to $\alpha = -0.8434$ and $\beta = -4.6257$. As expected, the A matrix of a realization of the closed-loop interconnection for $G + \Delta$ turns out to have $5i$ as an eigenvalue. We have hence found a stable destabilizing uncertainty whose frequency response is smaller than 1.

To summarize, we have seen that the loop is not robustly stable against all the uncertainties in the class we started out with. What can we conclude on the positive side? In fact, Figure 13 shows that

$$|M(i\omega)| = |(I + K(i\omega)G(i\omega))^{-1}K(i\omega)| \leq 4 \;\; \text{for all} \;\; \omega \in \mathbb{R}\{\infty\}.$$

Therefore, (27) holds for all stable Δ that satisfy

$$|\Delta(i\omega)| < \frac{1}{4} \;\; \text{for all} \;\; \omega \in \mathbb{R} \cup \{\infty\}.$$

Hence, we *can guarantee robust stability* for all uncertainty in this *smaller class*.

In fact, the largest bound r for which we can still guarantee robust stability for any stable Δ satisfying

$$|\Delta(i\omega)| < r \;\; \text{for all} \;\; \omega \in \mathbb{R} \cup \{\infty\}$$

is given by the reciprocal of the peak value of the magnitude plot:

$$r = \left(\sup_{\omega\in\mathbb{R}\cup\{\infty\}} |M(i\omega)|\right)^{-1} = \|M\|_\infty^{-1}.$$

We have discussed with this simple example how one can test robust stability by looking at a magnitude plot of the transfer function 'seen' by Δ. If robust stability does not hold, we have discussed how to construct a destabilizing perturbation.

3.1.2 A Modern MIMO Example

In the last section we have considered a very elementary example of a feedback interconnection in which only one uncertainty occurs.

Let us hence look at a model that is described by the 2×2 transfer matrix

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

with minimal state-space realization

$$G = \left[\begin{array}{cc|cc} 0 & a & 1 & 0 \\ -a & 0 & 0 & 1 \\ \hline 1 & a & 0 & 0 \\ -a & 1 & 0 & 0 \end{array}\right].$$

Suppose that this is a model of a system in which certain tolerances for the actuators have to be taken into account that are represented by parametric uncertainties. Let us hence assume that the input matrix is rather given by

$$\begin{pmatrix} 1 + \delta_1 & 0 \\ 0 & 1 + \delta_2 \end{pmatrix}.$$

Hence the actual system is

$$\frac{1}{s^2 + a^2} \begin{pmatrix} s - a^2 & a(s+1) \\ -a(s+1) & s - a^2 \end{pmatrix} \left(I + \begin{pmatrix} \delta_1 & 0 \\ 0 & \delta_2 \end{pmatrix} \right)$$

or

$$G(I + \Delta) \ \text{ with } \ \Delta = \begin{pmatrix} \delta_1 & 0 \\ 0 & \delta_2 \end{pmatrix}$$

for some real numbers δ_1, δ_2 with

$$|\delta_1| < r, \ |\delta_2| < r. \tag{29}$$

Again, we are faced with a whole set of systems rather than with a single one. Uncertainty now enters via the two real parameters δ_1, δ_2.

Let us take the unity feedback controller

$$K = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

and consider again the interconnection in Figure 14.

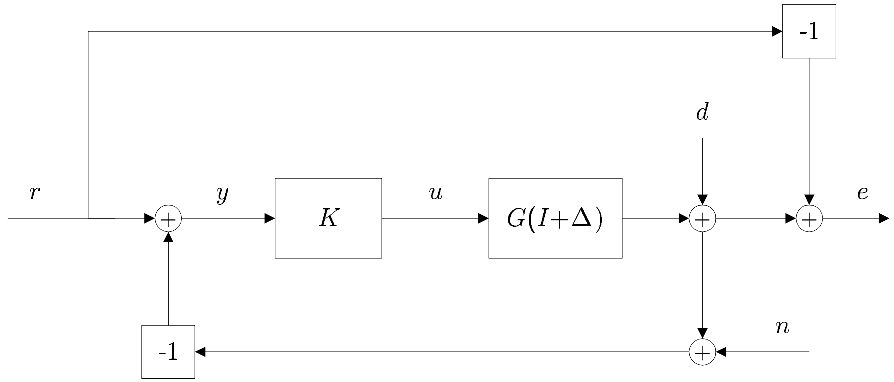


Figure 14: Uncertain closed-loop interconnection

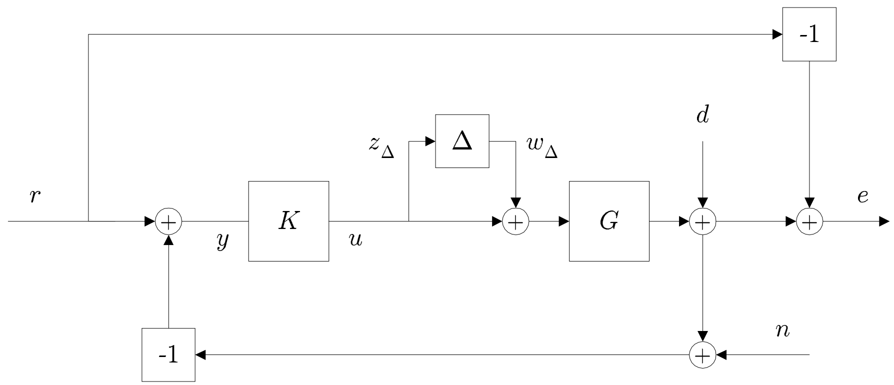


Figure 15: Rewritten uncertain closed-loop interconnection

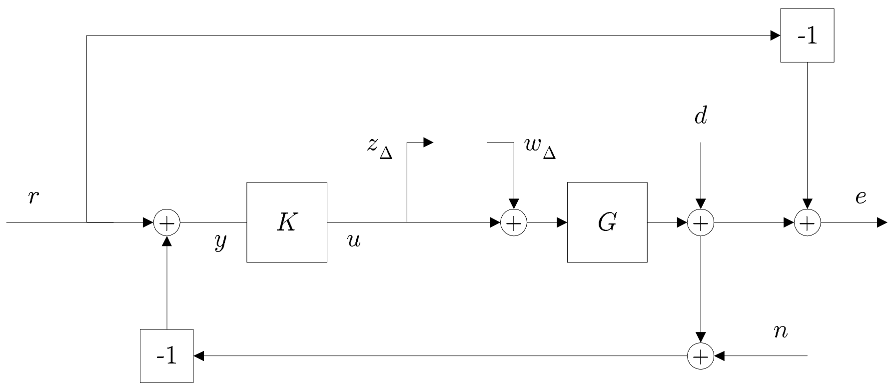


Figure 16: Rewritten uncertain closed-loop interconnection

As before we rewrite the interconnection in the obviously equivalent fashion as in Figure 15 and disconnect the uncertainty as in Figure 16.

The transfer matrix seen by Δ is given as

$$M(s) = \frac{1}{s+1}\begin{pmatrix} -1 & -a \\ a & -1 \end{pmatrix}. \tag{30}$$

As indicated earlier and as it will be developed in the general theory, for testing robust stability we have to verify whether $I - M\Delta$ has a proper and stable inverse for all Δ.

Recall that, by Lemma 2, this is true iff $I - M(s)\Delta(s)$ is non-singular for $s = \infty$ (properness, no pole at infinity) and for all s in the closed right-half plane (stability, no pole in closed right-half plane). Hence we have to check whether the determinant is non-zero for all $s \in \mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}$. The determinant of

$$I - M(s)\Delta = \begin{pmatrix} 1 + \frac{\delta_1}{s+1} & \frac{a\delta_2}{s+1} \\ \frac{-a\delta_1}{s+1} & 1 + \frac{\delta_2}{s+1} \end{pmatrix}$$

is easily calculated to

$$\frac{1}{(s+1)^2}\left(s^2 + (2 + \delta_1 + \delta_2)s + (1 + \delta_1 + \delta_2) + (a^2+1)\delta_1\delta_2\right).$$

It does not have a zero at ∞. Moreover, its finite zeros are certainly confined to $\mathbb{C}^-$ if and only if

$$2 + \delta_1 + \delta_2 > 0, \quad (1 + \delta_1 + \delta_2) + (a^2+1)\delta_1\delta_2 > 0.$$

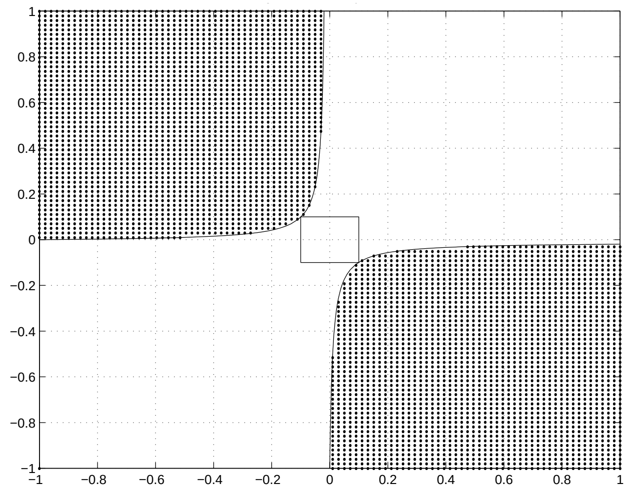


Figure 17: Dotted: Region of destabilizing parameters (δ_1, δ_2)

For $a = 10$, Figure 17 depicts the region of parameters where this condition is *not true*.

Let us now first concentrate on one uncertainty at a time. For $\delta_2 = 0$, the stability conditions holds for all δ_1 in the big interval $(-1, \infty)$. The same holds for $\delta_1 = 0$ and $\delta_2 \in (-1, \infty)$.

Let us now vary both parameters. If we try to find the largest r such that stability is preserved for all parameters with (29), we have to inflate a box around zero until it hits the region of instability as shown in Figure 17. (Why?) For the parameter $a = 10$, the largest r turns out to be 0.1, and this value *shrinks* with increasing a.

In summary, the analysis with a single varying uncertainty ($\delta_1 = 0$ or $\delta_2 = 0$) just gives a wrong picture of the robust stability region for *common* variations.

It is important to observe that we could very easily explicitly determine the region of stability and instability for this specific problem. Since this is by no means possible in general, we need to have a general tool that can be applied as well to arrive at similar insights for more sophisticated structures. This is the goal in the theory to be developed in the next sections.

3.2 Types of Uncertainties of System Components

Uncertainties that can be dealt with by the theory to be developed include parametric and LTI dynamic uncertainties. Parametric uncertainties are related to variations of real parameters (mass, spring constants, damping,...) in a system model, whereas LTI dynamic uncertainty should capture unmodeled dynamics of a system.

3.2.1 Parametric Uncertainties

Let us look at

$$\ddot{x} + c\dot{x} + x = u, \quad y = x.$$

Suppose we only know for the damping constant that

$$c_1 < c < c_2$$

for some real numbers $0 < c_1 < c_2$. Let us choose as the nominal value $c_0 := \frac{c_1+c_2}{2}$ and introduce the scaled error

$$\Delta = \frac{c - c_0}{c_2 - c_0}.$$

This implies

$$c = c_0 + W\Delta \quad \text{with} \quad W = c_2 - c_0.$$

With the class of uncertainties

$$\mathbf{\Delta} := \{\Delta \in \mathbb{R} \mid -1 < \Delta < 1\},$$

the uncertain system is then defined via the frequency-domain description

$$G_\Delta(s) = \frac{1}{s^2 + (c_0 + W\Delta)s + 1}.$$

Note that we have actually defined a whole set of systems G_Δ that is parameterized through Δ which varies in $\mathbf{\Delta}$. In addition, we have transformed the original parameter $c \in (c_1, c_2)$ into the new parameter $\Delta \in (-1, 1)$ by using a nominal value c_0 and a weight W.

3.2.2 Dynamic Uncertainties

One can estimate the frequency response of a real stable SISO plant by injecting sinusoidal signals. If performing measurements at one frequency, one does usually not obtain just one complex number that could be taken as an estimate for the plant's response at frequency ω, but, instead, it's a whole set of complex numbers that is denoted by $\mathcal{H}(\omega)$. Such an experiment would lead us to the conclusion that any proper and stable $H(s)$ that satisfies

$$H(i\omega) \in \mathcal{H}(\omega)$$

is an appropriate model for the underlying plant. Since one can only perform a finite number of measurements, $\mathcal{H}(\omega)$ is usually only available at finitely many frequencies and consists of finitely many points. Due to the lack of a nice description, this set is not appropriate for the theory to be developed.

Hence we try to *cover* $\mathcal{H}(\omega)$ with a set that admits a more appropriate description. This means

$$\mathcal{H}(\omega) \subset G(i\omega) + W(i\omega)\mathbf{\Delta}_c \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\},$$

where

- $G(s)$ is a real rational proper transfer matrix
- $\mathbf{\Delta}_c$ is the open unit disk around 0: $\mathbf{\Delta}_c := \{\Delta_c \in \mathbb{C} \mid |\Delta_c| < 1\}$
- $W(s)$ is a real rational weighting function.

At each frequency we have hence covered the unstructured set $\mathcal{H}(\omega)$ with the disk

$$G(i\omega) + W(i\omega)\mathbf{\Delta}_c \tag{31}$$

whose center is $G(i\omega)$ and whose radius is $|W(i\omega)|$. In this description, G admits the interpretation as a nominal system. The deviation from $G(i\omega)$ is given by the circle $W(i\omega)\mathbf{\Delta}_c$ whose radius $|W(i\omega)|$ varies with frequency. Hence, the weighting function W captures how the size of the uncertainties depends upon the frequency; this allows to take into account that models are, usually, not very accurate at high frequency; typically, W is a high-pass filter.

Note that we proceeded similarly as in the parametric case: At frequency ω, we represent the deviation by a nominal value $G(i\omega)$ and by a $W(i\omega)$-weighted version of the open unit disk.

The actual set of uncertainties is then defined as

$$\mathbf{\Delta} := \{\Delta(s) \in RH_\infty \mid \Delta(i\omega) \in \mathbf{\Delta}_c \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}\}, \tag{32}$$

the set of all proper and stable transfer functions that take their values along the imaginary in the open unit disk. Note that this set is nothing but

$$\{\Delta(s) \in RH_\infty \mid \|\Delta\|_\infty < 1\} \tag{33}$$

which is often called the open unit ball in RH_∞. (It is important to digest that (32) and (33) are just the same!)

Finally, the uncertain system is described by

$$G_\Delta := G + W\Delta \quad \text{with} \quad \Delta \in \mathbf{\Delta}.$$

As for real uncertainties, we have obtained a whole set of systems that is now parameterized by the uncertain dynamics Δ in $\mathbf{\Delta}$.

Remarks.

1) The set of values $\mathbf{\Delta}_c$ must not necessarily be a circle for our results to apply. It can be an arbitrary set that contains 0, such as a polytope. The required technical hypothesis are discussed in Section 3.5. The deviation set

$$W(i\omega)\mathbf{\Delta}_c \tag{34}$$

is then obtained by shrinking/stretching $\mathbf{\Delta}_c$ with factor $|W(i\omega)|$, and by rotating it according to the phase of $W(i\omega)$.

2) We could be even more general and simply allow for frequency dependent value sets $\mathbf{\Delta}_c(\omega)$ that are not necessarily described as (34). Then we can more accurately incorporate phase information about the uncertainty.

3.2.3 Mixed Uncertainties

Of course, in a certain system component, one might encounter both parametric and dynamic uncertainties. As an example, suppose that the diagonal elements of

$$G(s) = \begin{pmatrix} \frac{1}{s+1} & \frac{1}{s+2} \\ \frac{1}{s+3} & \frac{1}{2s+1} \end{pmatrix} \tag{35}$$

are not affected by uncertainties, but the numerator 1 of the right upper element is affected by perturbations such it actually equals

$$\frac{1+W_1\Delta_1}{s+2} = \frac{1}{s+2} + \frac{W_1}{s+2}\Delta_1 \quad \text{where} \quad |\Delta_1| < 1$$

and the left lower element equals

$$\frac{1}{s+3}(1 + W_2(s)\Delta_2(s)) \quad \text{where} \quad \|\Delta_2\|_\infty < 1.$$

Here W_1 is a constant weight, $W_2(s)$ is a real rational weighting function, and Δ_1 is a parametric uncertainty in the unit interval $(-1, 1)$, whereas $\Delta_2(s)$ is a (proper stable) dynamic uncertainty that takes its values $\Delta(i\omega)$ on the imaginary axis in the open unit disk $\{z \in \mathbb{C} \mid |z| < 1\}$.

Hence, the uncertain system is described as

$$G_\Delta(s) = \begin{pmatrix} \frac{1}{s+1} & \frac{1}{s+2} \\ \frac{1}{s+3} & \frac{1}{2s+1} \end{pmatrix} + \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2(s) \end{pmatrix} \begin{pmatrix} 0 & \frac{1}{s+2}W_1 \\ \frac{1}{s+3}W_2(s) & 0 \end{pmatrix} \tag{36}$$

where $\Delta_1 \in \mathbb{R}$ is bounded as $|\Delta_1| < 1$, and $\Delta_2 \in RH_\infty$ is bounded as $\|\Delta_2\|_\infty < 1$.

This amounts to

$$G_\Delta(s) = G(s) + \Delta(s)W(s)$$

with a nominal system $G(s)$, a matrix valued weighting $W(s)$, and *block-diagonally structured*

$$\Delta(s) = \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2(s) \end{pmatrix}.$$

Note also that the diagonal blocks of $\Delta(s)$ have a different nature (Δ_1 is real, Δ_2 is dynamic) and they are bounded in size over frequency, where the bound for both is rescaled to 1 by using weighting functions.

All these properties of $\Delta(s)$ (structure and bound on size) can be caputerd by simply specifying a set of values that consists of complex matrices as follows:

$$\mathbf{\Delta}_c := \{ \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \mid \Delta_1 \in \mathbb{R},\ |\Delta_1| < 1,\ \Delta_2 \in \mathbb{C},\ |\Delta_2| < 1 \}.$$

The set of uncertainties $\Delta(s)$ is, again, just given by (32). We have demonstrated the flexibiliy of the abstract setup (32) if we allow for subsets $\mathbf{\Delta}_c$ of matrices.

To conclude, we have brought the specific example back to the same general scheme: We have parameterized the actual set of systems G_Δ as $G + \Delta W$ where, necessarily, W has to be chosen as a matrix, and the uncertainty $\Delta \in \mathbf{\Delta}$ turns out to admit a *block-diagonal structure*.

Remark. As mentioned previously, we could considerably increase the flexibility in uncertainty modeling if not only allowing to constrain the elements of the matrices in $\mathbf{\Delta}_c$ by disks or real intervals; under the technical hypotheses as discussed in Section 3.5, all the results to follow still remain valid.

3.2.4 Unstructured Uncertainties

Let us again consider the plant model $G(s)$ in (35). Suppose this is an accurate model at low frequencies, but it is known that the accuracy of *all entries* decreases at high frequencies. With a (real rational) SISO high-pass filter $W(s)$, the actual frequency response is rather described as

$$G(i\omega) + W(i\omega)\Delta_c$$

where

$$\Delta_c = \begin{pmatrix} \Delta_{11} & \Delta_{12} \\ \Delta_{21} & \Delta_{22} \end{pmatrix}$$

is any complex matrix that is bounded as

$$\|\Delta_c\| = \sigma_{\max}(\Delta_c) < 1.$$

Obviously, the size of the deviation $W(i\omega)\Delta_c$ at frequency ω is bounded as

$$\|W(i\omega)\Delta_c\| = |W(i\omega)|\|\Delta_c\| \le |W(i\omega)|.$$

(If $|W(i\omega)|$ is not zero, we have a strict inequality.) Hence, the frequency dependence of the size is captured by the dependence of $|W(i\omega)|$ on ω. Note that this behavior is the same for all the elements of the 2×2 matrix deviation $W(i\omega)\Delta_c$.

We chose the maximal singular value to evaluate the size of the matrix $W(i\omega)\Delta_c$ since this is an appropriate measure for the gain of the error at this frequency, and since the theory to be developed will then turn out more satisfactory than for other choices.

Let us now subsume this specific situation in our general scenario: We take

$$\boldsymbol{\Delta}_c := \{\Delta_c \in \mathbb{C}^{2\times 2} \mid \|\Delta_c\| < 1\}$$

and describe the uncertain system as

$$G + W\Delta$$

where $\Delta \in \boldsymbol{\Delta}$ as given in (32). Since $\boldsymbol{\Delta}_c$ is a set of full matrices without any specific structural aspects, this type of uncertainty is called *unstructured* or a *full-block uncertainty*.

3.2.5 Unstructured versus Structured Uncertainties

Continuing with the latter example, we might know more about the individual deviation of each element of $G(s)$. Suppose that, at frequency ω, the actual model is

$$G(i\omega) + \begin{pmatrix} W_{11}(i\omega)\Delta_{11} & W_{12}(i\omega)\Delta_{12} \\ W_{21}(i\omega)\Delta_{21} & W_{22}(i\omega)\Delta_{22} \end{pmatrix} \tag{37}$$

where the complex numbers Δ_{jk} satisfy

$$|\Delta_{11}| < 1,\ |\Delta_{12}| < 1,\ |\Delta_{21}| < 1,\ |\Delta_{22}| < 1, \tag{38}$$

and the real rational (usually high-pass) SISO transfer functions $W_{11}(s)$, $W_{12}(s)$, $W_{21}(s)$, $W_{22}(s)$ capture the variation of size over frequency as in our SISO examples.

We could rewrite (37) as

$$G(i\omega) + \begin{pmatrix} W_{11}(i\omega) & 0 & W_{12}(i\omega) & 0 \\ 0 & W_{21}(i\omega) & 0 & W_{22}(i\omega) \end{pmatrix} \begin{pmatrix} \Delta_{11} & 0 \\ \Delta_{21} & 0 \\ 0 & \Delta_{12} \\ 0 & \Delta_{22} \end{pmatrix}$$

or as

$$G(i\omega) + \begin{pmatrix} W_{11}(i\omega) & 0 & W_{12}(i\omega) & 0 \\ 0 & W_{21}(i\omega) & 0 & W_{22}(i\omega) \end{pmatrix} \begin{pmatrix} \Delta_{11} & 0 & 0 & 0 \\ 0 & \Delta_{21} & 0 & 0 \\ 0 & 0 & \Delta_{12} & 0 \\ 0 & 0 & 0 & \Delta_{22} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 1 \end{pmatrix}.$$

Obviously, we have to live with *structure* in the uncertainty if we would like to use different weightings for the various elements in the uncertainty. However, the two displayed structures differ: In the first case, we have two 2×1 blocks on the diagonal, whereas in the second one we have four 1×1 blocks on the diagonal. What should we choose for?

As mentioned above, we would like to take as a measure of size of Δ_c the largest singular value; in fact, Δ_c is supposed to be bounded as $\|\Delta_c\| < 1$. Then we observe that

$$\left\| \begin{pmatrix} \Delta_{11} & 0 \\ \Delta_{21} & 0 \\ 0 & \Delta_{12} \\ 0 & \Delta_{22} \end{pmatrix} \right\| < 1$$

is equivalent to

$$\left\| \begin{pmatrix} \Delta_{11} \\ \Delta_{21} \end{pmatrix} \right\| < 1,\ \left\| \begin{pmatrix} \Delta_{12} \\ \Delta_{22} \end{pmatrix} \right\| < 1 \ \text{ or } \ |\Delta_{11}|^2 + |\Delta_{21}|^2 < 1 \ \text{ and } \ |\Delta_{12}|^2 + |\Delta_{22}|^2 < 1.$$

This is *not what we want*. If we insist on (38), we have to work with the second structure since

$$\left\| \begin{pmatrix} \Delta_{11} & 0 & 0 & 0 \\ 0 & \Delta_{21} & 0 & 0 \\ 0 & 0 & \Delta_{12} & 0 \\ 0 & 0 & 0 & \Delta_{22} \end{pmatrix} \right\| < 1$$

is equivalent to (38).

3.3 Summary on Uncertainty Modeling for Components

For MIMO models of system components, we can work with only rough descriptions of modeling errors. Typically, the uncertain component is described as

$$G_\Delta = G + W_1 \Delta W_2 \tag{39}$$

with real rational weighting matrices W_1 and W_2 and full block or unstructured uncertainties Δ that belongs to $\boldsymbol{\Delta}$ as defined in (32) where

$$\boldsymbol{\Delta}_c := \{\Delta_c \in \mathbb{C}^{p\times q} \mid \|\Delta_c\| < 1\}.$$

If we choose for a more refined description of the uncertainties, the uncertainties in (39) will admit a certain *structure* that is often *block-diagonal*. To be specific, the uncertainty

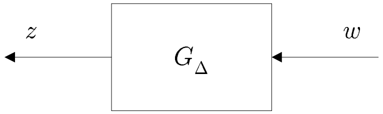


Figure 18: Uncertain Component

set $\mathbf{\Delta}$ will be given by (32) with

$$\mathbf{\Delta}_c := \left\{ \Delta_c = \begin{pmatrix} \delta_1 & & & & & 0 \\ & \ddots & & & & \\ & & \delta_r & & & \\ & & & \Delta_1 & & \\ & & & & \ddots & \\ 0 & & & & & \Delta_f \end{pmatrix} \mid \delta_j \in \mathbb{R},\ \ \Delta_j \in \mathbb{C}^{p_j \times q_j},\ \ \|\Delta_c\| < 1 \right\}.$$

Note that we have distinguished the *real blocks* δ_j that correspond to parametric uncertainties from the *complex blocks* that are related to dynamic uncertainties. Note also that

$$\|\Delta_c\| < 1 \text{ just means } |\delta_j| < 1,\ \ \|\Delta_j\| < 1.$$

The weighting matrices W_1 and W_2 capture the variation of the uncertainty with frequency, and they determine how each of the blocks of the uncertainty appears in G_Δ.

Finally, we have seen that there is a lot of flexibility in the choice of the structure. It is mainly dictated by how refined one wishes to describe the individual uncertainties that appear in the model.

3.4 Pulling out the Uncertainties

As we have seen in the example, a central ingredient in testing robust stabiltiy is to calculate the transfer matrix 'seen' by Δ in an open-loop interconnection. We would like to explain how one can systematically perform these calculations.

3.4.1 Pulling Uncertainties out of Subsystems

First we observe that an interconnection is usually built from subsystems. These subsystems themselves might be subject to uncertainties. Hence we assume that they are parameterized as G_Δ with $\Delta \in \mathbf{\Delta}$ as shown in Figure 18.

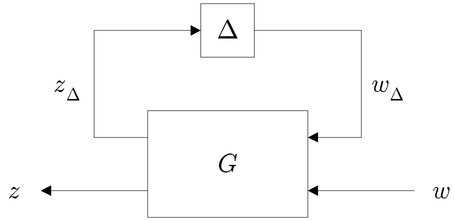


Figure 19: Uncertainty Pulled out of Component

In order to proceed one has to rewrite this system in the form as shown in Figure 19.

As an illustration, look at (36). This system can be rewritten as

$$z = (G_{22} + G_{21}\Delta G_{12})w$$

for

$$G_{22}(s) = \begin{pmatrix} \frac{1}{s+1} & \frac{1}{s+2} \\ \frac{1}{s+3} & \frac{1}{2s+1} \end{pmatrix},\quad G_{21}(s) = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix},\quad G_{12}(s) = \begin{pmatrix} 0 & \frac{1}{s+2}W_1 \\ \frac{1}{s+3}W_2(s) & 0 \end{pmatrix}.$$

If we define

$$G = \begin{pmatrix} 0 & G_{12} \\ G_{21} & G_{22} \end{pmatrix},$$

we observe that (36) is rewritten as

$$\begin{pmatrix} z_\Delta \\ z \end{pmatrix} = G \begin{pmatrix} w_\Delta \\ w \end{pmatrix},\quad w_\Delta = \Delta z_\Delta$$

which are the algebraic relations that correspond to Figure 19.

The step of rewriting a system as in Figure 18 into the structure of Figure 19 is most easily performed if just introducing extra signals that enter and leave the uncertainties. We illustrate this technique with examples that are of prominent importance:

- **Additive uncertainty**:

$$z = (G + \Delta)w \iff \begin{pmatrix} z_1 \\ z \end{pmatrix} = \begin{pmatrix} 0 & I \\ I & G \end{pmatrix} \begin{pmatrix} w_1 \\ w \end{pmatrix},\quad w_1 = \Delta z_1.$$

- **Input multiplicative uncertainty**.

$$z = G(I + \Delta)w \iff \begin{pmatrix} z_1 \\ z \end{pmatrix} = \begin{pmatrix} 0 & I \\ G & G \end{pmatrix} \begin{pmatrix} w_1 \\ w \end{pmatrix},\quad w_1 = \Delta z_1.$$

- **Input-output multiplicative uncertainty**.

$$z = (I + \Delta_1)G(I + \Delta_2)w$$

is equivalent to

$$\begin{pmatrix} z_1 \\ z_2 \\ z \end{pmatrix} = \begin{pmatrix} 0 & G & G \\ 0 & 0 & I \\ I & G & G \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w \end{pmatrix}, \quad \begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}.$$

Let us show explicitly how to proceed in this example. Observe that $z = (I + \Delta_1)G(I + \Delta_2)w$ can be written as

$$z = G(I + \Delta_2)w + w_1, \; z_1 = G(I + \Delta_2)w, \; w_1 = \Delta_1 z_1.$$

We have pulled out Δ_1. In a second step, we do the same with Δ_2. The above relations are equivalent to

$$z = Gw + Gw_2 + w_1, z_2 = w, \; z_1 = Gw + Gw_2, \; w_1 = \Delta_1 z_1, \; w_2 = \Delta_2 z_2.$$

The combination into matrix relations leads to the desired representation.

- **Factor uncertainty**. Let G_2 have a proper inverse. Then

$$z = (G_1 + \Delta_1)(G_2 + \Delta_2)^{-1} w$$

is equivalent to

$$\begin{pmatrix} z_1 \\ z \end{pmatrix} = \begin{pmatrix} 0 & -G_2^{-1} & G_2^{-1} \\ I & -G_1 G_2^{-1} & G_1 G_2^{-1} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w \end{pmatrix}, \quad \begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = \begin{pmatrix} \Delta_1 \\ \Delta_2 \end{pmatrix} z_1.$$

Again we perform the calculations for the purpose of illustration. We observe that $z = (G_1 + \Delta_1)(G_2 + \Delta_2)^{-1} w$ is nothing but

$$z = (G_1 + \Delta_1)\xi, \; (G_2 + \Delta_2)\xi = w$$

what can be rewritten as

$$z = G_1 \xi + w_1, \; z_1 = \xi, \; G_2 \xi + w_2 = w, \; w_1 = \Delta_1 z_1, \; w_2 = \Delta_2 z_1.$$

If we eliminate ξ via $\xi = G_2^{-1}(w - w_2)$, we arrive at

$$z = G_1 G_2^{-1} w - G_1 G_2^{-1} w_2 + w_1, \; z_1 = G_2^{-1} w - G_2^{-1} w_2, \; w_1 = \Delta_1 z_1, \; w_2 = \Delta_2 z_1.$$

Note that the manipulations are representatives of how to pull out the uncertainties, in particular if they occur in the denominator as it happens in factor uncertainty. It is often hard to pull out the uncertainties if just performing matrix manipulations. If we rather

use the input-output representations of systems *including the signals*, this technique is often pretty straightforward to apply. As a general rule, blocks that occur in a *rational* fashion can be pulled out. Finally, let us note that all these manipulations can also be performed directly for a state-space description where the state and its derivative are as well viewed as a signal.

Again, we include an example. Let

$$\dot{x} = \begin{pmatrix} -1 + \delta_1 & 2 \\ -1 & -2 + \delta_2 \end{pmatrix} x$$

denote a system with real uncertain parameters. This system can be written as

$$\dot{x} = Ax + Bw, \; z = Cx, \; w = \Delta z$$

with

$$A = \begin{pmatrix} -1 & 2 \\ -1 & -2 \end{pmatrix}, \; B = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \; C = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \; \Delta = \begin{pmatrix} \delta_1 & 0 \\ 0 & \delta_2 \end{pmatrix}.$$

Somewhat more general, suppose that

$$\dot{x} = A(\delta)x + B(\delta)w, \; z = C(\delta)x + D(\delta)w$$

where the matrices $A(.)$, $B(.)$, $C(.)$, $D(.)$ depend affinely on the parameter $\delta = \begin{pmatrix} \delta_1 & \cdots & \delta_k \end{pmatrix}$. This just means that they can be represented as

$$\begin{pmatrix} A(\delta) & B(\delta) \\ C(\delta) & D(\delta) \end{pmatrix} = \begin{pmatrix} A_0 & B_0 \\ C_0 & D_0 \end{pmatrix} + \sum_{j=1}^{k} \delta_j \begin{pmatrix} A_j & B_j \\ C_j & D_j \end{pmatrix}.$$

Let us factorize

$$\begin{pmatrix} A_j & B_j \\ C_j & D_j \end{pmatrix} = \begin{pmatrix} L_j^1 \\ L_j^2 \end{pmatrix} \begin{pmatrix} R_j^1 & R_j^2 \end{pmatrix} \tag{40}$$

where $\begin{pmatrix} L_j^1 \\ L_j^2 \end{pmatrix}$ and $\begin{pmatrix} R_j^1 & R_j^2 \end{pmatrix}$ have full column and row rank respectively. The original system can be described as

$$\begin{pmatrix} \dot{x} \\ z \\ \hline z_1 \\ \vdots \\ z_k \end{pmatrix} = \left(\begin{array}{cc|cccc} A_0 & B_0 & L_1^1 & \cdots & L_k^1 \\ C_0 & D_0 & L_1^2 & \cdots & L_k^2 \\ \hline R_1^1 & R_2^2 & 0 & & 0 \\ \vdots & & & \ddots & \\ R_k^1 & R_k^2 & 0 & & 0 \end{array}\right) \begin{pmatrix} x \\ w \\ \hline w_1 \\ \vdots \\ w_k \end{pmatrix}, \quad \begin{pmatrix} w_1 \\ \vdots \\ w_k \end{pmatrix} = \begin{pmatrix} \delta_1 I & & 0 \\ & \ddots & \\ 0 & & \delta_k I \end{pmatrix} \begin{pmatrix} z_1 \\ \vdots \\ z_k \end{pmatrix}$$

where the sizes of the identity block in $\delta_j I$ is equal to the number of columns or rows of $\begin{pmatrix} L_j^1 \\ L_j^2 \end{pmatrix}$ or $\begin{pmatrix} R_j^1 & R_j^2 \end{pmatrix}$ respectively.

Remark. We have chosen the factorization (40) such that the number of columns/rows of the factors are minimal. This renders the size of the identity blocks in the uncertainty minimal as well. One could clearly work with an arbitrary factorization; then, however, the identity blocks will be larger and the representation is not as efficient as possible.

Again, we remark that we can represent any

$$\begin{pmatrix} \dot{x} \\ z \end{pmatrix} = \begin{pmatrix} A(\delta) & B(\delta) \\ C(\delta) & D(\delta) \end{pmatrix} \begin{pmatrix} x \\ w \end{pmatrix}$$

with elements that are *rational* functions (quotients of polynomials) of $\delta = \begin{pmatrix} \delta_1 & \cdots & \delta_k \end{pmatrix}$ without pole at $\delta = 0$ by

$$\begin{pmatrix} \dot{x} \\ \hline z \\ z_\Delta \end{pmatrix} = \left(\begin{array}{c|cc} A & B_1 & B_2 \\ \hline C_1 & D_{11} & D_{12} \\ C_2 & D_{21} & D_{22} \end{array}\right) \begin{pmatrix} \dot{x} \\ \hline w \\ w_\Delta \end{pmatrix}, \quad w_\Delta = \Delta z_\Delta$$

where

$$\Delta = \begin{pmatrix} \delta_1 I & & 0 \\ & \ddots & \\ 0 & & \delta_k I \end{pmatrix}.$$

We observe that Δ has a block-diagonal structure. Each block is given as

$$\delta_j I = \begin{pmatrix} \delta_j & & 0 \\ & \ddots & \\ 0 & & \delta_j \end{pmatrix}$$

and is said to be a real ($\delta_j \in \mathbb{R}$) block that is repeated if the dimension of the identity matrix is at least two.

3.4.2 Pulling Uncertainties out of Interconnections

We have seen various possibilities how to represent (18) as (19) for components. Let us now suppose this subsystem is part of a (possibly large) interconnection.

Again for the purpose of illustration, we come back to the tracking configuration as in Figure 1 with a plant model G_Δ. If we employ the representation in Figure 19, we arrive at Figure 20.

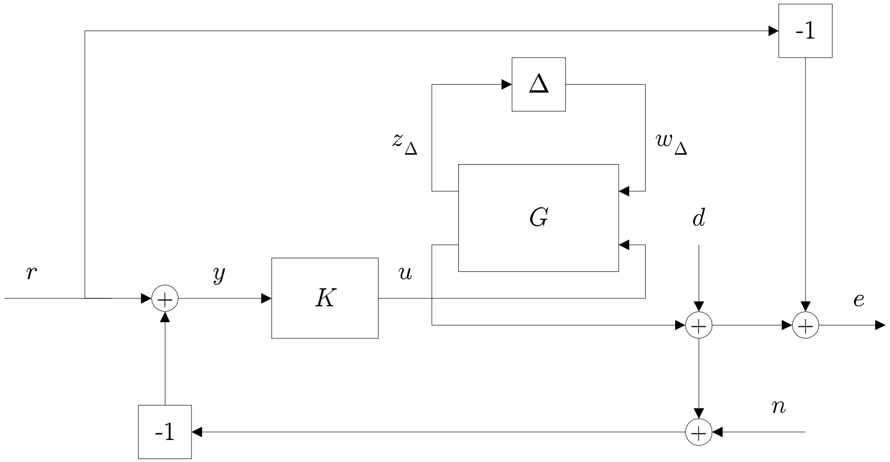


Figure 20: Uncertain closed-loop interconnection

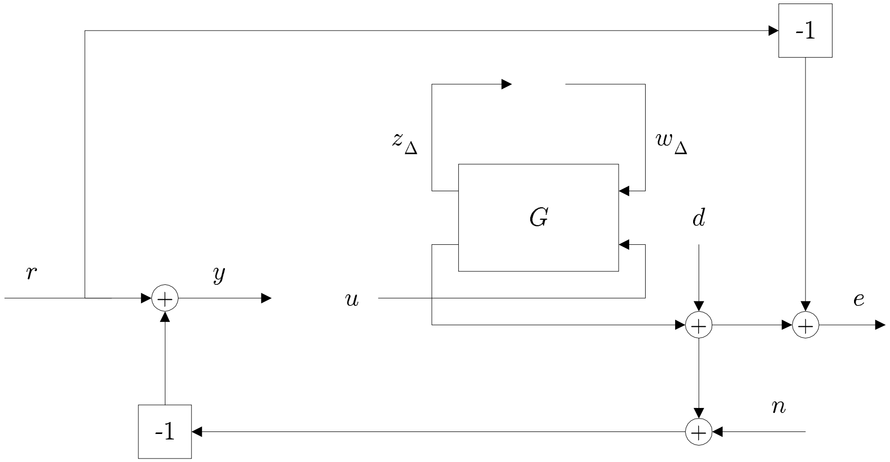


Figure 21: Uncertain open-loop interconnection

How do we pull Δ out of the interconnection? We simply disconnect Δ and K to arrive at Figure 21.

It is then not difficult to obtain the corresponding algebraic relations as

$$\begin{pmatrix} z_\Delta \\ \hline e \\ \hline y \end{pmatrix} = \left(\begin{array}{c|ccc|c} G_{11} & 0 & 0 & 0 & G_{12} \\ \hline G_{21} & I & 0 & -I & G_{22} \\ \hline G_{21} & -I & -I & I & -G_{22} \end{array}\right) \begin{pmatrix} w_\Delta \\ \hline d \\ n \\ r \\ \hline u \end{pmatrix}$$

for the open-loop interconnection. The command `sysic` is very useful in automizing the calculation of a state-space representation of this system.

After having determined this open-loop system, the uncertain uncontrolled system is obtained by re-connecting the uncertainty as

$$w_\Delta = \Delta z_\Delta.$$

Note that the uncertainty for the component is just coming back as uncertainty for the interconnection. Hence the structure for the interconnection is simply inherited.

This is different if several components of the system are affected by uncertainties that are to be pulled out. Then the various uncertainties for the components will appear on the diagonal of an uncertainty block for the interconnection.

Let us again look at an illustrative example. Suppose we would like to connect a SISO controller K to a real system. Since K has to be simulated (in a computer), the actually implemented controller will differ from K. Such a variation can be captured in an uncertainty description: the implemented controller is

$$K(I + \Delta_K)$$

where Δ_K is a proper and stable transfer matrix in some class that captures our knowledge of the accuracy of the implemented controller, very similar to what we have been discussing for a model of the plant.

Let us hence replace K by $K(I + \Delta_K)$ in the interconnection in Figure 9. Since this is a multiplicative input uncertainty, we arrive at Figure 22.

If we disconnect K, Δ_K, Δ_G, the resulting open-loop interconnection is given as

$$\begin{pmatrix} z_1 \\ z_2 \\ \hline e \\ \hline y \end{pmatrix} = \left(\begin{array}{cc|ccc|c} 0 & 0 & 0 & 0 & 0 & I \\ I & 0 & -I & -I & I & G \\ \hline I & 0 & I & 0 & -I & G \\ \hline 0 & I & I & 0 & -I & G \end{array}\right) \begin{pmatrix} w_1 \\ w_2 \\ \hline d \\ n \\ r \\ \hline u \end{pmatrix},$$

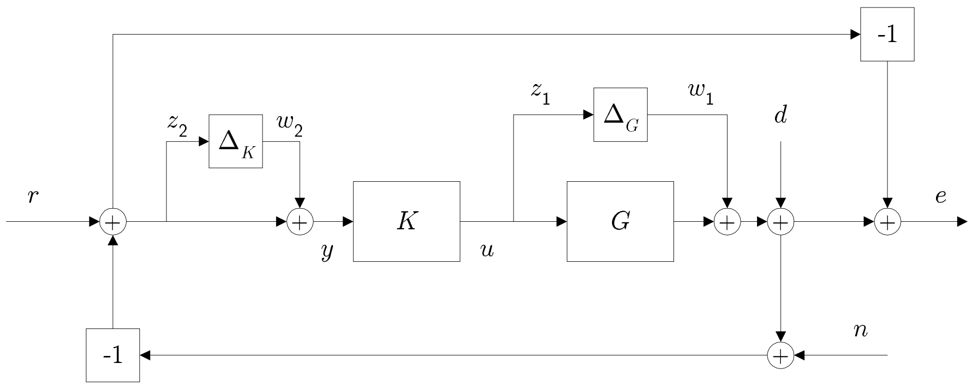


Figure 22: Uncertain closed-loop interconnection

and the perturbation enters as

$$\begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = \Delta \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}, \quad \Delta = \begin{pmatrix} \Delta_G & 0 \\ 0 & \Delta_K \end{pmatrix}.$$

Since the signals z_1, z_2 and the signals w_1, w_2 are *different*, Δ admits a block-diagonal structure with Δ_G and Δ_K appearing on its diagonal.

Remark. Suppose that two uncertainties Δ_1, Δ_2 enter an interconnection as in Figure 23. Then they can be pulled out as

$$\begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = \begin{pmatrix} \Delta_1 \\ \Delta_2 \end{pmatrix} z$$

or as

$$w = \begin{pmatrix} \Delta_1 & \Delta_2 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}$$

respectively. Instead, however, it is also possible to pull them out as

$$\begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}$$

by simply neglecting the fact that Δ_1 and Δ_2 are entered by the same signal, or that the outputs sum up to one signal.

In summary, uncertainties might be structured or not at the component level. If pulling them out of an interconnection, the resulting uncertainty for the interconnection is block-diagonal, and the uncertainties of the components appear, possibly repeated, on the diagonal.

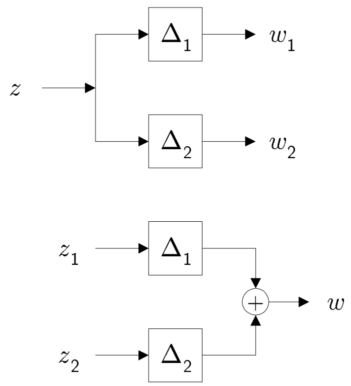


Figure 23: Special Configurations

If pulling uncertainties out of an interconnection, they will automatically have a block-diagonal structure, even if the component uncertainties are not structured themselves.

3.5 The General Paradigm

We have seen how to describe a possibly complicated interconnection in the form

$$\begin{pmatrix} z_\Delta \\ z \\ y \end{pmatrix} = P \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix} = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix} \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix}. \tag{41}$$

Here w_Δ, z_Δ are the signals that are introduced to pull out the uncertainties, w, z are generalized disturbance and controlled variable, and u, y are control input and measured output respectively.

The uncertainties will belong to a set $\mathbf{\Delta}$ that consists of proper and stable transfer matrices. The perturbed uncontrolled interconnection is obtained by re-connecting the uncertainty as

$$w_\Delta = \Delta z_\Delta \quad \text{with} \quad \Delta \in \mathbf{\Delta}.$$

This leads to

$$\begin{pmatrix} z \\ y \end{pmatrix} = S(\Delta, P) \begin{pmatrix} w \\ y \end{pmatrix} =$$
$$= \left(\begin{pmatrix} P_{22} & P_{23} \\ P_{32} & P_{33} \end{pmatrix} + \begin{pmatrix} P_{21} \\ P_{31} \end{pmatrix} \Delta (I - P_{11}\Delta)^{-1} \begin{pmatrix} P_{12} & P_{13} \end{pmatrix} \right) \begin{pmatrix} w \\ y \end{pmatrix}. \tag{42}$$

If we connect the controller to the unperturbed open-loop interconnection as

$$y = Ku,$$

we obtain

$$\begin{pmatrix} z_\Delta \\ z \end{pmatrix} = S(P, K) \begin{pmatrix} w_\Delta \\ w \end{pmatrix} =$$
$$= \left(\begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} + \begin{pmatrix} P_{13} \\ P_{23} \end{pmatrix} K (I - P_{33}K)^{-1} \begin{pmatrix} P_{31} & P_{32} \end{pmatrix} \right) \begin{pmatrix} w_\Delta \\ w \end{pmatrix} v.$$

The controlled and perturbed interconnection is obtained through

$$w_\Delta = \Delta z_\Delta \quad \text{and} \quad u = Ky.$$

In does not matter in which order we reconnect Δ or K. This reveals a nice property of linear fractional transformations:

$$S(\Delta, S(P, K)) = S(S(\Delta, P), K).$$

Hence the closed loop system admits the descriptions

$$z = S(\Delta, S(P, K))w = S(S(\Delta, P), K)w.$$

So far we were sloppy in not worrying about inverses that occur in calculating star products or about any other technicalities. Let us now get rigorous and include the exact hypotheses required in the general theory. All our technical results are subject to these assumption. Hence they need to be verified before any of the presented results can be applied.

Hypothesis 11

- *P is a generalized plant: there exists a controller $u = Ky$ that stabilizes (41) in the sense of Definition 4.*
- *The set of uncertainties is given as*

$$\mathbf{\Delta} := \{\Delta(s) \in RH_\infty \mid \Delta(i\omega) \in \mathbf{\Delta}_c \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\}\} \tag{43}$$

  where $\mathbf{\Delta}_c$ is a value set of complex matrices (motivating the index c for complex) that defines the structure and the size of the uncertainties. This set $\mathbf{\Delta}_c$ has to be star-shaped with center 0:

$$\Delta_c \in \mathbf{\Delta}_c \quad \Rightarrow \quad \tau\Delta_c \in \mathbf{\Delta}_c \ \text{ for all } \ \tau \in [0, 1]. \tag{44}$$

- *The direct feedthrough P_{11} and $\mathbf{\Delta}_c$ are such that*

$$I - P_{11}(\infty)\Delta_c \ \text{ is non-singular for all } \ \Delta_c \in \mathbf{\Delta}_c. \tag{45}$$

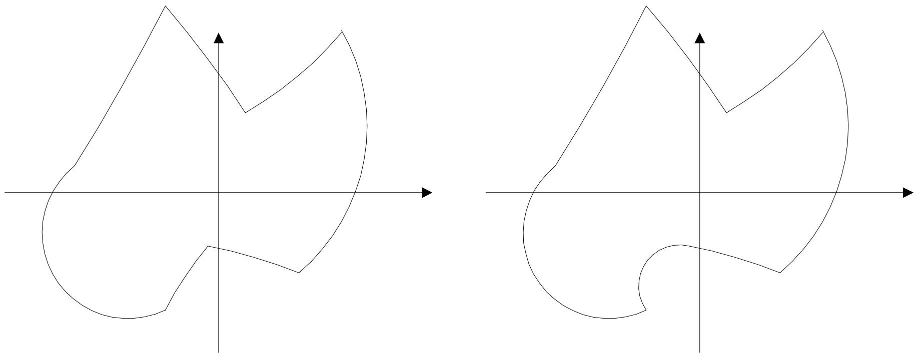


Figure 24: Star-shaped with center 0? Left: Yes. Right: No.

Comments on the hypothesis
As a fundamental requirement of any controller, it should stabilize an interconnection. Hence there should at least exist a stabilizing controller, and the tests developed in Section 2 can be applied to verify this fact.

In the second hypothesis, we define the considered class of uncertainties to be all proper and stable transfer matrices that take their values along the imaginary axis in the set $\mathbf{\Delta}_c$. We recall the specific examples we have seen earlier to illustrate this concept. It is very important to obey that this value has to be star-shapedness with center 0: If Δ_c is contained in $\mathbf{\Delta}_c$, then the whole line $\tau\Delta_c$, $\tau \in [0,1]$, that connects Δ_c with 0 belongs to $\mathbf{\Delta}_c$ as well. Note that this implies $0 \in \mathbf{\Delta}_c$ such that the zero transfer matrix is always in the class $\mathbf{\Delta}$; this is consistent with Δ_c to be viewed as a deviation from a nominal value. For sets of complex numbers, Figure 24 shows an example and a counterexample for star-shapedness.

Remark. If $\mathbf{\Delta}_c$ is a set of matrices whose elements are just supposed to be contained in real intervals or in circles around 0 (for individual elements) or in a unit ball of matrices (for sub-blocks), the hypothesis (44) of star-shapedness is automatically satisfied.

The last property implies that, for any Δ in our uncertainty set $\mathbf{\Delta}$, $I - P_{11}(\infty)\Delta(\infty)$ is non-singular such that $I - P_{11}\Delta$ does have a proper inverse. This is required to guarantee that $S(\Delta, P)$ can be calculated at all (existence of inverse), and that it defines a proper transfer matrix (properness of inverse). At this stage, we don't have a systematic technique to test whether (45) holds true or not; this will be the topic of Section 3.9.5. However, if P_{11} is strictly proper, it satisfies $P_{11}(\infty) = 0$ and (45) is trivially satisfied.

Comments on weightings

- Note that we assume all weightings that are required to accurately describe the uncertainty size or structure to be absorbed in P. These weightings do not need to obey any specific technical properties; they neither need to be stable nor even proper. The only requirement is to ask P being a generalized plant - this is the decisive condition to apply our results. Of course, a wrongly chosen weighting might preclude the existence of a stabilizing controller, and hence it might destroy this property; therefore, an adjustment of the weightings might be a possibility to enforce that P is a generalized plant.

- We could as well incorporate a weighting a posteriori in P. Suppose that we actually intend to work with $\widehat{\Delta}$ that is related with Δ by

$$\Delta = W_1 \widehat{\Delta} W_2$$

for real rational weightings W_1 and W_2. Then we simply replace P by $\widehat{P}$ given as

$$\widehat{P} = \begin{pmatrix} W_2 P_{11} W_1 & W_2 P_{12} & W_2 P_{13} \\ P_{21} W_1 & P_{22} & P_{23} \\ P_{31} W_1 & P_{32} & P_{33} \end{pmatrix}$$

and proceed with $\widehat{P}$ and $\widehat{\Delta}$. (Note that this just amounts to pulling out $\widehat{\Delta}$ in $z = W_1 \widehat{\Delta} W_2 w$.)

Comments on larger classes of uncertainties

- We could allow for value sets $\mathbf{\Delta}_c(\omega)$ that depend on the frequency $\omega \in \mathbb{R} \cup \{\infty\}$ in order to define the uncertainty class $\mathbf{\Delta}$. Then we require $\mathbf{\Delta}_c(\omega)$ to be star-shaped with star center 0 for all $\omega \in \mathbb{R} \cup \{\infty\}$.
- We could even just stay with a general set of $\mathbf{\Delta}$ of real rational proper and stable tranfer matrices that does not admit a specific description at all. We would still require that this set is star-shaped with center 0 ($\Delta \in \mathbf{\Delta}$ implies $\tau\Delta \in \mathbf{\Delta}$ for all $\tau \in [0,1]$), and that $I - P_{22}(\infty)\Delta(\infty)$ is non-singular for all $\Delta \in \mathbf{\Delta}$.

3.6 What is Robust Stability?

We have already seen when K achieves nominal stability: K should stabilize P in the sense of Definition 4.

Robust Stabilization
We say that K *robustly stabilizes* $S(\Delta, P)$ *against the uncertainties* $\Delta \in \mathbf{\Delta}$ if K stabilizes the system $S(\Delta, P)$ for any uncertainty Δ taken out of the underlying class $\mathbf{\Delta}$.

Robust Stability Analysis Problem
For a given fixed controller K, test whether it robustly stabilizes $S(\Delta, P)$ against all uncertainties in $\mathbf{\Delta}$.

Robust Stability Synthesis Problem
Find a controller K that robustly stabilizes $S(\Delta, P)$ against all uncertainties in $\mathbf{\Delta}$.

Although these definitions seem as tautologies, it is important to read them carefully: If we have not specified a set of uncertainty, it does not make sense to talk of a robustly stabilizing controller. Hence we explicitly included in the definition that robust stability is related to a well-specified set of uncertainties. Clearly, whether or not a controller robustly stabilizes an uncertain system, highly depends on the class of uncertainties that is considered. These remarks are particularly important for controller design: If one has found a controller that robustly stabilizes an uncertain system for a specific uncertainty class, there is, in general, no guarantee whatsoever that such a controller is robustly stabilizing for some other uncertainty class.[1]

3.7 Robust Stability Analysis

3.7.1 Simplify Structure

Starting from our general paradigm, we claim and prove that robust stability can be decided on the basis of the transfer matrix that is seen by Δ. Let us hence introduce the abbreviation

$$S(P,K) = N = \begin{pmatrix} N_{11} & N_{12} \\ N_{21} & N_{22} \end{pmatrix} = \begin{pmatrix} M & N_{12} \\ N_{21} & N_{22} \end{pmatrix}$$

where we highlight M; this is the block referred to as the transfer matrix seen by the uncertainty.

Theorem 12 *If K stabilizes P, and if*

$$I - M\Delta \ \ \textit{has a proper and stable inverse for all } \Delta \in \mathbf{\Delta},$$

then K robustly stabilizes $S(\Delta, P)$ against $\mathbf{\Delta}$.

[1]These remarks are included since, recently, it has been claimed in a publication that robust control design techniques are not useful, based on the following argument: The authors of this paper constructed a controller that robustly stabilizes a system for some uncertainty class, and they tested this controller against another class. It turned out that the robustness margins (to be defined later) for the alternative uncertainty class are poor. The authors conclude that the technique they employed is not suited to design robust controllers. This is extremely misleading since the actual conclusion should read as follows: There is no reason to expect that a robustly stabilizing controller for one class of uncertainties is also robustly stabilizing for another (possibly unrelated) class of uncertainties. Again, this is logical and seems almost tautological, but we stress these points since the earlier mentioned severe confusions arose in the literature.

Recall that $I - M(s)\Delta(s)$ has a proper and stable inverse if and only if $I - M(s)\Delta(s)$ is non-singular for all $s \in \mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}$ or, equivalently,

$$\det(I - M(s)\Delta(s)) \neq 0 \ \text{ for all } \ s \in \mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}.$$

Note that it is difficult to verify the latter property for all $\Delta \in \mathbf{\Delta}$. The crux of this result is a structural simplification: Instead of investigating $S(\Delta, P)$ that depends possibly in a highly involved fashion on Δ, we only need to investigate $I - M\Delta$ which is just linear in Δ. Hence, it is sufficient to look at this generic structure for all possible (potentially complicated) interconnections.

Proof. Taking any $\Delta \in \mathbf{\Delta}$, we have to show that $u = Ky$ stabilizes the system in (42) in the sense of Definition 4. At this point we benefit from the fact that we don't need to go back to the original definition, but, instead, we can argue in terms of input-output descriptions as formulated in Theorem 5. We hence have to show that

$$\begin{pmatrix} z \\ y \end{pmatrix} = S(\Delta, P) \begin{pmatrix} w \\ y \end{pmatrix}, \ u = Kv + v_1, \ v = y + v_2 \tag{46}$$

defines a proper and stable system $\begin{pmatrix} w \\ v_1 \\ v_2 \end{pmatrix} \to \begin{pmatrix} z \\ u \\ v \end{pmatrix}$. Clearly, we can re-represent this system as

$$\begin{pmatrix} z_\Delta \\ z \\ y \end{pmatrix} = P \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix}, \ u = Kv + v_1, \ v = y + v_2, \ \ w_\Delta = \Delta z_\Delta. \tag{47}$$

Recall that K stabilizes P. Hence the relations

$$\begin{pmatrix} z_\Delta \\ z \\ y \end{pmatrix} = P \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix}, \ u = Kv + v_1, \ v = y + v_2,$$

define a stable LTI system

$$\begin{pmatrix} z_\Delta \\ z \\ \hline u \\ v \end{pmatrix} = \left(\begin{array}{cc|cc} M & N_{12} & H_{13} & H_{14} \\ N_{21} & N_{22} & H_{23} & H_{24} \\ \hline H_{31} & H_{32} & H_{33} & H_{34} \\ H_{41} & H_{42} & H_{43} & H_{44} \end{array}\right) \begin{pmatrix} w_\Delta \\ w \\ \hline v_1 \\ v_2 \end{pmatrix}. \tag{48}$$

In addition to $N = \begin{pmatrix} M & N_{12} \\ N_{21} & N_{22} \end{pmatrix}$, several other blocks appear in this representation whose structure is not important; the only important fact is that they are all proper and stable.

If we reconnect $w_\Delta = \Delta z_\Delta$ in (48), we arrive at an alternative representation of (47) or of (46) that reads as

$$\begin{pmatrix} z \\ u \\ v \end{pmatrix} = \left(\begin{pmatrix} N_{22} & H_{23} & H_{24} \\ H_{32} & H_{33} & H_{34} \\ H_{42} & H_{43} & H_{44} \end{pmatrix} + \begin{pmatrix} N_{21} \\ H_{31} \\ H_{41} \end{pmatrix} \Delta (I - M\Delta)^{-1} \begin{pmatrix} N_{12} & H_{13} & H_{14} \end{pmatrix} \right) \begin{pmatrix} w \\ v_1 \\ v_2 \end{pmatrix}.$$

The essential point: Since both Δ and $(I - M\Delta)^{-1}$ are proper and stable, and since, as mentioned above, all the other blocks occuring in this formula are proper and stable as well, this system defines a proper and stable transfer matrix as we had to prove.

■

3.7.2 Reduction to Non-Singularity Test on Imaginary Axis

Recall that we need to verify whether $I - M\Delta$ has a proper and stable inverse; for that purpose one has to check whether the matrix $I - M\Delta$ itself does not have zeros in the closed right-half plane including infinity. Hence we need to check

$$\det(I - M(s)\Delta(s)) \neq 0 \quad \text{for all} \quad s \in \mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}, \ \Delta \in \mathbf{\Delta}. \tag{49}$$

This is complicated since we have to scan the full right-half plane, and we have to perform the test for all dynamic uncertainties under consideration.

The following result shows that it suffices to test $I - M(s)\Delta_c$ for non-singularity only for $s = i\omega$ with $\omega \in \mathbb{R} \cup \{\infty\}$, and only for $\Delta_c \in \mathbf{\Delta}_c$. Hence this reduces the original problem to a pure problem in linear algebra, what might considerably simplify the test.

Let us first formulate the precise result.

Theorem 13 *Suppose M is a proper and stable transfer matrix. If*

$$\det(I - M(i\omega)\Delta_c) \neq 0 \quad \textit{for all} \quad \Delta_c \in \mathbf{\Delta}_c, \ \omega \in \mathbb{R} \cup \{\infty\}, \tag{50}$$

then

$$I - M\Delta \quad \textit{has a proper and stable inverse for all } \Delta \in \mathbf{\Delta}. \tag{51}$$

Before we provide a formal proof, we would like to provide some intuition why the star-shapedness hypothesis plays an important role in this result. Let us hence assume that (50) is valid. Obviously, we can then conclude that

$$\det(I - M(\lambda)\Delta(\lambda)) \neq 0 \quad \text{for all} \quad \lambda \in \mathbb{C}^0 \cup \{\infty\}, \ \Delta \in \mathbf{\Delta}, \tag{52}$$

since $\Delta(\lambda)$ is contained in $\mathbf{\Delta}_c$ if $\lambda \in \mathbb{C}^0 \cup \{\infty\}$ and $\Delta \in \mathbf{\Delta}$. Note that (49) and (52) just differ by replacing $\mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}$ with $\mathbb{C}^0 \cup \{\infty\}$. Due to $\mathbb{C}^0 \cup \{\infty\} \subset \mathbb{C}^0 \cup \mathbb{C}^+ \cup \{\infty\}$,

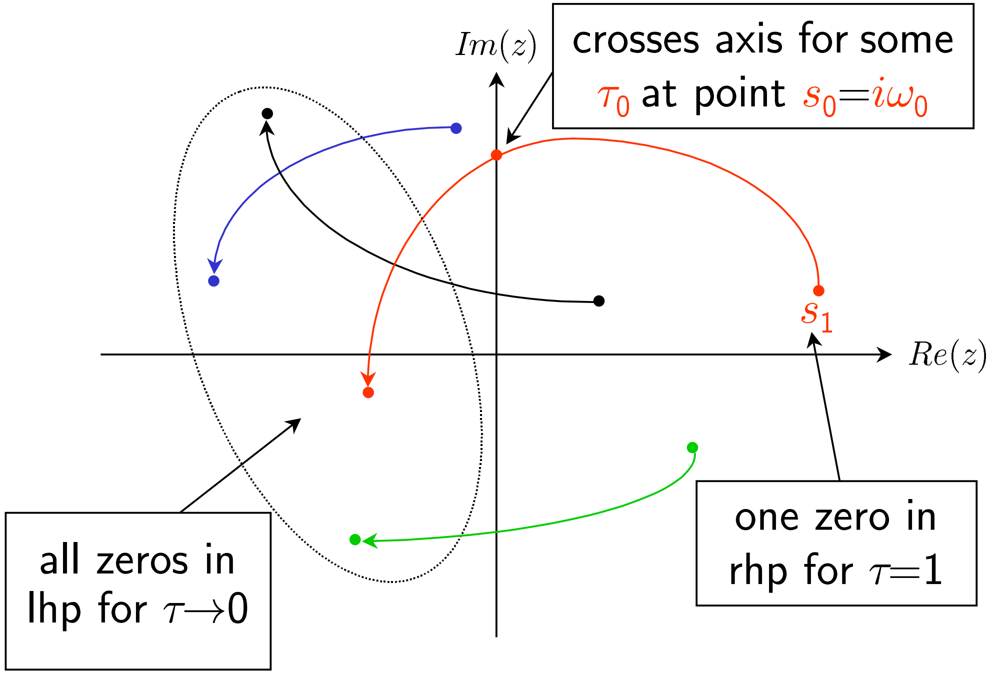


Figure 25: Movements of zeros

it is clear that (49) implies (52). However, we need the converse: We want to conclude that (52) implies (49), and this is the non-trivial part of the story.

Why does this implication hold? We have illustrated the following discussion in Figure 25. The proof is by contradiction: Assume that (49) is not valid, and that (52) is true. Then there exists a $\Delta \in \mathbf{\Delta}$ for which $I - M\Delta$ has a zero s_1 in $\mathbb{C}^+$ (due to (49)) where s_1 is certainly not contained in $\mathbb{C}^0 \cup \{\infty\}$ (due to (52)). For this single Δ, we cannot detect that it is destabilizing without scanning the right-half plane. However, apart from Δ, we can look at all the uncertainties $\tau\Delta$ obtained by varying $\tau \in [0, 1]$. Since $\mathbf{\Delta}_c$ is star-shaped, all these uncertainties are contained in the set $\mathbf{\Delta}$ as well. (Check that!) Let us now see what happens to the zeros of

$$\det(I - M(s)[\tau\Delta(s)]).$$

For $\tau = 1$, this function has the zero s_1 in $\mathbb{C}^+$. For τ close to zero, one can show that all its zeros must be contained in $\mathbb{C}^-$. (The loop is stable for $\tau = 0$ such that it remains stable for τ close to zero since, then, the perturbation $\tau\Delta$ is small as well; we provide a proof that avoids these sloppy reasonings.) Therefore, if we let τ decrease from 1 to 0, we can expect that the unstable zero s_1 has to move from $\mathbb{C}^+$ to $\mathbb{C}^-$. Since it moves continuously, it must hit the imaginary axis on its way for some parameter τ_0.[2] If this zero curve hits the imaginary axis at $i\omega_0$, we can conclude that

$$\det(I - M(i\omega_0)[\tau_0\Delta(i\omega_0)]) = 0.$$

Hence $\tau_0\Delta(s)$ is an uncertainty that is still contained in $\mathbf{\Delta}$ (star-shapeness!) and for which $I - M[\tau_0\Delta]$ has a zero at $i\omega_0$. We have arrive at the contradiction that (52) cannot be true either.

It is interesting to summarize what these arguments reveal: If we find a Δ such that $(I - M\Delta)^{-1}$ has a pole in the open right-half plane, then we can also find another $\tilde{\Delta}$ for which $(I - M\tilde{\Delta})^{-1}$ has a pole on the imaginary axis.

Comments on larger classes of uncertainties

- If $\mathbf{\Delta}_c(\omega)$ depends on frequency (and is star-shaped), we just have to check

  $$\det(I - M(i\omega)\Delta_c) \neq 0 \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\},\ \Delta_c \in \mathbf{\Delta}_c(\omega)$$

  in order to conclude (51). The proof remains unchanged.

- If $\mathbf{\Delta}$ is a general set of real rational proper and stable transfer matrices without specific description, we have to directly verify (52) in order to conclude (51).

Let us now provide the rigorous arguments to finish the proof of Theorem 13.

[2]Contrary to what is often stated in the literature, this is *not* an elementary continuity argument!

Proof. Recall that it remains to show (52) $\Rightarrow$ (49) by contradiction. Suppose (52) holds, but (49) is not valid. Hence there exists a $s_1 \in \mathbb{C}^+$, $s_1 \notin \mathbb{C}^0 \cup \{\infty\}$, and a $\Delta_1 \in \mathbf{\Delta}$ such that

$$\det(I - M(s_1)\Delta_1(s_1)) = 0. \tag{53}$$

If we can show that there exists a $s_0 \in \mathbb{C}^0$ and a $\tau_0 \in [0, 1]$ for which

$$\det(I - M(s_0)[\tau_0\Delta_1(s_0)]) = 0, \tag{54}$$

we arrive at a contradiction to (52) since $\tau_0\Delta \in \mathbf{\Delta}$ and $s_0 \in \mathbb{C}^0$.

To find s_0 and τ_0, let us take the realization

$$M\Delta_1 = \left[\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right].$$

We obviously have

$$I - M[\tau\Delta_1] = \left[\begin{array}{c|c} A & B \\ \hline -\tau C & I - \tau D \end{array}\right]$$

and the well-known Schur formula leads to

$$\det(I - M(s)[\tau\Delta(s)]) = \frac{\det(I - \tau D)}{\det(sI - A)} \det(sI - A(\tau)) \tag{55}$$

if we abbreviate

$$A(\tau) = A + B(I - \tau D)^{-1}\tau C.$$

If we apply (52) for $s = \infty$ and $\Delta = \tau\Delta_1$, we infer that $\det(I - \tau D) \neq 0$ for all $\tau \in [0, 1]$. In addition, A is stable such that $\det(s_1 I - A) \neq 0$. If we hence combine (55) and (53), we arrive at

$$\det(s_1 I - A(1)) = 0 \ \text{ or } \ s_1 \in \lambda(A(1)).$$

Let us now exploit as a fundamental result the continuous dependence of eigenvalues of matrices: Since $A(\tau)$ depends continuously on $\tau \in [0, 1]$, there exists a continuous function $s(.)$ defined on $[0, 1]$ and taking values in the complex plane such that

$$s(1) = s_1, \ \ \det(s(\tau)I - A(\tau)) = 0 \ \text{ for all } \ \tau \in [0, 1].$$

($s(.)$ defines a continuous curve in the complex plane that starts in s_1 and such that, for each τ, $s(\tau)$ is an eigenvalue of $A(\tau)$.) Now we observe that $A(0) = A$ is stable. Therefore, $s(0)$ must be contained in $\mathbb{C}^-$. We conclude: the continuous function $\mathrm{Re}(s(\tau))$ satisfies

$$\mathrm{Re}(s(0)) < 0 \ \text{ and } \ \mathrm{Re}(s(1)) > 0.$$

Hence there must exist a $\tau_0 \in (0, 1)$ with

$$\mathrm{Re}(s(\tau_0)) = 0.$$

Then $s_0 = s(\tau_0)$ and τ_0 lead to (54) what is the desired contradiction.

■

3.7.3 The Central Test for Robust Stability

We can easily combine Theorem 12 with Theorem 13 to arrive at the fundamental robust stability analysis test for controlled interconnections.

Corollary 14 *If K stabilizes P, and if*

$$\det(I - M(i\omega)\Delta_c) \neq 0 \ \text{ for all } \ \Delta_c \in \mathbf{\Delta}_c, \ \omega \in \mathbb{R} \cup \{\infty\}, \tag{56}$$

then K robustly stabilizes $S(\Delta, P)$ against $\mathbf{\Delta}$.

Contrary to what is often claimed in the literature, the converse does in general not hold in this result. Hence (56) might in general *not be a tight condition*. In practice and for almost all relevant uncertainty classes, however, it often turns out to be tight. In order to show that the condition is tight for a specific setup, one can simply proceed as follows: if (56) is not true, try to construct a *destabilizing perturbation*, an uncertainty $\Delta \in \mathbf{\Delta}$ for which K does not stabilize $S(\Delta, P)$.

The construction of destabilizing perturbations is the topic of the next section.

3.7.4 Construction of Destabilizing Perturbations

As already pointed out, this section is related to the question in how far condition (56) in Theorem 14 is also *necessary* for robust stability. We are not aware of definite answers to this questions in our general setup, but we are aware of some false statements in the literature! Nevertheless, we do not want to get into a technical discussion but we intend to take a pragmatic route in order to construct destabilizing perturbations.

Let us assume that (56) is not valid. This means that we can find a complex matrix $\Delta_0 \in \mathbf{\Delta}_c$ and a frequency $\omega_0 \in \mathbb{R} \cup \{\infty\}$ for which

$$I - M(i\omega_0)\Delta_0 \ \text{ is singular.}$$

First step in constructing a destabilizing perturbation
Find a real rational proper and stable $\Delta(s)$ with

$$\Delta(i\omega_0) = \Delta_0 \ \text{ and } \ \Delta(i\omega) \in \mathbf{\Delta}_c \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\}. \tag{57}$$

This implies that Δ is contained in our class $\mathbf{\Delta}$, and that $I - M\Delta$ does not have a proper and stable inverse (since $I - M(i\omega_0)\Delta(i\omega_0) = I - M(i\omega_0)\Delta_0$ is singular.)

Comments
Note that the construction of Δ amounts to solving an interpolation problem: The function $\Delta(s)$ should be contained in our class $\mathbf{\Delta}$ and it should take the value Δ_0 at the point $s = i\omega_0$.

This problem has a *trivial* solution if Δ_0 is a *real* matrix. Just set

$$\Delta(s) := \Delta_0.$$

If Δ_0 is *complex*, this choice is not suited since it is not contained in our perturbation class of *real* rational transfer matrices. In this case we need to do some work. Note that this was the whole purpose of Lemma 10 if Δ_c is the open unit disk in the complex plane. For more complicated sets (such as for block diagonal structures) we comment on the solution of this problem later.

Second step in constructing a destabilizing perturbation
For the constructed Δ, check whether K stabilizes $S(\Delta, P)$ by any of our tests developed earlier. If the answer is no, we have found a destabilizing perturbation. If the answer is yes, the question of whether K is robustly stabilizing remains undecided.

Comments
In most practical cases, the answer will be no and the constructed Δ is indeed destabilizing. However, one can find examples where this is not the case, and this point is largely overlooked in the literature.

Let us provide (without proofs) conditions under which *we can be sure that Δ is destabilizing*:

- If $\omega_0 = \infty$ then Δ is destabilizing.
- If ω_0 is finite, if

  $$\left(\begin{array}{c|cc|c} A - i\omega_0 I & 0 & B_1 & B_2 \\ \hline 0 & \Delta_0 & -I & 0 \\ C_1 & -I & D_{11} & D_{12} \end{array}\right) \ \text{ has full row rank,}$$

  and if

  $$\left(\begin{array}{c|cc} A - i\omega_0 I & 0 & B_1 \\ \hline 0 & \Delta_0 & -I \\ C_1 & -I & D_{11} \\ \hline C_2 & 0 & D_{21} \end{array}\right) \ \text{ has full column rank,}$$

  then Δ is destabilizing.
- This latter test can be re-formulated in terms of P. If ω_0 is finite, if $i\omega_0$ is not a pole of $P(s)$, if

  $$\begin{pmatrix} I - P_{11}(i\omega_0)\Delta_0 & P_{12}(i\omega) \end{pmatrix} \ \text{ has full row rank,}$$

  and if

  $$\begin{pmatrix} I - \Delta_0 P_{11}(i\omega_0) \\ P_{21}(i\omega_0) \end{pmatrix} \ \text{ has full column rank,}$$

  then Δ is destabilizing.

Note that these conditions are very easy to check, and they will be true in most practical cases. If they are not valid, the question of robust stability remains undecided. The failing of the latter conditions might indicate that the process of pulling out the uncertainties can be performed in a more efficient fashion by reducing the size of Δ.

3.8 Important Specific Robust Stability Tests

Testing (56) can be still pretty difficult in general, since the determinant is a complicated function of the matrix elements, and since we still have to test an infinite number of matrices for non-singularity.

On the other hand, very many robust stability test for LTI uncertainties have (56) at their roots, and this condition can be specialized to simple tests in various interesting settings. We can only touch upon the wealth of consequences.

3.8.1 M is Scalar

If it happens that $M(i\omega)$ has dimension 1×1, then $\mathbf{\Delta}_c$ is simply a set of complex numbers. In this case (56) just amounts to testing $1 - M(i\omega)\Delta_c \neq 0$ for all $\Delta_c \in \mathbf{\Delta}_c$. This amounts to testing, frequency by frequency, whether the set

$$M(i\omega)\mathbf{\Delta_c}$$

contains 1 or not. If no, condition (56) holds true and we conclude robust stability. If 1 is contained in this set for some frequency, (56) fails, and we might construct a destabilizing uncertainty as in Section 3.7.4.

In many cases, $\mathbf{\Delta}_c$ is the open unit circle in the complex plane. If $1 \in M(i\omega_0)\Delta_0$, Lemma 10 allows us to construct a proper real rational stable $\Delta(s)$ with $\Delta(i\omega_0) = \Delta_0$. This is the candidate for a destabilizing perturbation as discussed in Section 3.7.4.

3.8.2 The Small-Gain Theorem

Let us be specific and assume that the dimension of the uncertainty block is $p \times q$. Then we infer

$$\mathbf{\Delta}_c \subset \mathbb{C}^{p\times q}.$$

No matter whether or not $\mathbf{\Delta}_c$ consists of structure or unstructured matrices, it will certainly be a bounded set. Let us assume that we have found an r for which any

$$\Delta_c \in \mathbf{\Delta}_c \;\text{ satisfies }\; \|\Delta_c\| < r.$$

In order to check (56), we choose an arbitrary $\omega \in \mathbb{R} \cup \{\infty\}$, and any $\Delta_c \in \mathbf{\Delta}_c$.

We infer that

$$\det(I - M(i\omega)\Delta_c) \neq 0 \tag{58}$$

is equivalent, by the definition of eigenvalues, to

$$1 \notin \lambda(M(i\omega)\Delta_c). \tag{59}$$

1 is certainly not an eigenvalue of $M(i\omega)\Delta_c$ if all these eigenvalues are in absolute value smaller than 1. Hence (59) follows from

$$\rho(M(i\omega)\Delta_c) < 1. \tag{60}$$

Since the spectral radius is smaller than the spectral norm of $M(i\omega)\Delta_c$, (60) is implied by

$$\|M(i\omega)\Delta_c\| < 1. \tag{61}$$

Finally, since the norm is sub-multiplicative, (61) follows from

$$\|M(i\omega)\|\|\Delta_c\| < 1. \tag{62}$$

At this point we exploit our knowledge that $\|\Delta_c\| < r$ to see that (62) is a consequence of

$$\|M(i\omega)\| \leq \frac{1}{r}. \tag{63}$$

We have seen that all the properties (59)-(63) are *sufficient conditions* for (56) and, hence, for robust stability.

Why have we listed all these conditions in such a detail? They all appear - usually separately - in the literature under the topic 'small gain'. However, these conditions are not often related to each other such that it might be very confusing what the right choice is. The above chain of implications gives the answer: They all provide sufficient conditions for (58) to hold.

Recall that we have to guarantee (58) for all $\omega \in \mathbb{R} \cup \{\infty\}$. In fact, this is implied if (63) holds for all $\omega \in \mathbb{R} \cup \{\infty\}$, what is in turn easily expressed as $\|M\|_\infty \leq \frac{1}{r}$.

Theorem 15 *If any $\Delta_c \in \mathbf{\Delta}_c$ satisfies $\|\Delta_c\| < r$, and if*

$$\|M\|_\infty \leq \frac{1}{r}, \tag{64}$$

then $I - M\Delta$ has a proper and stable inverse for all $\Delta \in \mathbf{\Delta}$.

Again, one can combine Theorem 15 with Theorem 12 to see that (64) is a sufficient condition for K to robustly stabilize $S(\Delta, P)$.

Corollary 16 *If K stabilizes P, and if*

$$\|M\|_\infty \leq \frac{1}{r},$$

then K robustly stabilizes $S(\Delta, P)$ against $\boldsymbol{\Delta}$.

We stress again that (64) is only *sufficient*; it neglects any structure that might be characterized through $\boldsymbol{\Delta}_c$, and it only exploits that all the elements of this set are bounded by r.

Remarks. Note that this result also holds for an *arbitrary* class $\boldsymbol{\Delta}$ of real rational proper and stable matrices (no matter how they are defined) if they all satisfy the bound

$$\|\Delta\|_\infty < r.$$

Moreover, we are not at all bound to the specific choice of $\|.\| = \sigma_{\max}(.)$ as a measure for the size of the underlying complex matrices. We could replace (also in the definition of $\|.\|_\infty$) the maximal singular value by an *arbitrary* norm on matrices that is induced by vector norms, and all our results remain valid. This would lead to another bunch of small gain theorems that lead to *different* conditions. As specific examples, think of the maximal row sum or maximal column sum which are both induced matrix norms.

3.8.3 Full Block Uncertainties

Let us suppose we have an interconnection in which only one subsystem is subject to unstructured uncertainties. If this subsystem is SISO system, we can pull out the uncertainty of the interconnection and we end up with an uncertainty block Δ of dimension 1×1. If the subsystem is MIMO, the block will be matrix valued. Let us suppose that the dimension of this block is $p \times q$, and that is only restricted in size and bounded by r.

In our general scenario, this amounts to

$$\boldsymbol{\Delta}_c = \{\Delta \in \mathbb{C}^{p\times q} \mid \|\Delta\| < r\}.$$

In other words, $\boldsymbol{\Delta}$ simply consists of all real rational proper and stable $\Delta(s)$ whose H_∞ norm is smaller than r:

$$\boldsymbol{\Delta} := \{\Delta \in RH_\infty^{p\times q} \mid \|\Delta\|_\infty < r\}. \tag{65}$$

Recall from Theorem 15: $\|M\|_\infty \leq \frac{1}{r}$ implies that $I - M\Delta$ has a proper and stable inverse for all $\Delta \in \boldsymbol{\Delta}$.

The whole purpose of this section is to demonstrate that, since $\boldsymbol{\Delta}$ consists of unstructured uncertainties, the converse holds true as well: If $I - M\Delta$ has a proper and stable inverse for all $\Delta \in \boldsymbol{\Delta}$, then $\|M\|_\infty \leq \frac{1}{r}$.

Theorem 17 *Let $\boldsymbol{\Delta}$ be defined by (65). Then $\|M\|_\infty \leq \frac{1}{r}$ holds true if and only if $I - M\Delta$ has a proper and stable inverse for all $\Delta \in \boldsymbol{\Delta}$.*

We can put it in yet another form: In case that

$$\|M\|_\infty > \frac{1}{r}, \tag{66}$$

we can *construct* - as shown in the proof - a real rational proper and stable Δ with $\|\Delta\|_\infty < r$ such that

$$I - M\Delta \ \text{ does not have a proper and stable inverse.} \tag{67}$$

This construction leads to a destabilzing perturbation for $(I - M\Delta)^{-1}$, and it is a candidate for a destabilizing perturbation of the closed-loop interconnection as discussed in Section 3.7.4.

Proof. This is what we have to do: If (66) holds true, there exists a $\Delta \in \boldsymbol{\Delta}$ with (67).

First step. Suppose that we have found $\omega_0 \in \mathbb{R} \cup \{\infty\}$ with $\|M(i\omega_0)\| > \frac{1}{r}$ (which exists by (66)). Recall that $\|M(i\omega_0)\|^2$ is an eigenvalue of $M(i\omega_0)M(i\omega_0)^*$. Hence there exists an eigenvector $u \neq 0$ with

$$[M(i\omega_0)M(i\omega_0)^*]u = \|M(i\omega_0)\|^2 u.$$

Let us define

$$v := \frac{1}{\|M(i\omega_0)\|^2} M(i\omega_0)^* u \ \text{ and } \ \Delta_0 := v\frac{u^*}{\|u\|^2}.$$

(Note that Δ_0 has rank one; this is not important for our arguments.) We observe

$$\|\Delta_0\| \leq \frac{\|v\|}{\|u\|} \leq \frac{1}{\|M(i\omega_0)\|^2}\|M(i\omega_0)^* u\|\frac{1}{\|u\|} \leq \frac{1}{\|M(i\omega_0)\|} < r$$

and

$$[I - M(i\omega_0)\Delta_0]u = u - M(i\omega_0)v =$$
$$= u - \frac{1}{\|M(i\omega_0)\|^2} M(i\omega_0)M(i\omega_0)^* u = u - \frac{\|M(i\omega_0)\|^2}{\|M(i\omega_0)\|^2} u = 0.$$

We have constructed a complex matrix Δ_0 that satisfies

$$\|\Delta_0\| < r \ \text{ and } \ \det(I - M(i\omega_0)\Delta_0) = 0.$$

Second step. Once we are at this point, we have discussed in Section 3.7.4 that it suffices to construct a real rational proper and stable $\Delta(s)$ satisfying

$$\Delta(i\omega_0) = \Delta_0 \ \text{ and } \ \|\Delta\|_\infty < r.$$

Then this uncertainty renders $(I - M\Delta)^{-1}$ non-existent, non-proper, or unstable.

If $\omega_0 = \infty$ or $\omega_0 = 0$, $M(i\omega)$ is *real*. Then u can be chosen real such that Δ_0 is a real matrix. Obviously, $\Delta(s) := \Delta_0$ does the job.

Hence suppose $\omega_0 \in (0, \infty)$. Let us now apply Lemma 10 to each of the components of $\frac{u^*}{\|u\|^2} = \begin{pmatrix} u_1 & \cdots & u_q \end{pmatrix}$, $v = \begin{pmatrix} v_1 \\ \vdots \\ v_p \end{pmatrix}$: There exist $\alpha_j \geq 0$ and $\beta_j \geq 0$ with

$$u_j = \pm|u_j|\frac{i\omega_0 - \alpha_j}{i\omega_0 + \alpha_j}, \quad v_j = \pm|v_j|\frac{i\omega_0 - \beta_j}{i\omega_0 + \beta_j}.$$

Define the proper and stable

$$u(s) := \begin{pmatrix} \pm|u_1|\frac{s-\alpha_1}{s+\alpha_1} & \cdots & \pm|u_q|\frac{s-\alpha_q}{s+\alpha_q} \end{pmatrix}, \quad v(s) := \begin{pmatrix} \pm|v_1|\frac{s-\beta_1}{s+\beta_1} \\ \vdots \\ \pm|v_p|\frac{s-\beta_p}{s+\beta_p} \end{pmatrix}.$$

We claim that

$$\Delta(s) := v(s)u(s)$$

does the job. It is proper, stable, and it clearly satisfies $\Delta(i\omega_0) = v\frac{u^*}{\|u\|^2} = \Delta_0$. Finally, observe that

$$\|u(i\omega)\|^2 = \sum_{j=1}^{q} |u_j|^2 \left|\frac{i\omega - \alpha_j}{i\omega + \alpha_j}\right|^2 = \sum_{j=1}^{q} |u_j|^2 = \left\|\frac{u^*}{\|u\|^2}\right\|^2 = \frac{1}{\|u\|^2}$$

and

$$\|v(i\omega)\|^2 = \sum_{j=1}^{p} |v_j|^2 \left|\frac{i\omega - \beta_j}{i\omega + \beta_j}\right|^2 = \sum_{j=1}^{p} |v_j|^2 = \|v\|^2.$$

Hence $\|\Delta(i\omega)\| \leq \|u(i\omega)\|\|v(i\omega)\| = \frac{\|v\|}{\|u\|} < r$, what implies $\|\Delta\|_\infty < r$.

■

3.9 The Structured Singular Value in a Unifying Framework

All our specific examples could be reduced to uncertainties whose values on the imaginary axis admit the structure

$$\Delta_c = \begin{pmatrix} p_1 I & & & & & & & & & 0 \\ & \ddots & & & & & & & & \\ & & p_{n_r} I & & & & & & & \\ & & & \delta_1 I & & & & & & \\ & & & & \ddots & & & & & \\ & & & & & \delta_{n_c} I & & & & \\ & & & & & & \Delta_1 & & & \\ & & & & & & & \ddots & & \\ 0 & & & & & & & & & \Delta_{n_f} \end{pmatrix} \in \mathbb{C}^{p \times q} \tag{68}$$

and whose diagonal blocks satisfy

- $p_j \in \mathbb{R}$ with $|p_j| < 1$ for $j = 1, \ldots, n_r$,
- $\delta_j \in \mathbb{C}$ with $|\delta_j| < 1$ for $j = 1, \ldots, n_c$,
- $\Delta_j \in \mathbb{C}^{p_j \times q_j}$ with $\|\Delta_j\| < 1$ for $j = 1, \ldots, n_f$.

$p_j I$ is said to be a real repeated block, $\delta_j I$ is called a complex repeated block, and Δ_j is called a full (complex) block. The sizes of the identities can be different for different blocks. Real full blocks usually do not occur and are, hence, not contained in the list.

Let us denote the set of all this complex matrices as $\mathbf{\Delta}_c$. This set $\mathbf{\Delta}_c$ is very easy to describe: one just needs to fix for each diagonal block its structure (real repeated, complex repeated, complex full) and its dimension. If the dimension of $p_j I$ is r_j, and the dimension of $\delta_j I$ is c_j, the μ-tools expect a description of this set in the following way:

$$\texttt{blk} = \begin{pmatrix} -r_1 & 0 \\ \vdots & \vdots \\ -r_{n_r} & 0 \\ c_1 & 0 \\ \vdots & \vdots \\ c_{n_c} & 0 \\ p_1 & q_1 \\ \vdots & \vdots \\ p_{n_f} & q_{n_f} \end{pmatrix}.$$

Hence the row $(-r_j \;\; 0)$ indicates a real repeated block of dimension r_j, whereas $(c_j \;\; 0)$ corresponds to a complex repeated block of dimension c_j, and $(p_j \;\; q_j)$ to a full block dimension $p_j \times q_j$.

Remark. In a practical example it might happen that the *ordering* of the blocks is different from that in (68). Then the commands in the μ-Toolbox can still be applied as long as the block structure matrix `blk` reflects the correct order and structure of the blocks.

Remark. If Δ_c takes the structure (68), the constraint on the size of the diagonal blocks can be briefly expressed as $\|\Delta_c\| < 1$. Moreover, the set $r\boldsymbol{\Delta}_c$ consists of all complex matrices Δ_c that take the structure (68) and whose blocks are bounded in size by r: $\|\Delta_c\| < r$. Here r is just a scaling factor that will be relevant in introducing the structured singular value.

The actual set of uncertainties $\boldsymbol{\Delta}$ is, once again, the set of all real rational proper and stable Δ whose frequency response takes it values in $\boldsymbol{\Delta}_c$:

$$\boldsymbol{\Delta} := \{\Delta(s) \in RH_\infty \mid \Delta(i\omega) \in \boldsymbol{\Delta}_c \;\text{ for all }\; \omega \in \mathbb{R} \cup \{\infty\}\}.$$

Let us now apply the test (50) in Theorem 13. At a fixed frequency $\omega \in \mathbb{R} \cup \{\infty\}$, we have to verify whether

$$I - M(i\omega)\Delta_c \;\text{ is non-singular for all }\; \Delta_c \in \boldsymbol{\Delta}_c. \tag{69}$$

This is a pure problem of linear algebra.

3.9.1 The Structured Singular Value

Let us restate the linear algebra problem we have encountered for clarity: Given the complex matrix $M_c \in \mathbb{C}^{q\times p}$ and the (open) set of complex matrices $\boldsymbol{\Delta}_c \subset \mathbb{C}^{p\times q}$, decide whether

$$I - M_c\Delta_c \;\text{ is non-singular for all }\; \Delta_c \in \boldsymbol{\Delta}_c. \tag{70}$$

The answer to this question is yes or no.

We modify the problem a bit. In fact, let us consider the scaled set $r\boldsymbol{\Delta}_c$ in which we have multiplied every element of $\boldsymbol{\Delta}_c$ with the factor r. This stretches or shrinks the set $\boldsymbol{\Delta}_c$ by the factor r. Then we consider the following problem:

> Determine the largest r such that $I - M_c\Delta_c$ is non-singular for all Δ_c in the set $r\boldsymbol{\Delta}_c$. This largest value is denoted as r_*.

In other words, calculate

$$r_* = \sup\{r \mid \det(I - M_c\Delta_c) \neq 0 \;\text{ for all }\; \Delta_c \in r\boldsymbol{\Delta}_c\}. \tag{71}$$

What happens here? Via the scaling factor r, we inflate or shrink the set $r\boldsymbol{\Delta}_c$. For small r, $I - M_c\Delta_c$ will be non-singular for any $\Delta_c \in r\boldsymbol{\Delta}_c$. If r grows larger, we might find some $\Delta_c \in r\boldsymbol{\Delta}_c$ for which $I - M_c\Delta_c$ will turn out singular. If no such r exists, we have $r_* = \infty$. Otherwise, r_* is just the finite critical value for which we can assure non-singularity for the set $r\boldsymbol{\Delta}_c$ if r is smaller than r_*. This is the reason why r_* is called *non-singularity margin*.

Remark. r_* also equals the smallest r such that there exists a $\Delta_c \in r\boldsymbol{\Delta}_c$ that renders $I - M_c\Delta_c$ singular. The above given definition seems more intuitive since we are interested in non-singularity.

Definition 18 *The structured singular value (SSV) of the matrix M_c with respect to the set $\boldsymbol{\Delta}_c$ is defined as*

$$\mu_{\boldsymbol{\Delta}_c}(M_c) = \frac{1}{r_*} = \frac{1}{\sup\{r \mid \det(I - M_c\Delta_c) \neq 0 \;\textit{ for all }\; \Delta_c \in r\boldsymbol{\Delta}_c\}}.$$

Remark. The non-singularity margin r_* has been introduced by Michael Safonov, whereas the structured singular value has been defined by John Doyle. Both concepts are equivalent; the structured singular can be related in a nicer fashion to the ordinary singular value what motivates its definition as the reciprocal of r_*.

Let us now assume that we can compute the SSV. Then we can decide the original question whether (70) is true or not as follows: We just have to check whether $\mu_{\boldsymbol{\Delta}_c}(M_c) \leq 1$. If yes, then (70) is true, if no, then (70) is not true. This is the most important fact to remember about the SSV.

Theorem 19 *Let M_c be a complex matrix and $\boldsymbol{\Delta}_c$ an arbitrary (open) set of complex matrices. Then*

- $\mu_{\boldsymbol{\Delta}_c}(M_c) \leq 1$ *implies that $I - M_c\Delta_c$ is non-singular for all $\Delta_c \in \boldsymbol{\Delta}_c$.*
- $\mu_{\boldsymbol{\Delta}_c}(M_c) > 1$ *implies that there exists a $\Delta_c \in \boldsymbol{\Delta}_c$ for which $I - M_c\Delta_c$ is singular.*

Proof. Let us first assume that $\mu_{\boldsymbol{\Delta}_c}(M_c) \leq 1$. This implies that $r_* \geq 1$. Suppose that there exists a $\Delta_0 \in \boldsymbol{\Delta}_c$ that renders $I - M_c\Delta_0$ singular. Since $\boldsymbol{\Delta}_c$ is open, Δ_0 also belongs to $r\boldsymbol{\Delta}_c$ for some $r < 1$ that is close to 1. By the definition of r_*, this implies that r_* must be smaller than r. Therefore, we conclude that $r_* < 1$ what is a contradiction.

Suppose now that $\mu_{\boldsymbol{\Delta}_c}(M_c) > 1$. This implies $r_* < 1$. Suppose $I - M_c\Delta_c$ is non-singular for all $\Delta_c \in r\boldsymbol{\Delta}_c$ for $r = 1$. This would imply (since r_* was the largest among all r for which this property holds) that $r_* \geq r = 1$, a contradiction.

■

It is important to note that the number $\mu_{\boldsymbol{\Delta}_c}(M_c)$ is depending both on the matrix M_c and on the set $\boldsymbol{\Delta}_c$ what we explicitly indicate in our notation. For the computation of the SSV, the μ-tools expect, as well, a complex matrix `M` and the block structure `blk` as an input. In principle, one might wish to calculate the SSV exactly. Unfortunately, it has been shown through examples that this is a very hard problem in a well-defined sense introduced in computer science. Fortunately, one can calculate a *lower bound* and an *upper bound* for the SSV pretty efficiently. In the μ-tools, this computation is performed with the command `mu(M, blk)` which returns the row `[upperbound lowerbound]`.

For the reader's convenience we explicitly formulate the detailed conclusions that can be drawn if having computed a lower and an upper bound of the SSV.

Theorem 20 *Let M_c be a complex matrix and $\mathbf{\Delta}_c$ an arbitrary (open) set of complex matrices. Then*

- $\mu_{\mathbf{\Delta_c}}(M_c) \leq \gamma_1$ *implies that $I - M_c\Delta_c$ is nonsingular for all $\Delta_c \in \frac{1}{\gamma_1}\mathbf{\Delta_c}$.*
- $\mu_{\mathbf{\Delta_c}}(M_c) > \gamma_2$ *implies that there exists a $\Delta_c \in \frac{1}{\gamma_2}\mathbf{\Delta_c}$ for which $I - M_c\Delta_c$ is singular.*

This is a straightforward consequence of the following simple fact:

$$\alpha\, \mu_{\mathbf{\Delta_c}}(M_c) = \mu_{\mathbf{\Delta_c}}(\alpha M_c) = \mu_{\alpha\mathbf{\Delta_c}}(M_c). \tag{72}$$

A scalar scaling of the SSV with factor α is equivalent to scaling either the matrix M_c or the set $\mathbf{\Delta}_c$ with the same factor.

Let us briefly look as well at the case of *matrix valued scalings*. Suppose U and V are arbitrary complex matrices. Then we observe

$$\det(I - M_c[U\Delta_c V]) \neq 0 \;\text{ if and only if }\; \det(I - [VM_cU]\Delta_c) \neq 0. \tag{73}$$

This shows that

$$\mu_{U\mathbf{\Delta_c}V}(M_c) = \mu_{\mathbf{\Delta_c}}(VM_cU). \tag{74}$$

Hence, if we intend to calculate the SSV with respect to the set

$$U\mathbf{\Delta}_c V = \{U\Delta_c V \mid \Delta_c \in \mathbf{\Delta}_c\},$$

we can do that by calculating the SSV of VM_cU with respect to the original set $\mathbf{\Delta}_c$, and this latter task can be accomplished with the μ-tools.

Before we proceed to a more extended discussion of the background on the SSV, let us discuss its most important purpose, the application to robust stability analysis.

3.9.2 SSV Applied to Testing Robust Stability

For robust stability we had to check (69). If we recall Theorem 20, this condition holds true if and only if the SSV of $M(i\omega)$ calculated with respect to $\mathbf{\Delta}_c$ is smaller than 1. Since this has to be true for all frequencies, we immediately arrive at the following fundamental result of these lecture notes.

Theorem 21 *$I - M\Delta$ has a proper and stable inverse for all $\Delta \in \mathbf{\Delta}$ if and only if*

$$\mu_{\mathbf{\Delta_c}}(M(i\omega)) \leq 1 \;\text{ for all }\; \omega \in \mathbb{R} \cup \{\infty\}. \tag{75}$$

We can again combine Theorem 15 with Theorem 12 to obtain the test for the general interconnection.

Corollary 22 *If K stabilizes P, and if*

$$\mu_{\mathbf{\Delta_c}}(M(i\omega)) \leq 1 \;\text{ for all }\; \omega \in \mathbb{R} \cup \{\infty\},$$

then K robustly stabilizes $S(\Delta, P)$ against $\mathbf{\Delta}$.

Remark. In case that

$$\mathbf{\Delta}_c := \{\Delta \in \mathbb{C}^{p\times q} \mid \|\Delta\| < 1\}$$

consists of full block matrices only (what corresponds to $n_r = 0$, $n_c = 0$, $n_f = 1$), it follows from the discussion in Section 3.8.3 that

$$\mu_{\mathbf{\Delta_c}}(M(i\omega)) = \|M(i\omega)\|.$$

Hence Theorem 21 and Corollary 22 specialize to Theorem 15 and Corollary 16 in this particular case of full block uncertainties.

How do we apply the tests? We just calculate the number $\mu_{\mathbf{\Delta_c}}(M(i\omega))$ for each frequency and check whether it does does not exceed one. In practice, one simply plots the function

$$\omega \to \mu_{\mathbf{\Delta_c}}(M(i\omega))$$

by calculating the right-hand side for finitely many frequencies ω. This allows to visually check whether the curve stays below 1. If the answer is yes, we can conclude robust stability as stated in Theorem 21 and Corollary 22 respectively. If the answer is no, we reveal in the next section how to determine a destabilizing uncertainty.

In this ideal situation we assume that the SSV can be calculated exactly. As mentioned above, however, only upper bounds can be computed efficiently. Still, with the upper bound it is not difficult to guarantee robust stability. In fact, with a plot of the computed upper bound of $\mu_{\mathbf{\Delta_c}}M(i\omega)$ over the frequency ω, we can easily determine a number $\gamma > 0$ such that

$$\mu_{\mathbf{\Delta_c}}(M(i\omega)) \leq \gamma \;\text{ for all }\; \omega \in \mathbb{R} \cup \{\infty\} \tag{76}$$

is satisfied. As before, we can conclude robust stability for the uncertainty set

$$\{\frac{1}{\gamma}\Delta \mid \Delta \in \mathbf{\Delta}\} \tag{77}$$

which consists of all uncertainties that admit the same structure as those in $\mathbf{\Delta}$, but that are rather bounded by $\frac{1}{\gamma}$ instead of 1. This is an immediate consequence of Theorem 20.

We observe that the SSV-plot or a plot of the upper bound lets us decide the question of *how large we can let the structured uncertainties grow in order to still infer robust stability.*

If varying γ, the largest class $\frac{1}{\gamma}\mathbf{\Delta}$ is obtained with the smallest γ for which (76) is valid; this best value is clearly given as

$$\gamma_* = \sup_{\omega \in \mathbb{R} \cup \{\infty\}} \mu_{\mathbf{\Delta_c}}(M(i\omega)).$$

Since $\frac{1}{\gamma_*}$ is the largest possible inflating factor for the set of uncertainties, this number is often called *stability margin.*

3.9.3 Construction of Destabilizing Perturbations

Let us suppose that we have found some frequency ω_0 for which

$$\mu_{\mathbf{\Delta_c}}(M(i\omega_0)) > \gamma_0.$$

Such a pair of frequency ω_0 and value γ_0 can be found by visually inspecting a plot of the lower bound of the SSV over frequency as delivered by the μ-tools. Due to Theorem 20, there exists some $\Delta_0 \in \frac{1}{\gamma_0}\mathbf{\Delta}_c$ that renders $I - M(i\omega_0)\Delta_0$ singular. Note that the algorithm in the μ-tools to compute a lower bound of $\mu_{\mathbf{\Delta_c}}(M(i\omega_0))$ returns such a matrix Δ_0 for the calculated bound γ_0.

Based on ω_0, γ_0 and Δ_0, we intend to point out in this section how we can determine a candidate for a dynamic destabilizing perturbation as discussed in Section 3.7.4.

Let us denote the blocks of Δ_0 as

$$\Delta_0 = \begin{pmatrix} p_1 I & & & & & & & & 0 \\ & \ddots & & & & & & & \\ & & p_{n_r} I & & & & & & \\ & & & \delta_1^0 I & & & & & \\ & & & & \ddots & & & & \\ & & & & & \delta_{n_c}^0 I & & & \\ & & & & & & \Delta_1^0 & & \\ & & & & & & & \ddots & \\ 0 & & & & & & & & \Delta_{n_f}^0 \end{pmatrix} \in \mathbb{C}^{p \times q}$$

with $p_j \in \mathbb{R}$, $\delta_j^0 \in \mathbb{C}$, $\Delta_j^0 \in \mathbb{C}^{p_j \times q_j}$.

According to Lemma 10, there exists proper and stable $\delta_j(s)$ with

$$\delta_j(i\omega_0) = \delta_j^0 \ \text{ and } \ \|\delta_j\|_\infty \leq |\delta_j^0| < \gamma_0.$$

Since $I - M(i\omega_0)\Delta_0$ is singular, there exists a complex kernel vector $u \neq 0$ with $(I - M(i\omega_0)\Delta_0)u = 0$. Define $v = \Delta_0 u$. If we partition u and v according to Δ_0, we obtain $v_j = \Delta_j^0 u_j$ for those vector pieces that correspond to the full blocks. In the proof of Theorem 17 we have shown how to construct a real rational proper and stable $\Delta_j(s)$ that satisfies

$$\Delta_j(i\omega_0) = v_j \frac{u_j^*}{\|u_j\|^2} \ \text{ and } \ \|\Delta_j\|_\infty \leq \frac{\|v_j\|}{\|u_j\|} \leq \|\Delta_j^0\| < \gamma_0.$$

(Provide additional arguments if it happens that $u_j = 0$).

Let us then define the proper and stable dynamic perturbation

$$\Delta(s) = \begin{pmatrix} p_1 I & & & & & & & & 0 \\ & \ddots & & & & & & & \\ & & p_{n_r} I & & & & & & \\ & & & \delta_1(s) I & & & & & \\ & & & & \ddots & & & & \\ & & & & & \delta_{n_c}(s) I & & & \\ & & & & & & \Delta_1(s) & & \\ & & & & & & & \ddots & \\ 0 & & & & & & & & \Delta_{n_f}(s) \end{pmatrix}.$$

Since each of the diagonal blocks has an H_∞-norm that does not exceed γ_0, we infer $\|\Delta\|_\infty < \gamma_0$. Hence $\Delta \in \frac{1}{\gamma_0}\mathbf{\Delta}$. Moreover, by inspection one verifies that $\Delta(i\omega_0)u = v$. This implies that $[I - M(i\omega_0)\Delta(i\omega_0)]u = u - M(i\omega_0)v = 0$ such that $I - M(s)\Delta(s)$ has a zero at $i\omega_0$ and, hence, its inverse is certainly not stable.

We have found an uncertainty Δ that is destabilizing for $(I - M\Delta)^{-1}$, and that is a candidate for rendering the system $S(\Delta, P)$ controlled with K unstable.

3.9.4 Example: Two Uncertainty Blocks in Tracking Configuration

Let us come back to Figure 22 with

$$G(s) = \frac{200}{(10s+1)(0.05s+1)^2} \ \text{ and } \ K(s) = 0.2\frac{0.1s+1}{(0.65s+1)(0.03s+1)}.$$

In this little example we did not include any weightings for the uncertainties what is, of course, unrealistic. Note that the uncertainties Δ_1 and Δ_2 have both dimension 1×1. Pulling them out leads to the uncertainty

$$\Delta = \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix}$$

for the interconnection. Since both uncertainties are dynamic, we infer for this setup that we have to choose

$$\mathbf{\Delta}_c := \{ \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \mid \Delta_j \in \mathbb{C},\ |\Delta_j| < 1,\ j = 1,2\}.$$

For any complex matrix M, the command mu(M,[1 1;1 1]) calculates the SSV of M with respect to $\mathbf{\Delta}_c$. The matrix [1 1;1 1] just indicates that the structure consists of two blocks (two rows) that are both of dimension 1×1.

The code

```
G=nd2sys( [200],conv([10 1],conv([0.05 1],[0.05 1])) );
K=nd2sys( [0.1 1], conv([0.65 1],[0.03 1]),0.2 );

systemnames='G';
inputvar='[w1;w2;d;n;r;u]';
outputvar='[u;r-n-d-w1-G;G+w1+d-r;r+w2-n-d-w1-G]';
input_to_G='[u]';
sysoutname='P';
cleanupsysic='yes';
sysic
N=starp(P,K);
M11=sel(N,1,1);
M22=sel(N,2,2);
M=sel(N,[1 2],[1 2]);
om=logspace(0,1);
clf;
vplot('liv,m',frsp(M11,om),':',frsp(M22,om),':',vnorm(frsp(M,om)),'--');
hold on;grid on
Mmu=mu(frsp(M,om),[1 1;1 1]);
vplot('liv,m',Mmu,'-');
```

computes the transfer matrix M seen by the uncertainty. Note that M_{jj} is the transfer function seen by Δ_j for $j = 1,2$. We plot $|M_{11}(i\omega)|$, $|M_{22}(i\omega)|$, $\|M(i\omega)\|$, and $\mu_{\mathbf{\Delta_c}}(M(i\omega))$ over the frequency interval $\omega \in [0,10]$, as shown in Figure 26. For good reasons to be revealed in Section 3.10, the upper bound of the SSV coincides with the lower bound such that, in this example, we have exactly calculated the SSV.

How do we have to interpret this plot? Since the SSV is not larger than 2, we conclude robust stability for all uncertainties that take their values in

$$\frac{1}{2}\mathbf{\Delta}_c = \{ \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \mid \Delta_j \in \mathbb{C},\ |\Delta_j| < \frac{1}{2},\ j = 1,2\}.$$

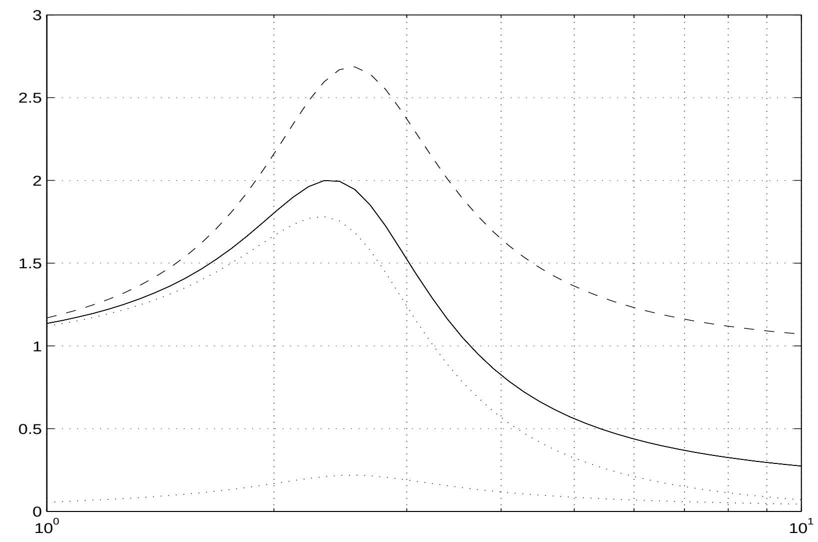


Figure 26: Magnitudes of M_{11}, M_{22} (dotted), norm of M (dashed), SSV of M (solid)

For this statement, we did not take into account that the SSV plot shows a variation in frequency. To be specific, at the particular frequency ω, we can not only allow for $\|\Delta_c\| < 0.5$ but even for

$$\|\Delta_c\| < r(\omega) := \frac{1}{\mu_{\mathbf{\Delta_c}}(M(i\omega))}$$

and we can still conclude that $I - M(i\omega)\Delta_c$ is non-singular. Therefore, one can guarantee robust stability for uncertainties that take their values at $i\omega$ in the set

$$\mathbf{\Delta}_c(\omega) := \{ \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \in \mathbb{C}^{2\times 2} \mid |\Delta_1| < r(\omega),\ |\Delta_2| < r(\omega)\}.$$

The SSV plot only leads to insights if re-scaling the *whole matrix* Δ_c. How can we explore robust stability for *different bounds on the different uncertainty blocks*? This would correspond to uncertainties that take their values in

$$\{ \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \in \mathbb{C}^{2\times 2} \mid |\Delta_1| < r_1,\ |\Delta_2| < r_2\}$$

for different $r_1 > 0$, $r_2 > 0$. The answer is simple: just employ weightings! Observe that this set is nothing but

$$R\mathbf{\Delta}_c \ \text{ with } \ R = \begin{pmatrix} r_1 & 0 \\ 0 & r_2 \end{pmatrix}.$$

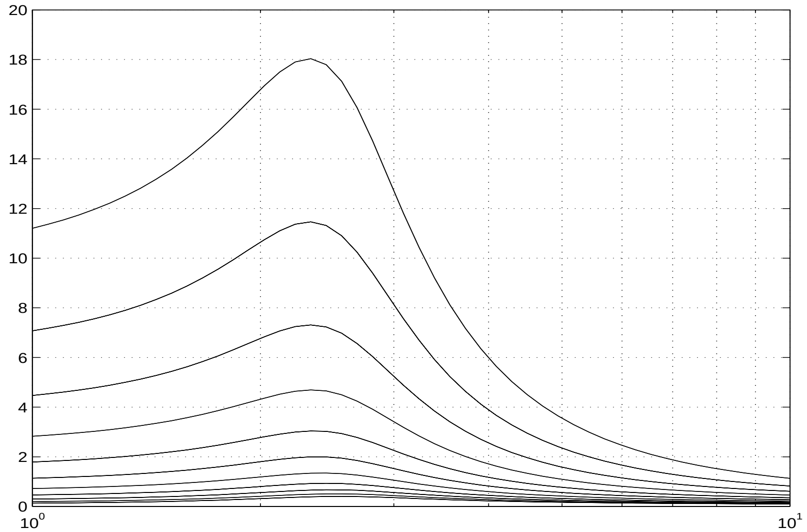


Figure 27: SSV of RM with $r_1 = 1$, $r_2 \in [0.1, 10]$.

In order to guarantee robust stability, we have to test $\mu_{R\mathbf{\Delta_c}}(M(i\omega)) \leq 1$ for all $\omega \in \mathbb{R} \cup \{\infty\}$, what amounts to verifying

$$\mu_{\mathbf{\Delta_c}}(RM(i\omega)) < 1 \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}$$

by the property (74). Again, we look at our example where we vary r_2 in the interval $[0.1, 10]$ and fix $r_1 = 1$. Figure 27 presents the SSV plots for these values.

Important task. Provide an interpretation of the plots!

Remark. For the last example, we could have directly re-scaled the two uncertainty blocks in the interconnection, and then pulled out the normalized uncertainties. The resulting test will lead, of course, to the same conclusions.

Similar statements can be made for the dashed curve and full block uncertainties; the discussion is related to the set

$$\{\Delta_c = \begin{pmatrix} \Delta_{11} & \Delta_{12} \\ \Delta_{21} & \Delta_{22} \end{pmatrix} \in \mathbb{C}^{2\times 2} \mid \|\Delta_c\| < 1\}.$$

The dotted curves lead to robust stability results for

$$\{\begin{pmatrix} \Delta_1 & 0 \\ 0 & 0 \end{pmatrix} \mid \Delta_1 \in \mathbb{C},\ |\Delta_1| < 1\}$$

or

$$\{\begin{pmatrix} 0 & 0 \\ 0 & \Delta_2 \end{pmatrix} \mid \Delta_2 \in \mathbb{C},\ |\Delta_2| < 1\}$$

respectively.

Important task. Formulate the exact results and interpretations for the last three cases.

3.9.5 SSV Applied to Testing the General Hypothesis

Let us recall that we always have to verify the hypotheses 11 before we apply our results. So far we were not able to check (45). For the specific set considered in this section, this simply amounts to a SSV-test: (45) is true if and only if

$$\mu_{\mathbf{\Delta_c}}(P_{11}(\infty)) \leq 1.$$

Remark. We observe that the SSV is a tool that is by no means restricted to stability tests in control. In fact, it is useful in any problem where one needs to check whether a family of matrices is non-singular.

3.10 A Brief Survey on the Structured Singular Value

This section serves to provide some important properties of $\mu_{\mathbf{\Delta_c}}(M_c)$, and it should clarify how it is possible to compute bounds on this quantity.

An important property of the SSV is its 'monotonicity' in the set $\mathbf{\Delta}_c$: If two sets of complex matrices $\mathbf{\Delta}_1$ and $\mathbf{\Delta}_2$ satisfy

$$\mathbf{\Delta}_1 \subset \mathbf{\Delta}_2,$$

then we infer

$$\mu_{\mathbf{\Delta_1}}(M_c) \leq \mu_{\mathbf{\Delta_2}}(M_c).$$

In short: The larger the set $\mathbf{\Delta}_c$ (with respect to inclusion), the larger $\mu_{\mathbf{\Delta_c}}(M_c)$.

Now it is simple to understand the basic idea of how to bound the SSV. For that purpose let us introduce the specific sets

$$\begin{aligned}
\mathbf{\Delta}_1 &:= \{pI \in \mathbb{R}^{p\times q} \mid |p| < 1\} \\
\mathbf{\Delta}_2 &:= \{pI \in \mathbb{C}^{p\times q} \mid |p| < 1\} \\
\mathbf{\Delta}_3 &:= \{\Delta_c \in \mathbb{C}^{p\times q} \mid \|\Delta_c\| < 1\}
\end{aligned}$$

that correspond to one real repeated block ($n_r = 1$, $n_c = 0$, $n_f = 0$), one complex repeated block ($n_r = 0$, $n_c = 1$, $n_f = 0$), or one full block ($n_r = 0$, $n_c = 0$, $n_f = 1$). For these specific structures one can easily compute the SSV explicitly:

$$\begin{aligned}\mu_{\mathbf{\Delta_1}}(M_c) &= \rho_{\mathbb{R}}(M_c)\\ \mu_{\mathbf{\Delta_2}}(M_c) &= \rho(M_c)\\ \mu_{\mathbf{\Delta_3}}(M_c) &= \|M_c\|.\end{aligned}$$

Here, $\rho_{\mathbb{R}}(M)$ denotes the *real* spectral radius of M_c defined as

$$\rho_{\mathbb{R}}(M_c) = \max\{|\lambda| \mid \lambda \text{ is a real eigenvalue of } M_c\},$$

whereas $\rho(M)$ denotes the *complex* spectral radius of M_c that is given as

$$\rho(M_c) = \max\{|\lambda| \mid \lambda \text{ is a complex eigenvalue of } M_c\}.$$

In general, we clearly have

$$\mathbf{\Delta}_1 \subset \mathbf{\Delta}_c \subset \mathbf{\Delta}_3$$

such that we immediately conclude

$$\mu_{\mathbf{\Delta_1}}(M_c) \le \mu_{\mathbf{\Delta_c}}(M_c) \le \mu_{\mathbf{\Delta_3}}(M_c).$$

If there are *no real blocks* ($n_r = 0$), we infer

$$\mathbf{\Delta}_2 \subset \mathbf{\Delta}_c \subset \mathbf{\Delta}_3$$

what implies

$$\mu_{\mathbf{\Delta_2}}(M_c) \le \mu_{\mathbf{\Delta_c}}(M_c) \le \mu_{\mathbf{\Delta_3}}(M_c).$$

Together with the above given explicit formulas, we arrive at the following result.

Lemma 23 *In general,*

$$\rho_{\mathbb{R}}(M_c) \le \mu_{\mathbf{\Delta_c}}(M_c) \le \|M_c\|.$$

If $n_r = 0$, then

$$\rho(M_c) \le \mu_{\mathbf{\Delta_c}}(M_c) \le \|M_c\|.$$

Note that these bounds are pretty rough. The main goal in computational techniques is to refine these bounds to get close to the actual value of the SSV.

3.10.1 Continuity

We have seen that the SSV of M_c with respect to the set $\{pI \in \mathbb{R}^{p\times q} \mid |p| < 1\}$ is the real spectral radius. This reveals that the SSV does, in general, not depend continuously on M_c. Just look at the simple example

$$\rho_{\mathbb{R}}\begin{pmatrix} 1 & m \\ -m & 1\end{pmatrix} = \begin{cases} 0 & \text{for } m \neq 1 \\ 1 & \text{for } m = 0.\end{cases}$$

It shows that the value of the SSV can jump with only slight variations in m.

This is an important observation for practice. If the structure (68) comprises real blocks ($n_r \neq 0$), then

$$\mu_{\mathbf{\Delta_c}}(M(i\omega))$$

might have *jumps* if we vary ω. Even more dangerously, since we compute the SSV at only a finite number of frequencies, we might miss a frequency where the SSV jumps to very high levels. The plot could make us believe that the SSV is smaller than one and we would conclude robust stability; in reality, the plot jumps above one at some frequency which we have missed, and the conclusion was false.

The situation is more favorable if there are no real blocks $n_r = 0$. Then $\mu_{\mathbf{\Delta_c}}(M_c)$ depends continuously on M_c, and jumps do not occur.

Theorem 24 *If $n_r = 0$ such that no real blocks appear in (68), the function*

$$M_c \to \mu_{\mathbf{\Delta_c}}(M_c)$$

is continuous. In particular, If M is real-rational, proper and stable,

$$\omega \to \mu_{\mathbf{\Delta_c}}(M(i\omega))$$

defines a continuous function on $\mathbb{R} \cup \{\infty\}$.

3.10.2 Lower Bounds

If one can compute some

$$\Delta_0 \in \frac{1}{\gamma}\mathbf{\Delta}_c \text{ that renders } I - M_c\Delta_0 \text{ singular,} \tag{78}$$

one can conclude that

$$\gamma \le \mu_{\mathbf{\Delta_c}}(M_c).$$

The approach taken in the μ-tools is to maximize γ such that there exists a Δ_0 as in (78). There is no guarantee whether one can compute the global optimum for the resulting maximization problem. Nevertheless, any step in increasing the value γ improves the lower bound and is, hence, beneficial.

Note that the algorithm outputs a matrix Δ_0 as in (78) for the best achievable lower bound γ. Based on this matrix Δ_0, one can compute a destabilizing perturbation as described in Section 3.9.3.

If the structure (68) only comprises real blocks ($n_c = 0$, $n_f = 0$), it often happens that the algorithm fails and that the lower bound is actually just zero. In general, if real blocks in the uncertainty structure do exist ($n_r \neq 0$), the algorithm is less reliable if compared to the case when these blocks do not appear ($n_r = 0$). We will not go into the details of these quite sophisticated algorithms.

3.10.3 Upper Bounds

If one can test that

$$\text{for all } \Delta_c \in \frac{1}{\gamma}\mathbf{\Delta}_c \text{ the matrix } I - M_c\Delta_c \text{ is non-singular,} \tag{79}$$

one can conclude that

$$\mu_{\mathbf{\Delta_c}}(M_c) \leq \gamma.$$

We have already seen in Section (3.8.2) that $\|M_c\| \leq \gamma$ is a sufficient condition for (79) to hold.

How is it possible to refine this condition?

Simple Scalings

Let us assume that all the full blocks in (68) are square such that $p_j = q_j$. Suppose that D is any non-singular matrix that satisfies

$$D\Delta_c = \Delta_c D \text{ for all } \Delta_c \in \frac{1}{\gamma}\mathbf{\Delta}_c. \tag{80}$$

Then

$$\|D^{-1}M_cD\| < \gamma \tag{81}$$

implies that

$$I - [D^{-1}M_cD]\Delta_c \tag{82}$$

is non-singular for all $\Delta_c \in \frac{1}{\gamma}\mathbf{\Delta}_c$. If we exploit $D\Delta_c = \Delta_c D$, (82) is nothing but

$$I - D^{-1}[M_c\Delta_c]D = D^{-1}[I - M_c\Delta_c]D.$$

Therefore, not only (82) but even $I - M_c\Delta_c$ itself is non-singular. This implies that (79) is true such that γ is an upper bound for $\mu_{\mathbf{\Delta_c}}(M_c)$.

In order to find the *smallest* upper bound, we hence need to minimize

$$\|D^{-1}M_cD\|$$

over the set of all matrices D that satisfy (80). Since $D = I$ is in the class of all these matrices, the minimal value is certainly better than $\|M_c\|$, and we can indeed possibly refine this rough upper bound through the introduction of the extra variables D. Since the object of interest is a scaled version $D^{-1}M_cD$ of M_c, these variables D are called *scalings*. Let us summarize what we have found so far.

Lemma 25 *We have*

$$\mu_{\mathbf{\Delta_c}}(M_c) \leq \inf_{D \text{ satisfies (80) and is non-singular}} \|D^{-1}M_cD\|.$$

In order to find the best upper bound, we have to solve the minimization problem on the right. Both from a theoretical and a practical view-point, it has very favorable properties: It is a convex optimization problem for which fast solvers are available. Convexity implies that one can really find the global optimum.

In these notes we only intend to reveal that the fundamental reason for the favorable properties can be attributed to the following fact: Finding a non-singular D with (80) and (81) is a so-called **L**inear **M**atrix **I**nequality (LMI) problem. For such problems very efficient algorithms have been developed in recent years.

As a first step it is very simple to see that (80) holds if and only if D admits the structure

$$D = \begin{pmatrix} D_1 & & & & & & & & 0 \\ & \ddots & & & & & & & \\ & & D_{n_r} & & & & & & \\ & & & D_{n_r+1} & & & & & \\ & & & & \ddots & & & & \\ & & & & & D_{n_r+n_c} & & & \\ & & & & & & d_1 I & & \\ & & & & & & & \ddots & \\ 0 & & & & & & & & d_{n_f} I \end{pmatrix} \tag{83}$$

with

$$D_j \text{ a non-singular complex matrix and } d_j \text{ a non-zero complex scalar}$$

of the same size as the corresponding blocks in the partition (68). It is interesting to observe that any repeated block in (68) corresponds to a full block in (83), and any full block in (68) corresponds to a repeated block in (83).

In a second step, one transforms (81) into a linear matrix inequality: (81) is equivalent to

$$[D^{-1}M_cD][D^{-1}M_cD]^* < \gamma^2 I.$$

If we left-multiply with D and right-multiply with D^*, we arrive at the equivalent inequality

$$M_c[DD^*]M_c^* < \gamma^2[DD^*].$$

Let us introduce the Hermitian matrix

$$Q := DD^*$$

such that the inequality reads as

$$M_cQM_c^* < \gamma^2 Q. \tag{84}$$

Moreover, Q has the structure

$$Q = \begin{pmatrix} Q_1 & & & & & & & & 0 \\ & \ddots & & & & & & & \\ & & Q_{n_r} & & & & & & \\ & & & Q_{n_r+1} & & & & & \\ & & & & \ddots & & & & \\ & & & & & Q_{n_r+n_c} & & & \\ & & & & & & q_1 I & & \\ & & & & & & & \ddots & \\ 0 & & & & & & & & q_{n_f} I \end{pmatrix} \tag{85}$$

with

$$Q_j \text{ a Hermitian positive definite matrix and } q_j \text{ a real positive scalar.} \tag{86}$$

Testing whether there exists a Q with the structrue (85) that satisfies the matrix inequality (84) is an LMI problem.

Here we have held γ fixed. Typical LMI algorithms also allow to directly minimize γ in order to find the best upper bound. Alternatively, one can resort to the standard bisection algorithm as discussed in Section A.

A Larger Class of Scalings

Clearly, the larger the class of considered scalings, the more freedom is available to approach the actual value of the SSV. Hence a larger class of scalings might lead to the computation of better upper bounds.

These arguments turn out to be valid, in particular, if the structure (68) comprises real blocks. The fundamental idea to arrive at better upper bounds is formulated in the following simple lemma.

Lemma 26 *Suppose there exists a Hermitian P such that*

$$\begin{pmatrix} \Delta_c \\ I \end{pmatrix}^* P \begin{pmatrix} \Delta_c \\ I \end{pmatrix} \geq 0 \;\; \textit{for all} \;\; \Delta_c \in \frac{1}{\gamma}\boldsymbol{\Delta}_c \tag{87}$$

and that satisfies

$$\begin{pmatrix} I \\ M_c \end{pmatrix}^* P \begin{pmatrix} I \\ M_c \end{pmatrix} < 0. \tag{88}$$

Then (79) holds true and, hence, γ is an upper bound for $\mu_{\boldsymbol{\Delta_c}}(M_c)$.

Proof. The proof is extremely simple. Fix $\Delta_c \in \frac{1}{\gamma}\boldsymbol{\Delta}_c$. We have to show that $I - M_c\Delta_c$ is non-singular. Let us assume the contrary: $I - M_c\Delta_c$ is singular. Then there exists an $x \neq 0$ with $(I - M_c\Delta_c)x = 0$. Define $y := \Delta_c x$ such that $x = M_c y$. Then (87) leads to

$$0 \leq x^* \begin{pmatrix} \Delta_c \\ I \end{pmatrix}^* P \begin{pmatrix} \Delta_c \\ I \end{pmatrix} x = \begin{pmatrix} y \\ x \end{pmatrix}^* P \begin{pmatrix} y \\ x \end{pmatrix}.$$

On the other hand, (88) implies

$$0 > y^* \begin{pmatrix} I \\ M_c \end{pmatrix}^* P \begin{pmatrix} I \\ M_c \end{pmatrix} y = \begin{pmatrix} y \\ x \end{pmatrix}^* P \begin{pmatrix} y \\ x \end{pmatrix}.$$

(Since $x \neq 0$, the vector $\begin{pmatrix} y \\ x \end{pmatrix}$ is also non-zero.) This contradiction shows that $I - M_c\Delta_c$ cannot be singular.

■

Remark. In Lemma 26 the converse holds as well: If the SSV is smaller than γ, there exists a Hermitian P with (87) and (88). In principle, based on this lemma, one could compute the exact value of the SSV; the only crux is to parametrize the set of all scalings P with (87) what cannot be achieved in an efficient manner.

Remark. In order to work with (80) in the previous section, we need to assume that the full blocks Δ_j are square. For (87) no such condition is required. The μ-tools can handle non-square blocks as well.

For practical applications, we need to find a set of scalings that all fulfill (87). A very straightforward choice that is implemented in the μ-tools is as follows: Let $\mathcal{P}_\gamma$ cnsist of all matrices

$$P = \begin{pmatrix} -\gamma^2 Q & S \\ S^* & Q \end{pmatrix}$$

where Q has the structure (85) and (86), and S is given by

$$S = \begin{pmatrix} S_1 & & & & & & & & 0 \\ & \ddots & & & & & & & \\ & & S_{n_r} & & & & & & \\ & & & 0 & & & & & \\ & & & & \ddots & & & & \\ & & & & & 0 & & & \\ & & & & & & 0 & & \\ & & & & & & & \ddots & \\ 0 & & & & & & & & 0 \end{pmatrix} \tag{89}$$

with

$$S_j \quad \text{a complex skew-Hermitian matrix: } S_j^* + S_j = 0.$$

For any $P \in \mathcal{P}_\gamma$, the matrix $\begin{pmatrix} \Delta_c \\ I \end{pmatrix}^* P \begin{pmatrix} \Delta_c \\ I \end{pmatrix}$ is block-diagonal. Let us now check for each diagonal block that it is positive semidefinite: We observe for

- real uncertainty blocks:

$$p_j(-\gamma^2 Q_j)p_j + p_j S_j + S_j^* p_j + Q_j = Q_j(-\gamma^2 p_j^2 + 1) \geq 0.$$

- complex repeated blocks:

$$\delta_j^*(-\gamma^2 Q_j)\delta_j + Q_j = Q_j(-\gamma^2 |\delta_j|^2 + 1) \geq 0.$$

- complex full blocks:

$$\Delta_j^*(-\gamma^2 q_j I)\Delta_j + q_j I = q_j(-\gamma^2 \Delta_j^* \Delta_j + I) \geq 0.$$

We conclude that (87) holds for any $P \in \mathcal{P}_\gamma$.

If we can find one $P \in \mathcal{P}_\gamma$ for which also condition (88) turns out to be true, we can conclude that γ is an upper bound for the SSV. Again, testing the existence of $P \in \mathcal{P}_\gamma$ that also satisfies (88) is a standard LMI problem.

The best upper bound is of course obtained as follows:

$$\text{Minimize } \gamma \text{ such that there exists a } P \in \mathcal{P}_\gamma \text{ that satisfies (88).} \tag{90}$$

Again, the best bound can be compute by bisection as described in Section A.

Remark. Only if real blocks do exist, the matrix S will be non-zero, and only in that case we will benefit from the extension discussed in this section. We have described the class of scalings that is employed in the μ-tools. However, Lemma 26 leaves room for considerable improvements in calculating upper bounds for the SSV.

3.11 When is the Upper Bound equal to the SSV?

Theorem 27 *If*

$$2(n_r + n_c) + n_f \leq 3,$$

then the SSV $\mu_{\mathbf{\Delta_c}}(M_c)$ *is not only bounded by but actually* coincides *with the optimal value of problem (90).*

Note that this result is tight in the following sense: If $2(n_r + n_c) + n_f > 3$, one can construct examples for which there is a gap between the SSV and the best upper bound, the optimal value of (90).

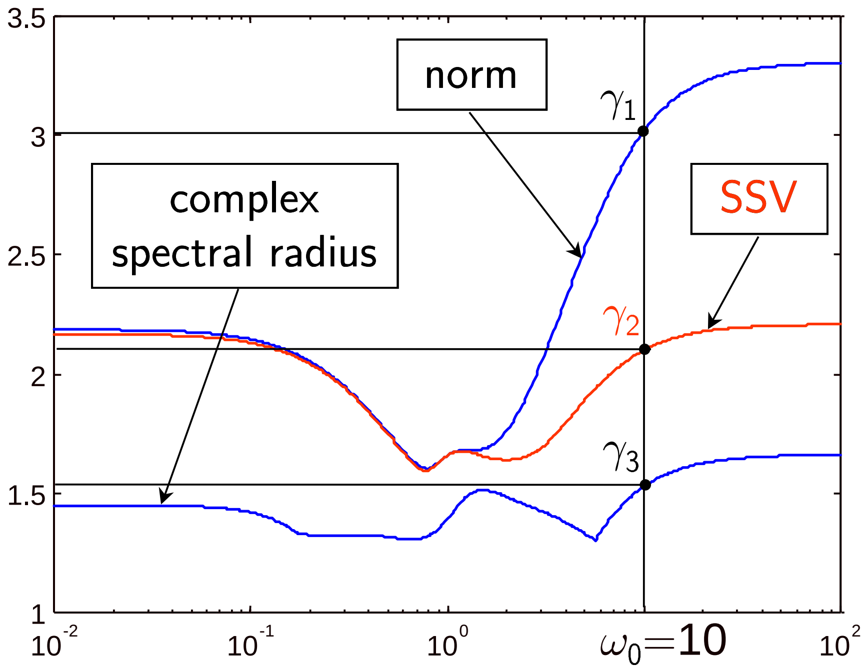


Figure 28: Plots of $\|M(i\omega)\|$, $\mu_{\mathbf{\Delta_1}}(M(i\omega))$ and $\rho(M(i\omega))$ over frequency.

3.11.1 Example: Different Lower and Upper Bounds

Let

$$M(s) = \begin{pmatrix} \frac{1}{2s+1} & 1 & \frac{s-2}{2s+4} \\ -1 & \frac{s}{s^2+s+1} & \frac{1}{(s+1)^2} \\ \frac{3s}{s+5} & \frac{-1}{4s+1} & 1 \end{pmatrix}.$$

Moreover, consider three different structures.

The first consists of two full complex blocks

$$\mathbf{\Delta}_1 := \left\{ \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix} \mid \Delta_1 \in \mathbb{C}^{2\times 2},\ \|\Delta_1\| < 1,\ \Delta_2 \in \mathbb{C},\ |\Delta_2| < 1 \right\}.$$

We plot in Figure 28 $\|M(i\omega)\|$, $\mu_{\mathbf{\Delta_1}}(M(i\omega))$, $\rho(M(i\omega))$ over frequency.

We conclude that $I - M(i\omega_0)\Delta_c$ is non-singular for all

- full blocks $\Delta_c \in \mathbb{C}^{3\times 3}$ with $\|\Delta_c\| < \frac{1}{\gamma_1}$
- structured blocks $\Delta_c \in \frac{1}{\gamma_2}\boldsymbol{\Delta}_1$
- complex repeated blocks $\begin{pmatrix} \delta & 0 & 0 \\ 0 & \delta & 0 \\ 0 & 0 & \delta \end{pmatrix}$ with $|\delta| < \frac{1}{\gamma_3}$.

In addition, there exists a Δ_c that is

- a full block $\Delta_c \in \mathbb{C}^{3\times 3}$ with $\|\Delta_c\| < \frac{1}{\gamma}$, $\gamma < \gamma_1$
- a structured block $\Delta_c \in \frac{1}{\gamma}\boldsymbol{\Delta}_1$, $\gamma < \gamma_2$
- a complex repeated block $\begin{pmatrix} \delta & 0 & 0 \\ 0 & \delta & 0 \\ 0 & 0 & \delta \end{pmatrix}$ with $|\delta| < \frac{1}{\gamma}$, $\gamma < \gamma_3$

that renders $I - M(i\omega_0)\Delta_c$ singular.

As a second case, we take one repeated complex block and one full complex block:

$$\boldsymbol{\Delta}_2 := \left\{ \begin{pmatrix} \delta_1 I_2 & 0 \\ 0 & \Delta_2 \end{pmatrix} \mid \delta_1 \in \mathbb{C},\ |\delta_1| < 1,\ \Delta_2 \in \mathbb{C},\ |\Delta_2| < 1 \right\}.$$

As observed in Figure 29, the upper and lower bounds for the SSV are *different*. Still, the complex spectral radius bounds the lower bound on the SSV from below.

We conclude that $I - M(i\omega_0)\Delta_c$ is non-singular for all structured Δ_c in $\frac{1}{\gamma_1}\boldsymbol{\Delta}_2$. There exists a structured Δ_c in $\frac{1}{\gamma}\boldsymbol{\Delta}_2$, $\gamma < \gamma_2$, that renders $I - M(i\omega_0)\Delta_c$ singular.

As a last case, let us consider a structure with one real repeated block and one full complex block:

$$\boldsymbol{\Delta}_3 := \left\{ \begin{pmatrix} \delta_1 I_2 & 0 \\ 0 & \Delta_2 \end{pmatrix} \mid \delta_1 \in \mathbb{R},\ |\delta_1| < 1,\ \Delta_2 \in \mathbb{C},\ |\Delta_2| < 1 \right\}.$$

Figure 30 shows that lower bound and upper bound of the SSV are further apart than in the previous example, what reduces the quality of the information about the SSV. Since the structure comprises a real block, the complex spectral radius is no lower bound on the SSV (or its lower bound) over all frequencies, as expected.

The upper bound is smaller than γ_1 for all frequencies. Hence $I - M\Delta$ has proper and stable inverse for all $\Delta \in \frac{1}{\gamma_1}\boldsymbol{\Delta}$.

There exists a frequency for which the lower bound is larger that γ_2: Hence there exists a $\Delta \in \frac{1}{\gamma_2}\boldsymbol{\Delta}$ such that $I - M\Delta$ does not have a proper and stable inverse.

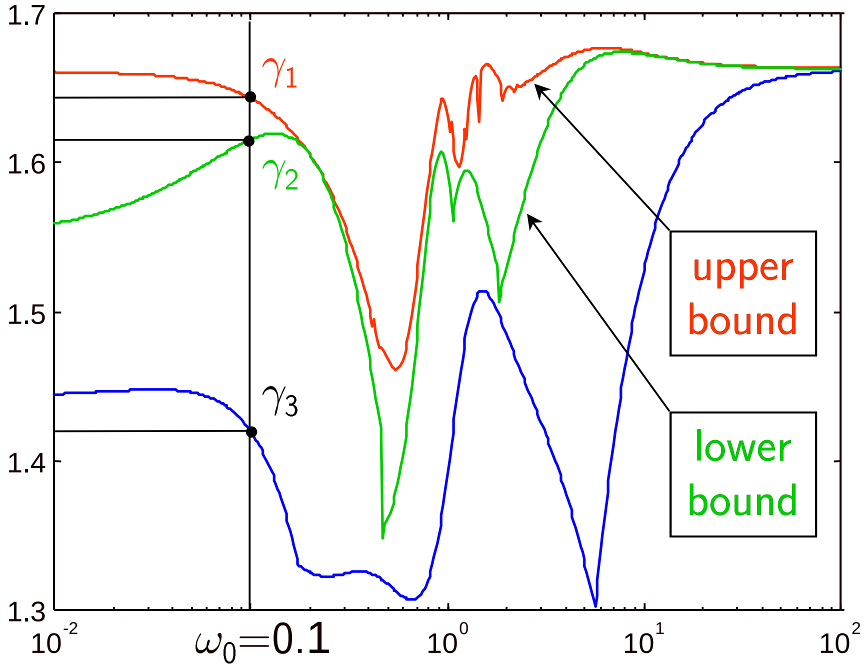


Figure 29: Plots of bounds on $\mu_{\boldsymbol{\Delta}_1}(M(i\omega))$ and of $\rho(M(i\omega))$ over frequency.

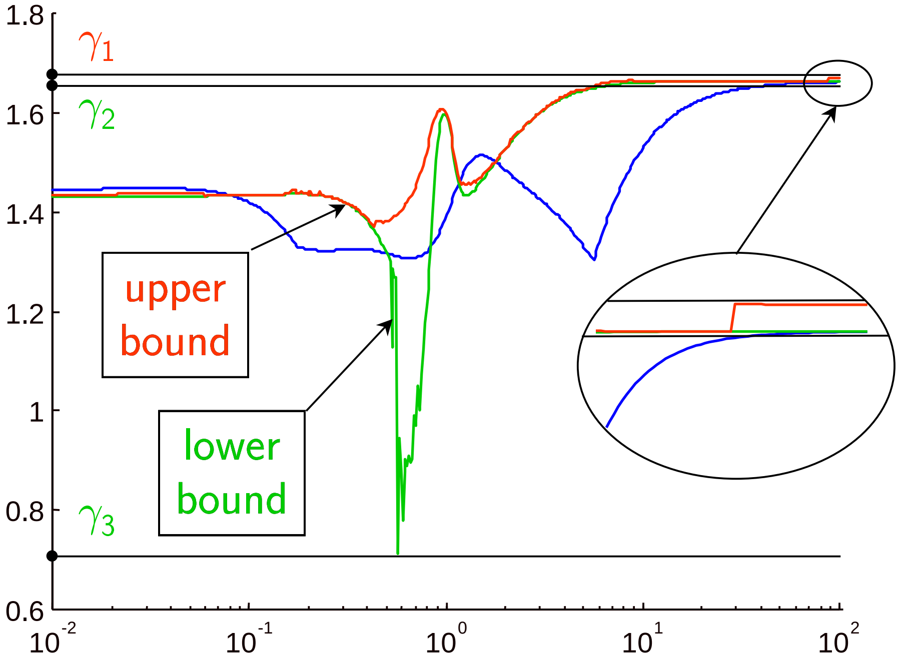


Figure 30: Plots of bounds on $\mu_{\mathbf{\Delta_1}}(M(i\omega))$ and of $\rho(M(i\omega))$ over frequency.

Exercises

1) This is a continuation of Exercise 3 in Section 2.
(Matlab) Let the controller K be given as

$$K = \left[\begin{array}{cccccc|cc} -4.69 & -1.28 & -1.02 & 7.29 & -0.937 & -0.736 & 5.69 & 1.6 \\ -2.42 & -3.29 & -3.42 & 6.53 & -1.17 & -0.922 & 2.42 & 4.12 \\ -1.48 & 0.418 & -0.666 & 2.52 & 0 & 0 & 1.48 & 1.05 \\ 19 & -0.491 & 1.34 & -0.391 & -6.16 & -5.59 & 0.943 & -0.334 \\ 24.8 & 2.35 & 3.73 & -8.48 & -7.58 & -3.61 & -3.45 & -3.96 \\ 4.38 & 4.02 & 3.2 & -9.41 & 2.54 & 0 & -4.38 & -5.03 \\ \hline 20 & -0.757 & 1.13 & -1 & -6.16 & -5.59 & 0 & 0 \end{array}\right].$$

Suppose the component G_1 is actually given by

$$G_1 + W_1\Delta \quad \text{with} \quad W_1(s) = \frac{s-2}{s+2}.$$

For the above controller, determine the largest r such that the loop remains stable for all Δ with

$$\Delta \in \mathbb{R},\ |\Delta| < r \quad \text{or} \quad \Delta \in RH_\infty,\ \|\Delta\|_\infty < r.$$

Argue in terms of the Nyquist or Bode plot seen by the uncertainty Δ. Construct for both cases destabilizing perturbations of smallest size, and check that they lead, indeed, to an unstable controlled interconnection as expected.

a) (Matlab) Use the same data as in the previous exercise. Suppose now that the *pole* of G_2 is uncertain:

$$G_2(s) = \frac{1}{s-p}, \quad p \in \mathbb{R},\ |p-1| < r.$$

What is the largest possible r such that K still stabilizes P for all possible real poles p. What happens if the pole variation is allowed to be complex?

b) (Matlab) With W_1 as above, let G_1 be perturbed as

$$G_1 + W_1\Delta, \quad \Delta \in RH_\infty,\ \|\Delta\|_\infty < r_1$$

and let G_2 be given as

$$G_2(s) = \frac{1}{s-p}, \quad p \in \mathbb{R},\ |p-1| < r_2.$$

Find the largest $r = r_1 = r_2$ such that K still robustly stabilizes the system in face of these uncertainties. Plot a trade-off curve: For each r_1 in a suitable interval (which?), compute the largest $r_2(r_1)$ for which K is still robustly stabilizing and plot the graph of $r_2(r_1)$; comment!

2) Suppose $\mathbf{\Delta_c}$ is the set of all matrices with $\|\Delta\| < 1$ that have the structure

$$\Delta = \operatorname{diag}(\delta_1, \ldots, \delta_m) \in \mathbb{R}^{m\times m},$$

and consider the rationally perturbed matrix $A_\Delta = A + B\Delta(I - D\Delta)^{-1}C$ for real matrices A, B, C, D of compatible size. Derive a μ-test for the following properties:

a) Both $I - D\Delta$ and A_Δ are non-singular for all $\Delta \in \mathbf{\Delta_c}$.

b) For all $\Delta \in \mathbf{\Delta_c}$, $I - D\Delta$ is non-singular and A_Δ has all its eigenvalues in the open left-half plane.

c) For all $\Delta \in \mathbf{\Delta_c}$, $I - D\Delta$ is non-singular and A_Δ has all its eigenvalues in the open unit disk $\{z \in \mathbb{C} \mid |z| < 1\}$.

3) Let $\mathbf{\Delta_c}$ be the same as in Exercise 2. For real vectors $a \in \mathbb{R}^m$ and $b \in \mathbb{R}^m$, give a formula for $\mu_{\mathbf{\Delta_c}}(ab^T)$. (SSV of rank one matrices.)

4) a) For the data

$$M_c = \begin{pmatrix} 12 & -3 & 2 \\ -1 & 7 & 8 \\ 5 & 3 & -1 \end{pmatrix} \quad \text{and} \quad \mathbf{\Delta_c} = \{\Delta_c = \begin{pmatrix} \Delta_{11} & \Delta_{12} & 0 \\ \Delta_{21} & \Delta_{22} & 0 \\ 0 & 0 & \Delta_{33} \end{pmatrix} \in \mathbb{C}^{3\times 3} \mid \|\Delta_c\| < 1\}$$

compute $\mu_{\mathbf{\Delta_c}}(M_c)$ with a Matlab m-file. You are allowed to use only the functions `max`, `eig` and a `for`-loop; in particular, don't use `mu`.

b) Let $M_c = \begin{pmatrix} M_1 & M_{12} \\ M_{21} & M_2 \end{pmatrix}$ and let $\mathbf{\Delta_c}$ be the set of all $\Delta_c = \operatorname{diag}(\Delta_1, \Delta_2)$ with full square blocks Δ_j satisfying $\|\Delta_j\| < 1$. Give a formula for the value

$$d_* = \min_{d>0} \left\| \begin{pmatrix} M_1 & dM_{12} \\ \frac{1}{d}M_{21} & M_2 \end{pmatrix} \right\|_2 .$$

where $\|M\|_2^2 = \operatorname{trace}(M^*M)$. How does d_* lead to an upper bound of $\mu_{\mathbf{\Delta}_c}(M)$? (Matlab) Compare this bound with the exact value in the previous exercise.

4 Nominal Performance Specifications

In our general scenario (Figure 5), we have collected various signals into the generalized disturbance w and the controlled variable z, and we assume that these signals are chosen to characterize the performance properties to be achieved by the controller. So far, however, we only included the requirement that K should render $z = S(P, K)w$ stable.

For any stabilizing controller, one can of course just directly investigate the transfer function elements of $S(P, K)$ and decide whether they are satisfactory or not. Most often, this just means that the Bode plots of these transfer functions should admit a desired shape that is dictated by the interpretation of the underlying signals. In this context you should remember the desired shapes for the sensitivity and the complementary sensitivity transfer matrices in a standard tracking problem.

For the purpose of analysis, a direct inspection of the closed-loop transfer matrix is no problem at all. However, if the interconnection is affected by uncertainties and if one would like to verify *robust performance*, or if one wishes to *design a controller*, it is required to translate the desired performance specifications into a weighted H_∞-norm criterion.

4.1 An Alternative Interpretation of the H_∞ Norm

We have seen in Section 1.2 that the H_∞-norm of a proper and stable G is just the energy gain of the corresponding LTI system.

Most often, reference or disturbance signals are persistent and can be assumed to be sinusoids. Such a signal is given as

$$w(t) = w_0 e^{i\omega_0 t} \tag{91}$$

with $w_0 \in \mathbb{C}^n$ and $\omega_0 \in \mathbb{R}$. If $\omega_0 = 0$ and $w_0 \in \mathbb{R}^n$, this defines the step function $w(t) = w_0$ of height w_0. (We note that this class of complex valued signals includes the set of all real-valued sinusoids. We work with this enlarged class to simplify the notation in the following arguments.) Let us choose as a measure of size for (91) the Euclidean norm of its amplitude:

$$\|w(.)\|_{\text{RMS}} := \|w_0\|.$$

As indicated, this defines indeed a norm on the vector space of all sinusoids.

Let $w(.)$ as defined by (91) pass the LTI system defined by the proper and stable transfer matrix G to obtain $z(.)$. As well-known, $\lim_{t\to\infty}[z(t) - G(i\omega_0)w_0 e^{i\omega_0 t}] = 0$ such that the *steady-state response* is

$$(Gw)_s(t) = G(i\omega_0)w_0 e^{i\omega_0 t}.$$

(The subscript means that we only consider the steady-state response of Gw.) We infer

$$\|(Gw)_s\|_{\text{RMS}} = \|G(i\omega_0)w_0\|$$

and hence, due to $\|G(i\omega_0)w_0\| \leq \|G(i\omega)\|\|w_0\|$,

$$\frac{\|(Gw)_s\|_{\mathrm{RMS}}}{\|w\|_{\mathrm{RMS}}} \leq \|G(i\omega_0)\| \leq \|G\|_\infty.$$

Hence the gain of $w \to (Gw)_s$ is bounded by $\|G\|_\infty$. The gain actually turns out to be equal to $\|G\|_\infty$.

Theorem 28 *Let G be proper and stable. Then*

$$\sup_{w \text{ a sinusoid with } \|w\|_{\mathrm{RMS}}>0} \frac{\|(Gw)_s\|_{\mathrm{RMS}}}{\|w\|_{\mathrm{RMS}}} = \|G\|_\infty.$$

The proof is instructive since it shows how to *construct a signal that leads to the largest amplification if passed through the system.*

Proof. Pick the frequency $\omega_0 \in \mathbb{R} \cup \{\infty\}$ with $\|G(i\omega_0)\| = \|G\|_\infty$.

Let us first assume that ω_0 is finite. Then take $w_0 \neq 0$ with $\|G(i\omega_0)w_0\| = \|G(i\omega_0)\|\|w_0\|$. (Direction of largest gain of $G(i\omega_0)$.) For the signal $w(t) = w_0 e^{i\omega_0 t}$ we infer

$$\frac{\|(Gw)_s\|_{\mathrm{RMS}}}{\|w\|_{\mathrm{RMS}}} = \frac{\|G(i\omega_0)w_0\|}{\|w_0\|} = \frac{\|G(i\omega_0)\|\|w_0\|}{\|w_0\|} = \|G(i\omega_0)\| = \|G\|_\infty.$$

Hence the gain $\frac{\|(Gw)_s\|_{\mathrm{RMS}}}{\|w\|_{\mathrm{RMS}}}$ for this signal is largest possible.

If ω_0 is infinite, take any sequence $\omega_j \in \mathbb{R}$ with $\omega_j \to \infty$, and construct at each ω_j the signal $w_j(.)$ as before. We infer

$$\frac{\|(Gw_j)_s\|_{\mathrm{RMS}}}{\|w_j\|_{\mathrm{RMS}}} = \|G(i\omega_j)\|$$

and this converges to $\|G(i\omega_0)\| = \|G\|_\infty$. Hence we cannot find a signal for which the worst amplification is attained, but we can come arbitrarily close.

$\blacksquare$

As a generalization, sums of sinusoids are given as

$$w(t) = \sum_{j=1}^{N} w_j e^{i\omega_j t} \tag{92}$$

where N is the number of *pair-wise different* frequencies $\omega_j \in \mathbb{R}$, and $w_j \in \mathbb{C}^n$ is the complex amplitude at the frequency ω_j. As a measure of size for the signal (92) we employ

$$\|w\|_{\mathrm{RMS}} := \sqrt{\sum_{j=1}^{N} \|w_j\|^2}.$$

Again, this defines a norm on the vector space of all sums of sinusoids. For any $w(.)$ defined by (92), the steady-state response is

$$(Gw)_s(t) = \sum_{j=1}^{N} G(i\omega_j) w_j e^{i\omega_j t}$$

and has norm

$$\|(Gw)_s\|_{\mathrm{RMS}} = \sqrt{\sum_{j=1}^{N} \|G(i\omega_j)w_j\|^2}.$$

Again by $\|G(i\omega_j)w_j\| \leq \|G(i\omega_j)\|\|w_j\| \leq \|G\|_\infty \|w_j\|$, we infer

$$\|(Gw)_s\|_{\mathrm{RMS}} \leq \|G\|_\infty \|w\|_{\mathrm{RMS}}.$$

We arrive at the following generalization of the result given above.

Theorem 29 *Let G be proper and stable. Then*

$$\sup_{w \text{ a sum of sinusoids with } \|w\|_{\mathrm{RMS}}>0} \frac{\|(Gw)_s\|_{\mathrm{RMS}}}{\|w\|_{\mathrm{RMS}}} = \|G\|_\infty.$$

Remark. We have separated the formulation of Theorem 28 from that of Theorem 29 in order to stress that $\frac{\|(Gw)_s\|_{\mathrm{RMS}}}{\|w\|_{\mathrm{RMS}}}$ can be rendered arbitrarily close to $\|G\|_\infty$ by using simple sinusoids as in (91); we do not require sums of sinusoids to achieve this approximation.

4.2 The Tracking Interconnection

Let us come back to the interconnection in Figure 1, and let K stabilize the interconnection.

4.2.1 Bound on Frequency Weighted System Gain

Often, performance specifications arise by specifying how signals have to be attenuated in the interconnection.

Typically, the reference r and the disturbance d are most significant at low frequencies. With real-rational proper and stable low-pass filters W_r, W_d, we hence assume that r, d are given as

$$r = W_r \tilde{r}, \quad d = W_d \tilde{d}$$

where $\tilde{r}(.)$, $\tilde{d}(.)$ are sinusoids or sums of sinusoids. Similarly, the measurement noise n is most significant at high frequencies. With a real-rational proper and stable high-pass filter W_n, we hence assume that n is given as

$$n = W_n \tilde{n}$$

where $\tilde{n}(.)$ is a sum of sinusoids. Finally, the size of the unfiltered signals is assumed to be bounded as

$$\left\| \begin{pmatrix} \tilde{d} \\ \tilde{n} \\ \tilde{r} \end{pmatrix} \right\|_{\mathrm{RMS}}^2 = \|\tilde{r}\|_{\mathrm{RMS}}^2 + \|\tilde{d}\|_{\mathrm{RMS}}^2 + \|\tilde{n}\|_{\mathrm{RMS}}^2 \leq 1.$$

Remark. In our signal-based approach all signals are assumed to enter the interconnection together. Hence it is reasonable to bound the stacked signal instead of working with individual bounds on $\|\tilde{r}\|_{\mathrm{RMS}}$, $\|\tilde{d}\|_{\mathrm{RMS}}$, $\|\tilde{n}\|_{\mathrm{RMS}}$. Recall, however, that the above inequality implies

$$\|\tilde{r}\|_{\mathrm{RMS}}^2 \leq 1, \quad \|\tilde{d}\|_{\mathrm{RMS}}^2 \leq 1, \quad \|\tilde{n}\|_{\mathrm{RMS}}^2 \leq 1,$$

and that it is implied by

$$\|\tilde{r}\|_{\mathrm{RMS}}^2 \leq \frac{1}{3}, \quad \|\tilde{d}\|_{\mathrm{RMS}}^2 \leq \frac{1}{3}, \quad \|\tilde{n}\|_{\mathrm{RMS}}^2 \leq \frac{1}{3}.$$

The goal is to keep the norm of the steady-state error e_s small, no matter which of these signals enters the interconnection. If we intend to achieve $\|e_s\|_{\mathrm{RMS}} \leq \epsilon$, we can as well rewrite this condition with $W_e := \frac{1}{\epsilon}$ as $\|\tilde{e}_s\|_{\mathrm{RMS}} \leq 1$ for

$$\tilde{e} = W_e e.$$

To proceed to the general framework, let us introduce

$$z = e, \ \tilde{z} = \tilde{e} \ \text{ and } \ w = \begin{pmatrix} d \\ n \\ r \end{pmatrix}, \ \tilde{w} = \begin{pmatrix} \tilde{d} \\ \tilde{n} \\ \tilde{r} \end{pmatrix}$$

as well as the weightings

$$W_z = W_e \ \text{ and } \ W_w = \begin{pmatrix} W_d & 0 & 0 \\ 0 & W_n & 0 \\ 0 & 0 & W_r \end{pmatrix}.$$

In the general framework, the original closed-loop interconnection was described as

$$z = S(P, K)w.$$

Since the desired performance specification is formulated in terms of $\tilde{z}$ and $\tilde{w}$, we introduce these signals with

$$\tilde{z} = W_z z \ \text{ and } \ w = W_w \tilde{w}$$

to get the weighted closed-loop interconnection (Figure 31)

$$\tilde{z} = [W_z S(P, K) W_w]\tilde{w}.$$

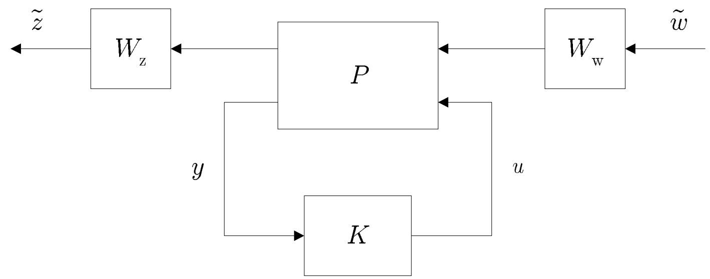


Figure 31: Weighted closed-loop interconnection

Recall that the desired performance specification was reduced to the fact that

$$\|\tilde{w}\|_{\mathrm{RMS}} \leq 1 \ \text{ implies } \ \|\tilde{z}_s\|_{\mathrm{RMS}} \leq 1.$$

By Theorem 29, this requirement is *equivalent* to

$$\|W_z S(P, K) W_w\|_\infty \leq 1. \tag{93}$$

We have arrived at those performance specifications that can be handled with the techniques developed in these notes: Bounds on the weighted H_∞-norm of the performance channels.

Let us recall that this specification is equivalent to

$$\|W_z(i\omega) S(P, K)(i\omega) W_w(i\omega)\| \leq 1 \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\}.$$

This reveals the following two interpretations:

- **Loop-shape interpretation**. The shape of the frequency response $\omega \to S(P, K)(i\omega)$ is compatible with the requirement that the maximal singular value of the weighted frequency response $\omega \to W_z(i\omega) S(P, K)(i\omega) W_w(i\omega)$ does not exceed one. Roughly, this amounts to bounding all singular values of $S(P, K)(i\omega)$ from above with a bound that varies according the variations of the singular values of $W_z(i\omega)$ and $W_w(i\omega)$. This rough interpretation is accurate if $W_z(i\omega)$ and $W_w(i\omega)$ are just scalar valued since (93) then just amounts to

$$\|S(P, K)(i\omega)\| \leq \frac{1}{|W_z(i\omega) W_w(i\omega)|} \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\}.$$

  It is important to note that one cannot easily impose a lower bound on the smallest singular value of $S(P, K)(i\omega)$! Instead, desired minimal amplifications are enforced by imposing upper bounds on the largest singular value of 'complementary' transfer functions - for that purpose one should recall the interplay of sensitivity and complementary sensitivity matrices.

- **Disturbance attenuation interpretation**. For all disturbances that are defined through
$$w(t) = \sum_{j=1}^{N} W(i\omega_j) w_j e^{i\omega_j t} \text{ with } \sum_{j=1}^{N} \|w_j\|^2 \leq 1,$$
(93) implies that the steady-state response z_s of $z = S(P,K)w$ satisfies
$$z_s(t) = \sum_{j=1}^{N} z_j e^{i\omega_j t} \text{ with } \sum_{j=1}^{N} \|Z(i\omega_j) z_j\|^2 \leq 1.$$
For pure sinusoids, any disturbance satisfying
$$w(t) = W(i\omega) w e^{i\omega t} \text{ with } \|w\|^2 \leq 1$$
leads to a steady-state response
$$z_s(t) = z e^{i\omega t} \text{ with } \|Z(i\omega) z\|^2 \leq 1.$$
This leads to a very clear interpretation of *matrix valued weightings*: Sinusoids of frequency ω with an amplitude in the ellipsoid $\{W_w(i\omega)w \mid \|w\| \leq 1\}$ lead to a steady-state sinusoidal response with amplitude in the ellipsoid $\{z \mid \|W_z(i\omega)z\| \leq 1\}$. Hence W_w defines the ellipsoid which captures the a priori knowledge of the amplitudes of the incoming disturbances and W_z defines the ellipsoids that captures desired amplitudes of the controlled output. Through the use of matrix valued weightings one can hence enforce spatial effects, such as quenching the output error mainly in a certain direction.

Note that $W_z S(P,K) W_w$ is nothing but $S(\tilde{P},K)$ for
$$\begin{pmatrix} \tilde{z} \\ y \end{pmatrix} = \tilde{P} \begin{pmatrix} \tilde{w} \\ u \end{pmatrix} = \begin{pmatrix} W_z P_{11} W_w & W_z P_{12} \\ P_{21} W_w & P_{22} \end{pmatrix} \begin{pmatrix} \tilde{w} \\ u \end{pmatrix}.$$
Instead of first closing the loop and then weighting the controlled system, one can as well first weight the open-loop interconnection and then close the loop.

4.2.2 Frequency Weighted Model Matching

In design, a typical specification is to let one or several transfer matrices in an interconnection come close to an ideal model. Let us suppose that the real-rational proper and stable W_m is an ideal model. Moreover, the controller should render $S(P,K)$ to match this ideal model over certain frequency ranges. With suitable real-rational weightings W_1 and W_2, this amounts to render $\|W_1(i\omega)[S(P,K)(i\omega) - W_m(i\omega)]W_2(i\omega)\| \leq \gamma$ satisfied for all frequencies $\omega \in \mathbb{R} \cup \{\infty\}$ where γ is small. By incorporating the desired bound γ into the weightings (replace W_1 by $\frac{1}{\gamma}W_1$), we arrive at the performance specification
$$\|W_1[S(P,K) - W_m]W_2\|_\infty \leq 1. \tag{94}$$

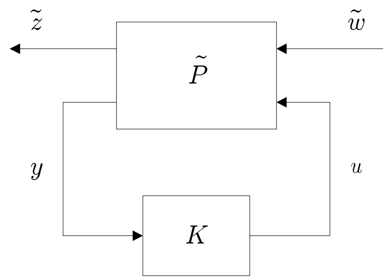


Figure 32: Weighted closed-loop interconnection

To render this inequality satisfied, one tries 'shape the closed-loop frequency response by pushing it towards a desired model'. In this fashion, one can incorporate for each transfer function of $S(P,K)$ both amplitude and phase specifications. If there is no question about which ideal model W_m to take, this is the method of choice.

Again, we observe that this performance specification can be rewritten as
$$\|S(\tilde{P},K)\|_\infty \leq 1$$
where $\tilde{P}$ is defined as
$$\tilde{P} = \begin{pmatrix} W_1[P_{11} - W_m]W_2 & W_1 P_{12} \\ P_{21} W_2 & P_{22} \end{pmatrix}.$$

Remark. Note that the choice $W_m = 0$ of the ideal model leads back to imposing a direct bound on the system gain as discussed before.

In summary, typical signal based performance specifications can be re-formulated as a general frequency weighted model-matching requirement which leads to a *bound on the H_∞-norm of the matrix-weighted closed-loop transfer matrix*.

4.3 The General Paradigm

Starting from
$$\begin{pmatrix} z \\ y \end{pmatrix} = P \begin{pmatrix} w \\ u \end{pmatrix} = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \begin{pmatrix} w \\ u \end{pmatrix}, \tag{95}$$
we have seen how to translate the two most important performance specifications on the closed-loop system
$$S(P,K),$$

weighted gain-bounds and weighted model-matching, into the specification

$$\|S(\tilde{P},K)\|_\infty \leq 1 \tag{96}$$

for the weighted open-loop interconnection

$$\begin{pmatrix} \tilde{z} \\ y \end{pmatrix} = \tilde{P} \begin{pmatrix} \tilde{w} \\ u \end{pmatrix} = \begin{pmatrix} \tilde{P}_{11} & \tilde{P}_{12} \\ \tilde{P}_{21} & P_{22} \end{pmatrix} \begin{pmatrix} \tilde{w} \\ u \end{pmatrix}. \tag{97}$$

So far, we have largely neglected any technical hypotheses on the weighting matrices that are involved in building $\tilde{P}$ from P. In fact, any controller to be considered should stabilize both P and $\tilde{P}$. Hence we have to require that both interconnections define generalized plants, and these are the only properties to be obeyed by any weighting matrices that are incorporated in the interconnection.

Hypothesis 30 *The open-loop interconnections (95) and (97) are generalized plants.*

Note that P and $\tilde{P}$ have the same lower right block P_{22}. This is the reason why any controller that stabilizes P also stabilizes $\tilde{P}$, and vice versa.

Lemma 31 *Let P and $\tilde{P}$ be generalized plants. A controller K stabilizes P if and only if K stabilizes $\tilde{P}$.*

Proof. If K stabilizes P, then K stabilizes P_{22}. Since $\tilde{P}$ is a generalized plant and has P_{22} as its right-lower block, K also stabilizes $\tilde{P}$. The converse follows by interchanging the role of P and $\tilde{P}$.

■

Hence the class of stabilizing controller for P and for $\tilde{P}$ are identical.

From now on we assume that all performance weightings are already incorporated in P. Hence the performance specification is given by $\|S(P,K)\|_\infty \leq 1$.

Remark. In practical controller design, it is often important to keep P and $\tilde{P}$ separated. Indeed, the controller will be *designed* on the basis of $\tilde{P}$ to obey $\|S(\tilde{P},K)\|_\infty \leq 1$, but then it is often much more instructive to directly investigate the unweighted frequency response $\omega \to S(P,K)(i\omega)$ in order to judge whether the designed controller leads to the desired closed-loop specifications.

5 Robust Performance Analysis

5.1 Problem Formulation

To test robust performance, we proceed as for robust stability: We identify the performance signals, we pull out the uncertainties and introduce suitable weightings for the uncertainties such that we arrive at the framework as described in Section 3.5. Moreover, we incorporate in this framework the performance weightings as discussed in Section 4 to reduce the desired performance specification to an H_∞ norm bound on the performance channel. In Figure 33 we have displayed the resulting open-loop interconnection, the interconnection if closing the loop as $u = Ky$, and the controlled interconnection with uncertainty.

We end up with the controlled uncertain system as described by

$$\begin{pmatrix} z_\Delta \\ z \\ y \end{pmatrix} = P \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix} = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix} \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix}, \; u = Ky, \; w_\Delta = \Delta z_\Delta, \; \Delta \in \mathbf{\Delta}.$$

Let us now formulate the precise hypotheses on P, on the uncertainty class Δ, and on the performance specification as follows.

Hypothesis 32

- *P is a generalized plant.*
- *The set of uncertainties is given as*

  $$\mathbf{\Delta} := \{\Delta \in RH_\infty \mid \Delta(i\omega) \in \mathbf{\Delta}_c \;\; \textit{for all} \;\; \omega \in \mathbb{R} \cup \{\infty\}\}$$

  where $\mathbf{\Delta}_c$ is the set of all matrices Δ_c structured as (68) and satisfying $\|\Delta_c\| < 1$.
- *The direct feed-through P_{11} and $\mathbf{\Delta}_c$ are such that*

  $$I - P_{11}(\infty)\Delta_c \;\; \textit{is non-singular for all} \;\; \Delta_c \in \mathbf{\Delta}_c.$$

- *The performance of the system is as desired if the H_∞-norm of the channel $w \to z$ is smaller than one.*

We use the the brief notation

$$P_\Delta = S(\Delta, P) = \begin{pmatrix} P_{22} & P_{23} \\ P_{32} & P_{33} \end{pmatrix} + \begin{pmatrix} P_{21} \\ P_{32} \end{pmatrix} \Delta (I - P_{11}\Delta)^{-1} \begin{pmatrix} P_{12} & P_{13} \end{pmatrix}$$

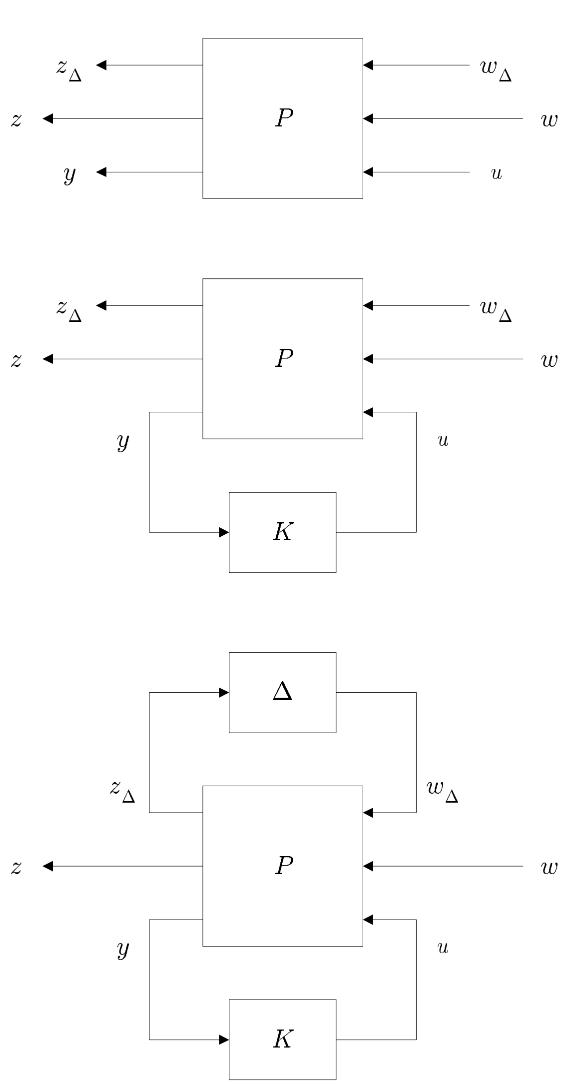


Figure 33: Open-loop interconnection, controlled interconnection, uncertain controlled interconnection.

for the perturbed open-loop interconnection. Then the unperturbed open-loop interconnection is nothing but

$$P_0 = S(0, P) = \begin{pmatrix} P_{22} & P_{23} \\ P_{32} & P_{33} \end{pmatrix}.$$

Suppose that K stabilizes P. Then the perturbed and unperturbed controlled interconnections are described by

$$z = S(P_\Delta, K)w \quad \text{and} \quad z = S(P_0, K)w$$

respectively. If K stabilizes P and if it leads to

$$\|S(P_0, K)\|_\infty \leq 1,$$

we say that K achieves **nominal performance** for P.

Accordingly, we can formulate the corresponding analysis and synthesis problems.

Nominal Performance Analysis Problem
For a given fixed controller K, test whether it achieves nominal performance for P.

Nominal Performance Synthesis Problem
Find a controller K that achieves nominal performance for P.

The analysis problem is very easy to solve: Check whether K stabilizes P, and plot $\omega \to \|S(P_0, K)(i\omega)\|$ in order to verify whether this value remains smaller than 1. Note that H_∞-norm bounds of this sort can be verified much more efficiently on the basis of a state-space test, as will be discussed in Section 6.2.

The synthesis problem amounts to finding a stabilizing controller K for P that renders the H_∞-norm $\|S(P_0, K)\|_\infty$ smaller than 1. This is the celebrated H_∞-control problem and will be discussed in Section 6.4.

The main subject of this section is robust performance analysis. If

$$K \ \text{ stabilizes } \ P_\Delta = S(\Delta, P) \ \text{ and } \ \|S(P_\Delta, K)\|_\infty \leq 1 \ \text{ for all } \ \Delta \in \mathbf{\Delta},$$

we say that

$$K \ \text{ achieves } \textbf{robust performance} \text{ for } \ S(\Delta, P) \ \text{ against } \ \mathbf{\Delta}.$$

Let us again formulate the related analysis and synthesis problems explicitly.

Robust Performance Analysis Problem
For a given fixed controller K, test whether it achieves robust performance for $S(\Delta, P)$ against $\mathbf{\Delta}$.

Robust Performance Synthesis Problem
Find a controller K that achieves robust performance for $S(\Delta, P)$ against $\mathbf{\Delta}$.

5.2 Testing Robust Performance

Let us assume throughout that K stabilizes P what implies that $N := S(P,K)$ is stable. Introduce the partition

$$\begin{pmatrix} z_\Delta \\ z \end{pmatrix} = S(P,K)\begin{pmatrix} w_\Delta \\ w \end{pmatrix} = N\begin{pmatrix} w_\Delta \\ w \end{pmatrix} = \begin{pmatrix} M & N_{12} \\ N_{21} & N_{22} \end{pmatrix}\begin{pmatrix} w_\Delta \\ w \end{pmatrix}.$$

Then we infer

$$S(P_\Delta, K) = S(\Delta, N) = N_{22} + N_{21}\Delta(I - M\Delta)^{-1}N_{12}.$$

Hence, K achieves robust performance if the robust stability condition

$$\mu_{\boldsymbol{\Delta_c}}(M(i\omega)) \leq 1 \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}$$

or equivalently

$$\det(I - M(i\omega)\Delta_c) \quad \text{for all} \quad \Delta_c \in \boldsymbol{\Delta_c},\ \omega \in \mathbb{R}\cup\{\infty\}$$

and the performance bound

$$\|N_{22} + N_{21}\Delta(I - M\Delta)^{-1}N_{12}\| \leq 1 \quad \text{for all} \quad \Delta \in \boldsymbol{\Delta}$$

or equivalently

$$\|N_{22}(i\omega) + N_{21}(i\omega)\Delta(i\omega)(I - M(i\omega)\Delta(i\omega))^{-1}N_{12}(i\omega)\| \leq 1 \quad \text{for all} \quad \Delta \in \boldsymbol{\Delta},\ \omega \in \mathbb{R}\cup\{\infty\}$$

or equivalently

$$\|N_{22}(i\omega) + N_{21}(i\omega)\Delta_c(I - M(i\omega)\Delta_c)^{-1}N_{12}(i\omega)\| \leq 1 \quad \text{for all} \quad \Delta_c \in \boldsymbol{\Delta_c},\ \omega \in \mathbb{R}\cup\{\infty\}$$

hold true.

Similarly as for robust stability, for a fixed frequency we arrive at a problem in linear algebra which is treated in the next section.

5.3 The Main Loop Theorem

Here is the linear algebra problem that needs to be investigated: Given the set $\boldsymbol{\Delta_c}$ and the complex matrix

$$N_c = \begin{pmatrix} M_c & N_{12} \\ N_{21} & N_{22} \end{pmatrix} \quad \text{with} \quad N_{22} \quad \text{of size} \quad q_2 \times p_2,$$

test whether the following two conditions hold:

$$\det(I - M_c\Delta_c) \neq 0 \quad \text{and} \quad \|N_{22} + N_{21}\Delta_c(I - M_c\Delta_c)^{-1}N_{12}\| \leq 1 \quad \text{for all} \quad \Delta_c \in \boldsymbol{\Delta_c}.$$

Here is the fundamental **trick** to solve this problem: The condition $\|N_{22} + N_{21}\Delta_c(I - M_c\Delta_c)^{-1}N_{12}\| = \|S(\Delta_c, N_c)\| \leq 1$ is *equivalent* to

$$\det(I - S(\Delta_c, N_c)\widehat{\Delta}_c) \neq 0 \quad \text{for all} \quad \widehat{\Delta}_c \in \mathbb{C}^{p_2\times q_2},\ \|\widehat{\Delta}_c\| < 1.$$

We just need to recall that the SSV of a complex matrix equals its norm if the uncertainty structure just consists of one full block.

Let us hence define

$$\widehat{\boldsymbol{\Delta}}_{\boldsymbol{c}} = \{\widehat{\Delta}_c \in \mathbb{C}^{p_2\times q_2} \mid \|\widehat{\Delta}_c\| < 1\}.$$

We infer that, for all $\Delta_c \in \boldsymbol{\Delta_c}$,

$$\det(I - M_c\Delta_c) \neq 0 \quad \text{and} \quad \|S(\Delta_c, N_c)\| \leq 1$$

if and only if, for all $\Delta_c \in \boldsymbol{\Delta_c}$ and $\widehat{\Delta}_c \in \widehat{\boldsymbol{\Delta}}_{\boldsymbol{c}}$,

$$\det(I - M_c\Delta_c) \neq 0 \quad \text{and} \quad \det(I - S(\Delta_c, N_c)\widehat{\Delta}_c) \neq 0$$

if and only if, for all $\Delta_c \in \boldsymbol{\Delta_c}$ and $\widehat{\Delta}_c \in \widehat{\boldsymbol{\Delta}}_{\boldsymbol{c}}$,

$$\det\begin{pmatrix} I - M_c\Delta_c & -N_{12}\widehat{\Delta}_c \\ -N_{21}\Delta_c & I - N_{22}\widehat{\Delta}_c \end{pmatrix} \neq 0$$

if and only if, for all $\Delta_c \in \boldsymbol{\Delta_c}$ and $\widehat{\Delta}_c \in \widehat{\boldsymbol{\Delta}}_{\boldsymbol{c}}$,

$$\det\left(I - \begin{pmatrix} M_c & N_{12} \\ N_{21} & N_{22} \end{pmatrix}\begin{pmatrix} \Delta_c & 0 \\ 0 & \widehat{\Delta}_c \end{pmatrix}\right) \neq 0.$$

Note that we have used in these derivation the following simple consequence of the well-known Schur formula for the determinant:

$$\det(I - S(\Delta_c, N_c)\widehat{\Delta}_c) = \det(I - [N_{22} + N_{21}\Delta_c(I - M_c\Delta_c)^{-1}N_{12}]\widehat{\Delta}_c) =$$
$$= \det([I - N_{22}\widehat{\Delta}_c] - [N_{21}\Delta_c](I - M_c\Delta_c)^{-1}[N_{12}\widehat{\Delta}_c]) = \det\begin{pmatrix} I - M_c\Delta_c & -N_{12}\widehat{\Delta}_c \\ -N_{21}\Delta_c & I - N_{22}\widehat{\Delta}_c \end{pmatrix}.$$

This motivates to introduce the set of **extended** matrices

$$\boldsymbol{\Delta_e} := \left\{\begin{pmatrix} \Delta_c & 0 \\ 0 & \widehat{\Delta}_c \end{pmatrix} :\ \Delta_c \in \boldsymbol{\Delta_c},\ \widehat{\Delta}_c \in \mathbb{C}^{p_2\times q_2},\ \|\widehat{\Delta}_c\| < 1\right\}$$

which consists of adjoining to the original structure one full block. We have proved the following **Main Loop Theorem**.

Theorem 33 *The two conditions*

$$\mu_{\mathbf{\Delta_c}}(M_c) \leq 1 \quad \textit{and} \quad \|S(\Delta_c, N_c)\| \leq 1 \quad \textit{for all} \quad \Delta_c \in \mathbf{\Delta_c}$$

are equivalent to

$$\mu_{\mathbf{\Delta}_e}(N_c) \leq 1.$$

This result reduces the desired condition to just another SSV-test on the matrix N_c with respect to the extended structure $\mathbf{\Delta_e}$.

Typically, a computation of $\mu_{\mathbf{\Delta}_e}(N_c)$ will lead to an inequality

$$\mu_{\mathbf{\Delta}_e}(N_c) \leq \gamma$$

with a bound $\gamma > 0$ different from one. The consequences that can then be drawn can be easily obtained by re-scaling. In fact, this inequality leads to

$$\mu_{\mathbf{\Delta}_e}(\frac{1}{\gamma}N_c) \leq 1.$$

This is equivalent to

$$\mu_{\mathbf{\Delta_c}}(\frac{1}{\gamma}M_c) \leq 1$$

and

$$\|\frac{1}{\gamma}N_{22} + \frac{1}{\gamma}N_{21}\Delta_c(I - \frac{1}{\gamma}M_c\Delta_c)^{-1}\frac{1}{\gamma}N_{12}\| \leq 1 \quad \text{for all} \quad \Delta_c \in \mathbf{\Delta_c}.$$

Both conditions are clearly nothing but

$$\mu_{\mathbf{\Delta_c}}(M_c) \leq \gamma$$

and

$$\|N_{22} + N_{21}[\frac{1}{\gamma}\Delta_c](I - M_c[\frac{1}{\gamma}\Delta_c])^{-1}N_{12}\| \leq \gamma \quad \text{for all} \quad \Delta_c \in \mathbf{\Delta_c}.$$

We arrive at

$$\det(I - M_c\Delta_c) \neq 0 \quad \text{for all} \quad \Delta_c \in \frac{1}{\gamma}\mathbf{\Delta_c}$$

and

$$\|N_{22} + N_{21}\Delta_c(I - M_c\Delta_c)^{-1}N_{12}\| \leq \gamma \quad \text{for all} \quad \Delta_c \in \frac{1}{\gamma}\mathbf{\Delta_c}.$$

Hence a general bound γ different from one leads to non-singularity conditions and a performance bound γ for the class of complex matrices $\frac{1}{\gamma}\mathbf{\Delta_c}$.

A more general scaling result that is proved analogously can be formulated as follows.

Lemma 34 *The scaled SSV-inequality*

$$\mu_{\mathbf{\Delta_e}}\left(N_c\begin{pmatrix}\gamma_1 I & 0\\ 0 & \gamma_2 I\end{pmatrix}\right) \leq \gamma_3$$

is equivalent to

$$\det(I - M_c\Delta_c) \neq 0 \quad \textit{for all} \quad \Delta_c \in \frac{\gamma_1}{\gamma_3}\mathbf{\Delta_c}$$

and

$$\|S(\Delta_c, N_c)\| \leq \frac{\gamma_3}{\gamma_2} \quad \textit{for all} \quad \Delta_c \in \frac{\gamma_1}{\gamma_3}\mathbf{\Delta_c}.$$

This result allows to investigate the trade-off between the size of the uncertainty and the worst possible norm $\|S(\Delta_c, N_c)\|$ by varying γ_1, γ_2 and computing the SSV giving the bound γ_3.

Note that we can as well draw conclusions of the following sort: If one wishes to guarantee

$$\det(I - M_c\Delta_c) \neq 0 \quad \text{and} \quad \|S(\Delta_c, N_c)\| \leq \beta \quad \text{for all} \quad \Delta_c \in \alpha\mathbf{\Delta_c}$$

for some bounds $\alpha > 0$, $\beta > 0$, one needs to perform the SSV-test

$$\mu_{\mathbf{\Delta_e}}\left(N_c\begin{pmatrix}\alpha I & 0\\ 0 & \frac{1}{\beta}I\end{pmatrix}\right) \leq 1.$$

5.4 The Main Robust Stability and Robust Performance Test

If we combine the findings of Section (5.2) with the main loop theorem, we obtain the following result.

Theorem 35 *Let* $N = \begin{pmatrix}M & N_{12}\\ N_{21} & N_{22}\end{pmatrix}$ *be a proper and stable transfer matrix. For all* $\Delta \in \mathbf{\Delta}$,

$$(I - M\Delta)^{-1} \in RH_\infty \quad \textit{and} \quad \|S(\Delta, N)\|_\infty \leq 1$$

if and only if

$$\mu_{\mathbf{\Delta_e}}(N(i\omega)) \leq 1 \quad \textit{for all} \quad \omega \in \mathbb{R}\cup\{\infty\}.$$

Combining all the insights we have gained so far leads us to the most fundamental result in SSV-theory, the test of robust stability and robust performance against structured uncertainties.

Corollary 36 *If K stabilizes P, and if*

$$\mu_{\mathbf{\Delta_e}}(N(i\omega)) \leq 1 \quad \textit{for all} \quad \omega \in \mathbb{R}\cup\{\infty\},$$

then K achieves robust performance for $S(\Delta, P)$ against all $\Delta \in \mathbf{\Delta}$.

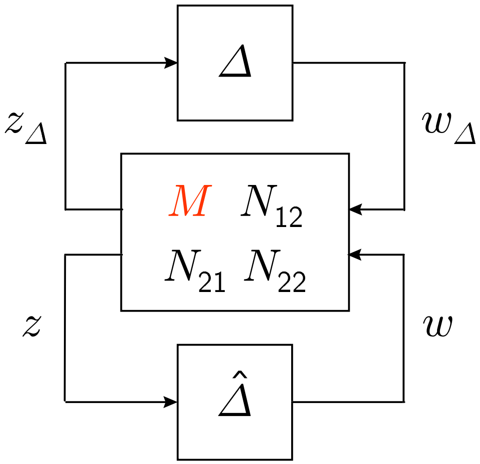


Figure 34: Equivalent Robust Stability Test

At the outset, it looks more complicated to test robust performance if compared to robust stability. However, the main loop theorem implies that the test of robust performance is just another SSV test with respect to the extended block structure $\boldsymbol{\Delta_e}$.

Accidentally (and with no really deep consequence), the SSV-test for robust performance can be viewed as a robust stability test for the interconnection displayed in Figure 34.

5.5 Summary

Suppose that K stabilizes the generalized plant P and suppose that the controlled uncertain system is described as

$$\begin{pmatrix} z_\Delta \\ z \end{pmatrix} = S(P,K)\begin{pmatrix} w_\Delta \\ w \end{pmatrix} = N\begin{pmatrix} w_\Delta \\ w \end{pmatrix} = \begin{pmatrix} M & N_{12} \\ N_{21} & N_{22} \end{pmatrix}\begin{pmatrix} w_\Delta \\ w \end{pmatrix}, \quad w_\Delta = \Delta z_\Delta$$

with proper and stable Δ satisfying

$$\Delta(i\omega) \in \boldsymbol{\Delta_c} \ \text{ for all } \ \omega \in \mathbb{R}\cup\{\infty\}.$$

Then the controller K achieves

- Robust stability if

$$\mu_{\boldsymbol{\Delta_c}}(M(i\omega)) \le 1 \ \text{ for all } \ \omega \in \mathbb{R}\cup\{\infty\}.$$

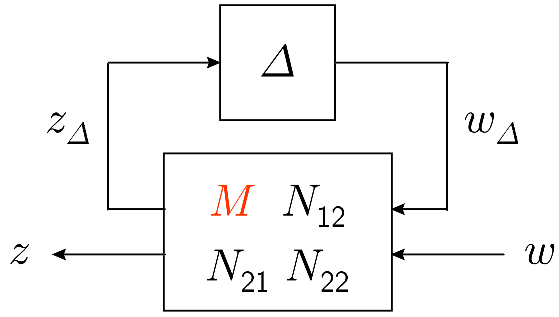


Figure 35: Summary

- Nominal performance if

$$\|N_{22}(i\omega)\| \le 1 \ \text{ for all } \ \omega \in \mathbb{R}\cup\{\infty\}.$$

- Robust performance if

$$\mu_{\boldsymbol{\Delta_e}}(N(i\omega)) \le 1 \ \text{ for all } \ \omega \in \mathbb{R}\cup\{\infty\}.$$

In pictures, this can be summarized as follows. Robust stability is guaranteed by an SSV-test on left-upper block M of $N = S(P,K)$, nominal performance is guaranteed by an SV-test on the right-lower block N_{22} of $N = S(P,K)$, and robust performance is guaranteed by an SSV-test on the whole $N = S(P,K)$ with respect to the extended block structure.

5.6 An Example

Suppose some controlled system is described with

$$N(s) = \left(\begin{array}{ccc|c} \frac{1}{2s+1} & 1 & \frac{s-2}{2s+4} & \frac{s-0.1}{s+1} \\ -1 & \frac{s}{s^2+s+1} & \frac{1}{(s+1)^2} & 0.1 \\ \frac{3s}{s+5} & \frac{-1}{4s+1} & 1 & \frac{10}{s+4} \\ \hline \frac{1}{s+2} & \frac{0.1}{s^2+s+1} & \frac{s-1}{s+1} & 1 \end{array}\right).$$

Let $\boldsymbol{\Delta_c}$ be the set of Δ_c with $\|\Delta_c\| < 1$ and

$$\Delta_c = \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{pmatrix}, \quad \Delta_1 \in \mathbb{C}^{2\times 2}, \quad \Delta_2 \in \mathbb{C}.$$

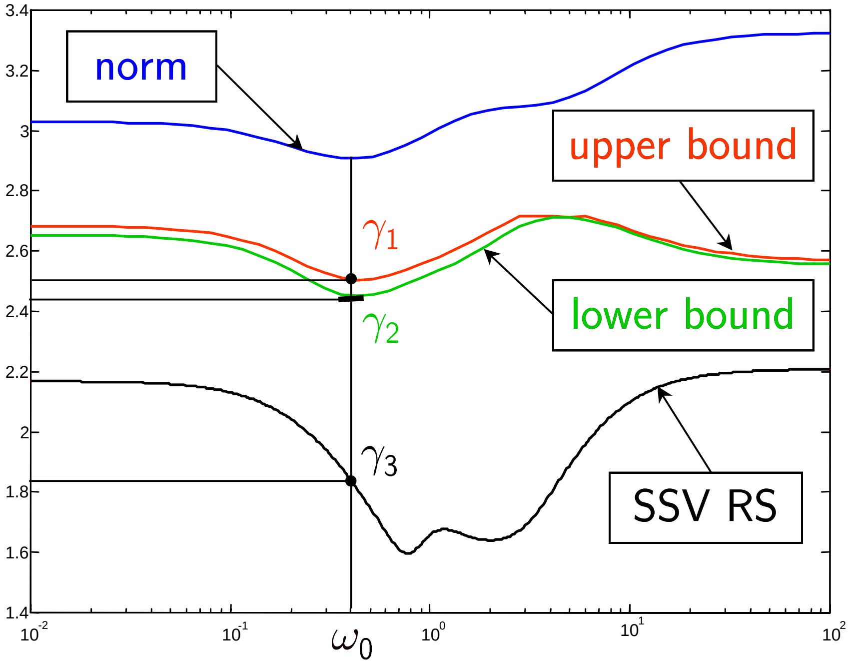


Figure 36: Norm of N, upper and lower bound on SSV of N, SSV of M.

The extended set $\mathbf{\Delta_e}$ consists of all Δ_e with $\|\Delta_e\| < 1$ and

$$\Delta_e = \left(\begin{array}{cc|c} \Delta_1 & 0 & 0 \\ 0 & \Delta_2 & 0 \\ \hline 0 & 0 & \hat{\Delta} \end{array}\right), \ \Delta_1 \in \mathbb{C}^{2\times 2}, \ \Delta_2 \in \mathbb{C}, \ \hat{\Delta} \in \mathbb{C}.$$

To test robust stability, we plot $\omega \to \mu_{\mathbf{\Delta_c}}(M(i\omega))$, to test nominal performance, we plot $\omega \to \|N_{22}(i\omega)\|$, and the robust performance test requires to plot $\omega \to \mu_{\mathbf{\Delta_e}}(N(i\omega))$.

Let us first look at a frequency-by-frequency interpretation of the SSV plot of N with respect to the extended structure (Figure 36).

With the upper bound, we infer $\mu_{\mathbf{\Delta}_e}(N(i\omega_0)) \le \gamma_1$ what implies

$$\|S(\Delta_c, N(i\omega_0))\| \le \gamma_1 \ \text{ for all } \ \Delta_c \in \frac{1}{\gamma_1}\mathbf{\Delta_c}.$$

At the frequency $i\omega_0$, one has a guaranteed performance level γ_1 for the uncertainty set $\frac{1}{\gamma_1}\mathbf{\Delta_c}$.

With the lower bound, we infer $\mu_{\mathbf{\Delta}_e}(N(i\omega_0)) > \gamma_2$. This implies that

$$\det(I - M(i\omega_0)\Delta_c) = 0 \ \text{ for some } \ \Delta_c \in \frac{1}{\gamma_2}\mathbf{\Delta_c}$$

or

$$\|S(\Delta_c, N(i\omega_0))\| > \gamma_2 \ \text{ for some } \ \Delta_c \in \frac{1}{\gamma_2}\mathbf{\Delta_c}.$$

We can exploit the knowledge of the SSV curve for robust stability to exclude the first property due to $\gamma_3 < \gamma_2$. (Provide all arguments!) Hence, at this frequency we can violate the performance bound γ_2 by some matrix in the complex uncertainty set $\frac{1}{\gamma_2}\mathbf{\Delta_c}$.

Let us now interpret the upper and lower bound plots of the SSV of N for all frequencies (Figure 37).

Since the upper bound is not larger than 2.72 for all frequencies, we infer that

$$\|S(\Delta, N)\|_\infty \le 2.72 \ \text{ for all } \ \Delta \in \frac{1}{2.72}\mathbf{\Delta} \approx 0.367\mathbf{\Delta}$$

Since the lower bound is larger that 2.71 for some frequency, we infer that either

$$(I - M\Delta)^{-1} \ \text{ is unstable for some } \ \Delta \in \frac{1}{2.71}\mathbf{\Delta} \approx 0.369\mathbf{\Delta}$$

or that

$$\|S(\Delta, N)\|_\infty > 2.71 \ \text{ for some } \ \Delta \in \frac{1}{2.71}\mathbf{\Delta} \approx 0.369\mathbf{\Delta}.$$

The first property can be certainly excluded since Figure 36 reveals that $\mu_{\mathbf{\Delta_c}}(M(i\omega)) \le 2.7$ for all $\omega \in \mathbb{R} \cup \{\infty\}$.

Let us finally ask ourselves for which size of the uncertainties we can guarantee a robust performance level of 2.

For that purpose let us plot (Figure 38) the SSV of

$$\begin{pmatrix} M & N_{12} \\ N_{21} & N_{22} \end{pmatrix} \begin{pmatrix} 0.5I & 0 \\ 0 & I \end{pmatrix} = \begin{pmatrix} 0.5M & N_{12} \\ 0.5N_{21} & N_{22} \end{pmatrix}.$$

Since the upper bound is not larger than 1.92 for all frequencies, we conclude

$$\|S(\Delta, N)\|_\infty \le 1.92 \ \text{ for all } \ \Delta \in \frac{0.5}{1.92}\mathbf{\Delta} \approx 0.26\mathbf{\Delta}.$$

Exercises

1) Look at a standard tracking configuration for a system $G(I + \Delta W)$ with input multiplicative uncertainty and a controller K that is described as

$$y = G(I + \Delta W)u, \ \ \|\Delta\|_\infty < 1, \ \ u = K(r - y).$$

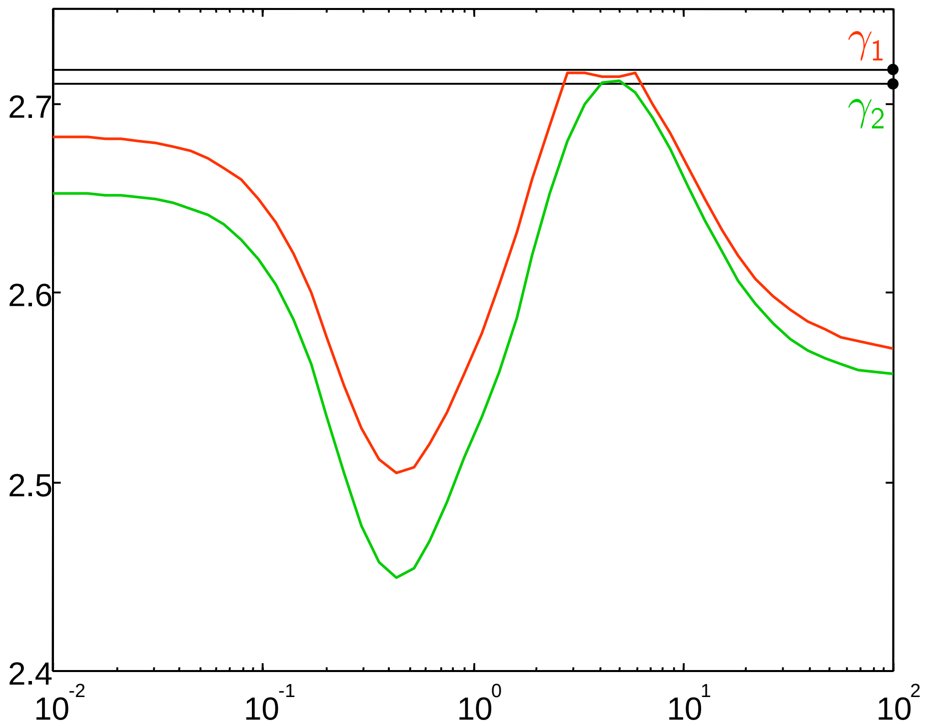


Figure 37: Upper and lower bound on SSV of N

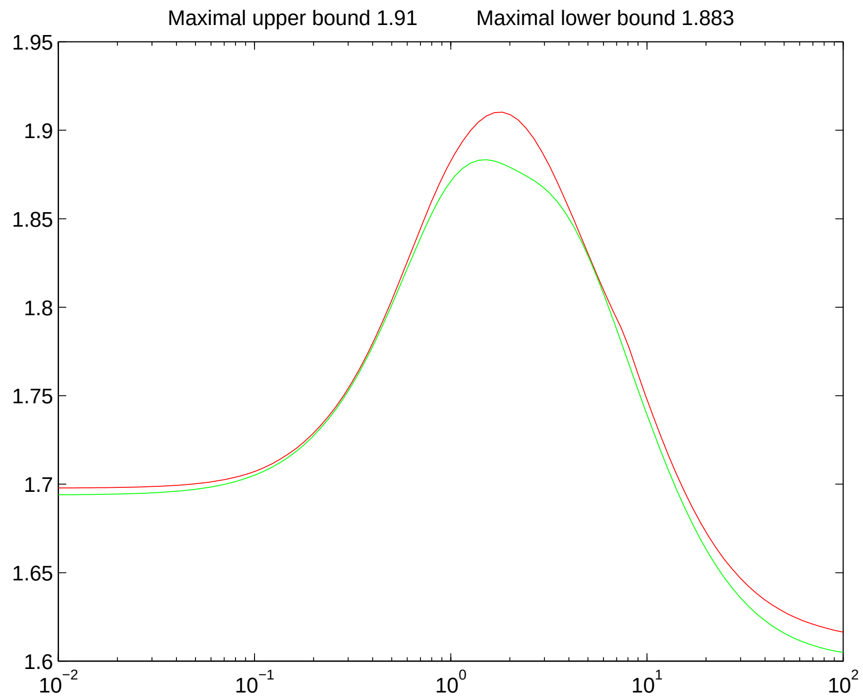


Figure 38: Upper and lower bound of SSV of scaled N.

The performance is as desired if the transfer matrix from references r to weighted error $V(r-y)$ has an H_∞-norm smaller than 1. Here G, K, Δ, V, W are LTI system and the latter three are stable.

a) Set up the generalized plant. Show that the weighted closed-loop transfer matrix has the structure $\begin{pmatrix} -M_1G & M_1 \\ -M_2G & M_2 \end{pmatrix}$ by computing M_1 and M_2. Formulate the μ-tests for robust stability, nominal performance and robust performance.

b) Now let all LTI systems G, K, Δ, V, W be SISO and define $S = (I + KG)^{-1}$, $T = (I + KG)^{-1}KG$. Show that K achieves robust performance iff

$$|V(i\omega)S(i\omega)| + |W(i\omega)T(i\omega)| \le 1 \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}. \tag{98}$$

(Hint: This is a SSV-problem for rank one matrices!) If a controller achieves robust stability and nominal performance, what can you conclude about robust performance? How would you design robustly performing controllers by solving an H_∞ problem?

c) Let's return to the MIMO case. Suppose that G is square and has a proper inverse G^{-1}. Show that the SSV for the robust performance test is (at frequency ω) bounded from above by

$$\|G(i\omega)\|\|G(i\omega)^{-1}\|\|M_1(i\omega)G(i\omega)\| + \|M_2(i\omega)\|.$$

If a controller achieves robust stability and nominal performance, what can you now conclude for robust performance? Discuss the role of the plant condition number $\|G(i\omega)\|\|G(i\omega)^{-1}\|$!

d) For any γ, construct complex matrices M_1, M_2 and G such that $\|M_1G\| \le 1$, $\|M_2\| \le 1$, but $\mu(\begin{pmatrix} -M_1G & M_1 \\ -M_2G & M_2 \end{pmatrix}) \ge \gamma$. Here, μ is computed with respect to an uncertainty structure with two full blocks. What does this example show? Hint: Construct the example such that $\|G\|\|G^{-1}\|$ is large.

2) Consider the block diagram in Figure 39 where G and H are described by the transfer functions

$$G(s) = \frac{1}{(0.05s+1)^2} \quad \text{and} \quad H(s) = \frac{200}{10s+1}.$$

The magnitude of the uncertainty is not larger than 1% at low frequencies, it does not exceed 100% at 30 rad/sec, and for larger frequencies it increases by 40 db per decade.

a) Design a weighting W that captures the specifications on the uncertainty, and build the open-loop interconnection that corresponds to the block diagram.

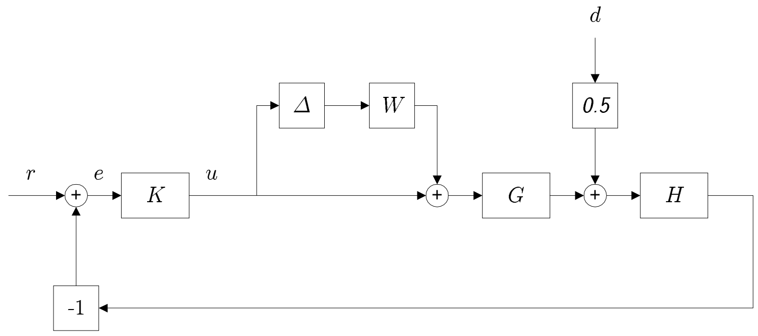


Figure 39: Tracking interconnection for exercise 2).

b) Consider static gain controllers $u = Ky$ with K in the interval $[1, 3]$. Which controllers stabilize the interconnection? What do you observe if you increase the gain of the controller for the tracking and disturbance suppression behavior of the controlled system? What is the effect on robust stability with respect to the given class of uncertainties?

c) With performance weightings of the form

$$a * \frac{s/b + 1}{s/c + 1}, \quad a, b, c \text{ real},$$

for the channels $d \to e$ and $r \to e$, design a controller with the H_∞ algorithm to achieve the following performance specifications:

i. Disturbance attenuation of a factor 100 up to 0.1 rad/sec.

ii. Zero steady state response of tracking error (smaller than 10^{-4}) for a references step input.

iii. Bandwidth (frequency where magnitude plot first crosses $1/\sqrt{2} \approx -3\,\text{dB}$ from below) from reference input to tracking error between 10 rad/sec and 20 rad/sec.

iv. Overshoot of tracking error is less than 7% in response to step reference.

Provide magnitude plots of all relevant transfer functions and discuss the results.

d) For the design you performed in 2c), what is the maximal size γ_* of uncertainties that do not destabilize the controlled system (stability margin). Compute a destabilizing perturbation of size larger than γ_*.

e) Extend the H_∞ specification of 2c) by the uncertainty channel and perform a new design with the same performance weightings. To what amount do you need to give up the specifications to guarantee robust stability? If you compare the two designs, what do you conclude about performing a nominal design without taking robustness specifications into account?

6 Synthesis of H_∞ Controllers

In this section we provide a self-contained and elementary route to solve the H_∞-problem. We first describe how to bound or compute the H_∞-norm of stable transfer matrix in terms of a suitable Hamiltonian matrix. Then we present a classical result, the so-called Bounded Real Lemma, that characterizes (in terms of a state-space realization) when a given transfer matrix has an H_∞-norm which is strictly smaller than a number γ. On the basis of the bounded real lemma, we will derive the celebrated solution of the H_∞ control problem in terms of two algebraic Riccati equations and a coupling condition on their solutions. We sacrifice generality to render most of the derivations as elementary as possible.

6.1 The Algebraic Riccati Equation and Inequality

The basis for our approach to the H_∞ problem is the algebraic Riccati equation or inequality. It occurs in proving the Bounded Real Lemma and it comes back in getting to the Riccati solution of the H_∞ problem.

Given symmetric matrices $R \geq 0$ and Q, we consider the strict algebraic Riccati inequality

$$A^T X + XA + XRX + Q < 0 \quad (ARI)$$

and the corresponding algebraic Riccati equation

$$A^T X + XA + XRX + Q = 0. \quad (ARE)$$

Note that X is always assumed to be real symmetric or complex Hermitian. Moreover, we allow for a general indefinite Q.

It will turn out that the solutions of the ARE with the property that $A + RX$ has all its eigenvalues in $\mathbb{C}^-$ or in $\mathbb{C}^+$ play a special role. Such a solutions are called *stabilizing* or *anti-stabilizing*. If (A, R) is controllable, we can summarize the results in this section as follows: The ARE or ARI have solutions if and only if a certain Hamiltonian matrix defined through A, R, Q has no eigenvalues on the imaginary axis. If the ARI or the ARE has a solution, there exists a unique stabilizing solution X_- and a unique anti-stabilizing solution X_+ of the ARE, and all other solutions X of the ARE or ARI satisfy $X_- \leq X \leq X_+$. Here is the main result whose proof is given in the appendix.

Theorem 37 *Suppose that Q is symmetric, that R is positive semi-definite, and that (A, R) is controllable. Define the Hamiltonian matrix*

$$H := \begin{pmatrix} A & R \\ -Q & -A^T \end{pmatrix}.$$

Then the following statements are equivalent:

(a) H has no eigenvalues on the imaginary axis.

(b) $A^T X + XA + XRX + Q = 0$ has a (unique) stabilizing solution X_-.

(c) $A^T X + XA + XRX + Q = 0$ has a (unique) anti-stabilizing solution X_+.

(d) $A^T X + XA + XRX + Q < 0$ has a symmetric solution X.

If one and hence all of these conditions are satisfied, then

$$\text{any solution } X \text{ of the ARE or ARI satisfies } X_- \leq X \leq X_+.$$

We conclude that the stabilizing solution is the smallest among all solutions of the ARE and the anti-stabilizing solution is the largest.

Remark. Note that H has a specific structure: The off-diagonal blocks are symmetric, and the second block on the diagonal results from the first by reversing the sign and transposing. Any such matrix is called a *Hamiltonian* matrix.

If (A, R) is only stabilizable, X_+ does, in general, not exist. All other statements, however, remain true. Here is the precise results that is proved in the appendix.

Theorem 38 *Suppose that all hypothesis in Theorem 37 hold true but that (A, R) is only stabilizable. Then the following statements are equivalent:*

(a) H has no eigenvalues on the imaginary axis.

(b) $A^T X + XA + XRX + Q = 0$ has a (unique) stabilizing solution X_-.

(c) $A^T X + XA + XRX + Q < 0$ has a symmetric solution X.

If one and hence all of these conditions are satisfied, then

$$\text{any solution } X \text{ of the ARE or ARI satisfies } X_- \leq X.$$

The proof reveals that it is not difficult to construct a solution once one has verified that H has no eigenvalues on the imaginary axis. We sketch the typical algorithm that is used in software packages like Matlab.

Indeed, let H have no eigenvalues in $\mathbb{C}^0$. Then it has n eigenvalues in $\mathbb{C}^-$ and n eigenvalues in $\mathbb{C}^+$ respectively. We can perform a Schur decomposition to obtain a unitary matrix T with

$$T^* H T = \begin{pmatrix} M_{11} & M_{12} \\ 0 & M_{22} \end{pmatrix}$$

where M_{11} of size $n \times n$ is stable and M_{22} of size $n \times n$ is anti-stable. Partition T into four $n \times n$ blocks as

$$T = \begin{pmatrix} U & * \\ V & * \end{pmatrix}.$$

The proof of Theorem 38 reveals that U is non-singular, and that the stabilizing solution of the ARE is given by

$$X = VU^{-1}.$$

If the Schur decomposition is chosen such that M_{11} has all its eigenvalues in $\mathbb{C}^+$ and M_{22} is stable, then the same procedure leads to the anti-stabilizing solution.

If Q is negative semi-definite, the eigenvalues of the Hamiltonian matrix on the imaginary axis are just given by uncontrollable or unobservable modes. The exact statement reads as follows.

Lemma 39 *If $R \geq 0$ and $Q \leq 0$ then*

$$\lambda \in \mathbb{C}^0 \ \text{ is an eigenvalue of } \ H = \begin{pmatrix} A & R \\ -Q & -A^T \end{pmatrix}$$

if and only if

$$\lambda \in \mathbb{C}^0 \text{ is an uncontrollable mode of } (A,R) \text{ or an unobservable mode of } (A,Q).$$

Proof. $i\omega$ is an eigenvalue of H if and only if

$$H - i\omega I = \begin{pmatrix} A - i\omega I & R \\ -Q & -A^T - i\omega I \end{pmatrix} = \begin{pmatrix} A - i\omega I & R \\ -Q & -(A - i\omega I)^* \end{pmatrix}$$

is singular.

If $i\omega$ is an uncontrollable mode of (A,R), then $\begin{pmatrix} A - i\omega I & R \end{pmatrix}$ does not have full row rank; if it is an unobservable mode of (A,Q), then $\begin{pmatrix} A - i\omega I \\ -Q \end{pmatrix}$ does not have full column rank; in both cases we infer that $H - i\omega I$ is singular.

Conversely, suppose that $H - i\omega I$ is singular. Then there exist x and y, not both zero, with

$$\begin{pmatrix} A - i\omega I & R \\ -Q & -(A - i\omega)^* \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = 0.$$

This implies

$$(A - i\omega I)x + Ry = 0 \ \text{ and } \ -Qx - (A - i\omega I)^* y = 0. \tag{99}$$

Left-multiply the first equation with y^* and the second equation with x^* to get

$$\begin{aligned} y^*(A - i\omega I)x + y^*Ry &= 0 \\ -x^*Qx - y^*(A - i\omega I)x = -x^*Qx - x^*(A - i\omega I)^* y &= 0. \end{aligned}$$

This leads to

$$y^*Ry = x^*Qx.$$

Since $R \geq 0$ and $Q \leq 0$, we infer $Qx = 0$ and $Ry = 0$. Then (99) implies $(A - i\omega I)x = 0$ and $(A - i\omega I)^* y = 0$. If $x \neq 0$, $i\omega$ is an unobservable mode of (A,Q), if $y \neq 0$, it is an uncontrollable mode of (A,R).

■

Hence, if (A,R) is stabilizable, if $Q \leq 0$, and if (A,Q) does not have unobservable modes on the imaginary axis, the corresponding Hamiltonian matrix does not have eigenvalues on the imaginary axis such that the underlying ARE has a stabilizing solution and the ARI is solvable as well.

6.2 Computation of H_∞ Norms

Consider the strictly proper transfer matrix M with realization

$$M(s) = C(sI - A)^{-1}B$$

where A is stable. Recall that the H_∞-norm of M is defined by

$$\|M\|_\infty := \sup_{\omega \in \mathbb{R}} \|M(i\omega)\|.$$

In general it is not advisable to compute the H_∞-norm of M by solving this optimization problem. In this section we clarify how one can arrive at a more efficient computation of this norm by looking, instead, at the following problem: Characterize in terms of A, B, C whether the inequality

$$\|M\|_\infty < 1 \tag{100}$$

is true or not. Just by the definition of the H_∞ norm, (100) is equivalent to

$$\|M(i\omega)\| < 1 \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\}.$$

Since M is strictly proper, this inequality is always true for $\omega = \infty$. Hence it remains to consider

$$\|M(i\omega)\| < 1 \ \text{ for all } \ \omega \in \mathbb{R}. \tag{101}$$

If follows by continuity that this is true if and only if

$$\det(M(i\omega)^* M(i\omega) - I) \neq 0 \ \text{ for all } \ \omega \in \mathbb{R}. \tag{102}$$

Indeed, $\|M(i\omega)\| < 1$ implies that the largest eigenvalue of $M(i\omega)^*M(i\omega)$ is smaller than 1 such that $\det(M(i\omega)^*M(i\omega) - I) \neq 0$. Hence (101) implies (102). Conversely, suppose (101) is not true. Then there exists a $\omega_0 \in \mathbb{R}$ for which $\|M(i\omega_0)\| \geq 1$. Consider the real-valued function $\omega \to \|M(i\omega)\|$ which is continuous (as the norm of a rational function without pole). Due to $\lim_{\omega\to\infty} \|M(i\omega)\| = 0$, there exists an $\omega_1 > \omega_0$ with $\|M(i\omega_1)\| < 1$. By the intermediate value theorem, there exists some point in the interval $\omega_* \in [\omega_0, \omega_1]$ with $\|M(i\omega_*)\| = 1$. This implies $\det(M(i\omega_*)^*M(i\omega_*) - I) = 0$ such that (102) is not true.

Since M is real rational we have $M(i\omega)^* = M(-i\omega)^T$. If we hence define

$$G(s) := M^T(-s)M(s) - I,$$

(102) is the same as

$$\det(G(i\omega)) \neq 0 \ \text{ for all } \ \omega \in \mathbb{R}.$$

Since

$$M(-s)^T = [C(-sI - A)^{-1}B]^T = B^T(-(sI + A^T)^{-1})C^T = B^T(sI - (-A^T))^{-1}(-C^T),$$

one easily obtains a state-space realization of G as

$$G = \left[\begin{array}{cc|c} A & 0 & B \\ -C^TC & -A^T & 0 \\ \hline 0 & B^T & -I \end{array}\right].$$

Let us now apply the Schur formula[3] to this realization for $s = i\omega$. If we introduce the abbreviation

$$H := \begin{pmatrix} A & 0 \\ -C^TC & -A^T \end{pmatrix} - \begin{pmatrix} B \\ 0 \end{pmatrix} (-I)^{-1} \begin{pmatrix} 0 & B^T \end{pmatrix} = \begin{pmatrix} A & BB^T \\ -C^TC & -A^T \end{pmatrix}, \tag{103}$$

we arrive at

$$\det(G(i\omega)) = \frac{\det(-I)}{\det(i\omega I - A)\det(i\omega I + A^T)} \det(i\omega I - H).$$

Now recall that A is stable such that both $\det(i\omega I - A)$ and $\det(i\omega I + A^T)$ do not vanish. Hence

$$\det(G(i\omega)) = 0 \ \text{ if and only if } \ i\omega \ \text{ is an eigenvalue of } \ H.$$

Hence (102) is equivalent to the fact that H does not have eigenvalues on the imaginary axis. This leads to the following characterization of the H_∞-norm bound $\|M\|_\infty < 1$.

Theorem 40 *$\|M\|_\infty < 1$ if and only if $\begin{pmatrix} A & BB^T \\ -C^TC & -A^T \end{pmatrix}$ has no eigenvalues on the imaginary axis.*

[3] If D is nonsingular, $\det(C(sI - A)^{-1}B + D) = \frac{\det(D)}{\det(sI-A)} \det(sI - (A - BD^{-1}C))$

To compute $\|M\|_\infty$, we actually need to verify whether, for any given positive number γ,

$$\|C(sI - A)^{-1}B\|_\infty < \gamma \tag{104}$$

is valid or not. Indeed, the inequality is the same as

$$\| \left[\frac{1}{\gamma}C\right] (sI - A)^{-1}B\|_\infty < 1 \ \text{ or } \ \|C(sI - A)^{-1} \left[\frac{1}{\gamma}B\right] \|_\infty < 1 \tag{105}$$

such that it suffices to re-scale either B or C by the factor $\frac{1}{\gamma}$ to reduce the test to the one with bound 1. We conclude: (104) holds if and only if

$$\begin{pmatrix} A & \frac{1}{\gamma^2}BB^T \\ -C^TC & -A^T \end{pmatrix} \ \text{ has no eigenvalues on the imaginary axis}$$

or, equivalently,

$$\begin{pmatrix} A & BB^T \\ -\frac{1}{\gamma^2}C^TC & -A^T \end{pmatrix} \ \text{ has no eigenvalues on the imaginary axis.}$$

Why does this result help? It allows to check $\|M\|_\infty < \gamma$, a test which involves computing the norm at infinitely many frequencies, by just verifying whether a Hamiltonian matrix that is defined through the data matrices A, B, C and the bound γ has an eigenvalue on the imaginary axis or not. This allows to compute $\|M\|_\infty$ by bisection (Appendix A).

6.3 The Bounded Real Lemma

The characterization of $\|M\|_\infty < 1$ in terms of the Hamiltonian matrix H is suitable for computing the H_∞-norm of M, but it is not convenient to derive a solution of the H_∞ problem. For that purpose we aim at providing an alternative characterization of $\|M\|_\infty < 1$ in terms of the solvability of Riccati equations or inequalities. In view of our preparations showing a relation of the solvability of the ARE or ARI with Hamiltonians, this is not too surprising.

Theorem 41 *Let $M(s) = C(sI - A)^{-1}B$ with A being stable. Then $\|M\|_\infty < 1$ holds if and only if the ARI*

$$A^TX + XA + XBB^TX + C^TC < 0 \tag{106}$$

has a solution. This is equivalent to the fact that the ARE

$$A^TX + XA + XBB^TX + C^TC = 0 \tag{107}$$

has a stabilizing solution.

We only need to observe that the stability of A implies that (A, BB^T) is stabilizable. Then we can just combine Theorem 38 with Theorem 40 to obtain Theorem 41.

Since the H_∞-norms of $C(sI - A)^{-1}B$ and of $B^T(sI - A^T)^{-1}C^T$ coincide, we can dualize this result.

Theorem 42 *Let $M(s) = C(sI - A)^{-1}B$ with A being stable. Then $\|M\|_\infty < 1$ holds if and only if the ARI*

$$AY + YA^T + BB^T + YC^TCY < 0 \tag{108}$$

has a solution. This is equivalent to the fact that the ARE

$$AY + YA^T + BB^T + YC^TCY = 0 \tag{109}$$

has a stabilizing solution.

Task. Provide the arguments why these statements are true.

Remarks.

- Recall how we reduced the bound (104) for some $\gamma > 0$ to (105). Hence (104) can be characterized by performing the substitutions

$$BB^T \to \frac{1}{\gamma^2}BB^T \quad \text{or} \quad C^TC \to \frac{1}{\gamma^2}C^TC$$

  in all the four AREs or ARIs.

- If X satisfies (106), it must be non-singular: Suppose $Xx = 0$ with $x \neq 0$. Then $x^T(106)x = x^TBB^Tx < 0$. This implies $\|B^Tx\| < 0$, a contradiction. If we note that $X^{-1}(107)X^{-1}$ implies

$$AX^{-1} + X^{-1}A^T + BB^T + X^{-1}C^TCX^{-1} < 0,$$

  we infer that $Y = X^{-1}$ satisfies (108). Conversely, if Y solves (108), then Y^{-1} exists and satisfies (106).

6.4 The H_∞-Control Problem

Let us consider the generalized plant

$$\begin{pmatrix} z \\ y \end{pmatrix} = P \begin{pmatrix} w \\ u \end{pmatrix} = \left[\begin{array}{c|cc} A & B_1 & B_2 \\ \hline C_1 & D_{11} & D_{12} \\ C_2 & D_{21} & D_{22} \end{array}\right] \begin{pmatrix} w \\ u \end{pmatrix}.$$

Recall that y is the measured output available for control, u is the control input, z is the controlled output, and w the disturbance input. We assume that P admits a stabilizing controller such that

$$(A, B_2) \text{ is stabilizable and } (A, C_2) \text{ is detectable.}$$

As controllers we allow for any LTI system

$$u = Ky = \left[\begin{array}{c|c} A_K & B_K \\ \hline C_K & D_K \end{array}\right] y$$

specified in the state-space through the parameter matrices A_K, B_K, C_K, D_K.

The goal in H_∞-control is to minimize the H_∞-norm of the transfer function $w \to z$ by using stabilizing controllers. With the previous notation for the controlled closed-loop system

$$z = S(P, K)w = \left[\begin{array}{c|c} \mathcal{A} & \mathcal{B} \\ \hline \mathcal{C} & \mathcal{D} \end{array}\right] w,$$

the intention is to minimize

$$\|S(P, K)\|_\infty = \left\| \left[\begin{array}{c|c} \mathcal{A} & \mathcal{B} \\ \hline \mathcal{C} & \mathcal{D} \end{array}\right] \right\|_\infty$$

over all K that stabilizes P, i.e., which render $\mathcal{A}$ stable.

Similarly as for just determining the H_∞-norm of a transfer matrix, we rather consider the so-called **sub-optimal H_∞ control problem**: Given the number $\gamma > 0$, find a controller K such that

$$K \text{ stabilizes } P \text{ and achieves } \|S(P, K)\|_\infty < \gamma$$

or conclude that no such controller exists.

As usual, we can rescale to the bound 1 by introducing weightings. This amounts to substituting P by either one of

$$\begin{pmatrix} \frac{1}{\gamma}P_{11} & \frac{1}{\gamma}P_{12} \\ P_{21} & P_{22} \end{pmatrix}, \quad \begin{pmatrix} \frac{1}{\gamma}P_{11} & P_{12} \\ \frac{1}{\gamma}P_{21} & P_{22} \end{pmatrix}, \quad \begin{pmatrix} \frac{1}{\gamma}P_{11} & \frac{1}{\sqrt{\gamma}}P_{12} \\ \frac{1}{\sqrt{\gamma}}P_{21} & P_{22} \end{pmatrix}$$

that read in the state-space as

$$\left[\begin{array}{c|cc} A & B_1 & B_2 \\ \hline \frac{1}{\gamma}C_1 & \frac{1}{\gamma}D_{11} & \frac{1}{\gamma}D_{12} \\ C_2 & D_{21} & D_{22} \end{array}\right], \quad \left[\begin{array}{c|cc} A & \frac{1}{\gamma}B_1 & B_2 \\ \hline C_1 & \frac{1}{\gamma}D_{11} & D_{12} \\ C_2 & \frac{1}{\gamma}D_{21} & D_{22} \end{array}\right], \quad \left[\begin{array}{c|cc} A & \frac{1}{\sqrt{\gamma}}B_1 & B_2 \\ \hline \frac{1}{\sqrt{\gamma}}C_1 & \frac{1}{\gamma}D_{11} & \frac{1}{\sqrt{\gamma}}D_{12} \\ C_2 & \frac{1}{\sqrt{\gamma}}D_{21} & D_{22} \end{array}\right].$$

Hence the problem is re-formulated as follows: Try to find a controller K such that

$$K \text{ stabilizes } P \text{ and achieves } \|S(P, K)\|_\infty < 1. \tag{110}$$

The conditions (110) read in the state-space as

$$\lambda(\mathcal{A}) \subset \mathbb{C}^- \quad \text{and} \quad \|\mathcal{C}(sI-\mathcal{A})^{-1}\mathcal{B}+\mathcal{D}\|_\infty < 1. \tag{111}$$

Note that a K might or might not exist. Hence our goal is to provide verifiable conditions formulated in terms of the generalized plant P for the existence of such a controller K. If a controller is known to exist, we also need to devise an algorithm that allows to construct a suitable controller K which renders the conditions in (110) or (111) satisfied.

6.5 H_∞-Control for a Simplified Generalized Plant Description

The generalized plant reads as

$$\begin{aligned} \dot{x} &= Ax + B_1 w + B_2 u \\ z &= C_1 x + D_{11} w + D_{12} u \\ y &= C_2 x + D_{21} w + D_{22} u. \end{aligned}$$

The derivation of a solution of the H_∞-problem in its generality is most easily obtained with LMI techniques. In these notes we only consider the so-called regular problem. This amounts to the hypothesis that

$$D_{12} \;\text{ has full column rank and }\; D_{21} \;\text{ has full row rank.}$$

These assumptions basically imply that the full control signal u appears via $D_{12}u$ in z, and that the whole measured output signal y is corrupted via $D_{21}w$ by noise.

In order to simplify both the derivation and the formulas, we confine the discussion to a generalized plant with the following stronger properties:

$$D_{11} = 0, \quad D_{22} = 0, \quad D_{12}^T \begin{pmatrix} C_1 & D_{12} \end{pmatrix} = \begin{pmatrix} 0 & I \end{pmatrix}, \quad \begin{pmatrix} B_1 \\ D_{21} \end{pmatrix} D_{21}^T = \begin{pmatrix} 0 \\ I \end{pmatrix}. \tag{112}$$

Hence we assume that both P_{11} and P_{22} are strictly proper. Moreover, D_{12} does not only have full column rank, but its columns are orthonormal, and they are orthogonal to the columns of C_1. Similarly, the rows of D_{21} are orthonormal, and they are orthogonal to the rows of B_1.

6.6 The State-Feedback Problem

Let us first concentrate on the specific control structure

$$u = Fx$$

what is often denoted as *static state-feedback*. The closed-loop system then reads as

$$\begin{aligned} \dot{x} &= (A + B_2 F)x + B_1 w \\ z &= (C_1 + D_{12} F)x. \end{aligned}$$

Hence the static-state feedback H_∞ control problem is formulated as follows: Find an F which renders the following two conditions satisfied:

$$\lambda(A + B_2 F) \subset \mathbb{C}^- \quad \text{and} \quad \|(C_1 + D_{12}F)(sI - A - B_2 F)^{-1} B_1\|_\infty < 1. \tag{113}$$

6.6.1 Solution in Terms of Riccati Inequalities

The gain F satisfies both conditions if and only if there exists a Y with

$$Y > 0, \;\; (A+B_2F)Y + Y(A+B_2F)^T + B_1B_1^T + Y(C_1+D_{12}F)^T(C_1+D_{12}F)Y < 0. \tag{114}$$

Indeed, if F satisfies (113), we can apply Theorem 42 to infer that the ARI in (114) has a symmetric solution Y. Since the inequality implies $(A + B_2F)Y + Y(A + B_2F)^T < 0$, and since $A + B_2F$ is stable, we infer that Y is actually positive definite. Conversely, if Y satisfies (114), then $(A + B_2F)Y + Y(A + B_2F)^T < 0$ implies that $A + B_2F$ is stable. Again by Theorem 42 we arrive at (113).

In a next step, we eliminate F from (114). This will be possible on the basis of the following lemma.

Lemma 43 *For any F,*

$$\begin{aligned} &(A + B_2F)Y + Y(A + B_2F)^T + B_1B_1^T + Y(C_1 + D_{12}F)^T(C_1 + D_{12}F)Y \geq \\ &\qquad \geq AY + YA^T + B_1B_1^T - B_2B_2^T + YC_1^TC_1Y. \end{aligned}$$

Equality holds if and only if

$$FY + B_2 = 0.$$

Proof. Note that (112) implies

$$Y(C_1 + D_{12}F)^T(C_1 + D_{12}F)Y = YC_1^TC_1Y + YF^TFY.$$

Moreover, we exploit (completion of the squares)

$$(B_2FY) + (B_2FY)^T + YF^TFY = -B_2B_2^T + (FY + B_2^T)^T(FY + B_2^T).$$

Both equations imply

$$\begin{aligned} &(A + B_2F)Y + Y(A + B_2F)^T + B_1B_1^T + Y(C_1 + D_{12}F)^T(C_1 + D_{12}F)Y = \\ &\qquad = AY + YA^T + B_1B_1^T - B_2B_2^T + YC_1^TC_1Y + (FY + B_2^T)^T(FY + B_2^T). \end{aligned}$$

Since $(FY + B_2^T)^T(FY + B_2^T) \geq 0$ and since $(FY + B_2^T)^T(FY + B_2^T) = 0$ if and only if $FY + B_2^T = 0$, the proof is finished.

■

Due to this lemma, any Y that satisfies (114) also satisfies

$$Y > 0, \quad AY + YA^T + B_1B_1^T - B_2B_2^T + YC_1^TC_1Y < 0. \tag{115}$$

Note that the resulting ARI is independent of F! Conversely, if Y is a matrix with (115), it is non-singular such that we can set

$$F := -B_2^TY^{-1}.$$

Since $FY + B_2$ vanishes, we can again apply Lemma 43 to see that (115) implies (114). To conclude, there exists an F and a Y with (114) if and only if there exists a Y with (115).

Let us summarize what we have found in the following Riccati inequality solution of the state-feedback H_∞ problem.

Theorem 44 *The gain F solves the state-feedback H_∞-problem (113) if and only if there exists a positive definite solution Y of the ARI*

$$AY + YA^T + B_1B_1^T - B_2B_2^T + YC_1^TC_1Y < 0. \tag{116}$$

If $Y > 0$ is any solution of this ARI, then the gain

$$F := -B_2^TY^{-1}$$

renders $A + B_2F$ stable and leads to $\|(C_1 + D_{12}F)(sI - A - B_2F)^{-1}B_1\|_\infty < 1$.

At this point it is unclear how we can test whether (116) has a positive definite solution. One possibility is as follows: Observe that $Y > 0$ and (116) are equivalent to (Schur complement)

$$Y > 0, \quad \begin{pmatrix} AY + YA^T + B_1B_1^T - B_2B_2^T & YC_1^T \\ C_1Y & -I \end{pmatrix} < 0.$$

These are two linear matrix inequalities and, hence, they can be readily solved by existing software.

6.6.2 Solution in Terms of Riccati Equations

There is an alternative. We can reduce the solvability of (116) to a test for a certain Hamiltonian matrix via Theorem 37. For that purpose we need an additional technical hypothesis; we have to require that $(A^T, C_1^TC_1)$ is controllable. By the Hautus test, this is

the same as (A, C_1) being observable. (Why?) It is important to note that this assumption is purely technical and makes it possible to provide a solution of the state-feedback H_∞ problem by Riccati equations; it might happen that this property fails to hold such that one has to rely on alternative techniques.

Theorem 45 *Suppose that*

$$(A, C_1) \quad \textit{is observable.} \tag{117}$$

Then there exists an F that solves the state-feedback H_∞-problem (113) if and only if the Riccati equation

$$AY + YA^T + B_1B_1^T - B_2B_2^T + YC_1^TC_1Y = 0 \tag{118}$$

has an anti-stabilizing solution Y_+, and this anti-stabilizing solution is positive definite. If $Y_+ > 0$ denotes the anti-stabilizing solution of the ARE, the gain

$$F := -B_2^TY_+^{-1}$$

leads to (113).

Proof. If there exists an F that satisfies (113), the ARI (116) has a solution $Y > 0$. By Theorem 38, the ARE (118) has an anti-stabilizing solution Y_+ that satisfies $Y \leq Y_+$. Hence Y_+ exists and is positive definite.

Conversely, suppose Y_+ exists and is positive definite. With $F = -B_2^TY_+^{-1}$ we infer $FY_+ + B_2 = 0$ and hence

$$AY_+ + Y_+A^T + GG^T - B_2B_2^T + Y_+C_1^TC_1Y_+ + (FY_+ + B_2^T)^T(FY_+ + B_2^T) = 0.$$

By Lemma 43, we arrive at

$$(A + B_2F)Y_+ + Y_+(A + B_2F)^T + B_1B_1^T + Y_+(C_1 + D_{12}F)^T(C_1 + D_{12}F)Y_+ = 0. \tag{119}$$

Let us first show that $A + B_2F$ is stable. For that purpose let $(A + B_2F)^Tx = \lambda x$ with $x \neq 0$. Now look at $x^*(119)x$:

$$\mathrm{Re}(\lambda)x^*Y_+x + x^*B_1B_1^Tx + x^*Y_+(C_1 + D_{12}F)^T(C_1 + D_{12}F)Y_+x = 0.$$

Since $Y_+ \geq 0$, this implies $\mathrm{Re}(\lambda) \geq 0$. Let us now exclude $\mathrm{Re}(\lambda) = 0$. In fact, this condition implies $(C_1 + D_{12}F)Y_+x = 0$. If we left-multiply D_{12}, we can exploit (112) to infer $FY_+x = 0$. This implies $B_2^Tx = 0$ and hence $A^Tx = \lambda x$. Since (A, B_2) is stabilizable, we obtain $\mathrm{Re}(\lambda) < 0$, a contradiction. Therefore, the real part of λ must be negative, what implies that $A + B_2F$ is stable.

Since

$$A + B_2F + Y_+(C_1 + D_{12}F)^T(C_1 + D_{12}F) = A + Y_+C_1^TC_1,$$

we infer that Y_+ is the anti-stabilizing solution of (119). Hence the corresponding Hamiltonian matrix has no eigenvalues on the imaginary axis (Theorem 37) such that (113) follows (Theorem 40).

■

6.7 H_∞-Control by Output-Feedback

Let us now come back to the H_∞-problem by output feedback control. This amounts to finding the matrices A_K, B_K, C_K, D_K such that the conditions (111) are satisfied.

We proceed as in the state-feedback problem. We use the Bounded Real Lemma to rewrite the H_∞ norm bound into the solvability of a Riccati inequality, and we try to eliminate the controller parameters to arrive at verifiable conditions.

6.7.1 Solution in Terms of Riccati Inequalities

For the derivation to follow we assume that the controller is strictly proper: $D_K = 0$. The proof for a controller with $D_K \neq 0$ is only slightly more complicated and fits much better into the LMI framework what will be discussed in the LMI course.

There exists a controller A_K, B_K, C_K, $D_K = 0$ that satisfies (111) if and only if there exists some $\mathcal{X}$ with

$$\mathcal{X} > 0, \quad \mathcal{A}^T\mathcal{X} + \mathcal{X}\mathcal{A} + \mathcal{X}\mathcal{B}\mathcal{B}^T\mathcal{X} + \mathcal{C}^T\mathcal{C} < 0. \tag{120}$$

Indeed, (111) implies the existence of a symmetric solution of the ARI in (120) by Theorem 41. Since $\mathcal{A}$ is stable, $\mathcal{A}^T\mathcal{X} + \mathcal{X}\mathcal{A} < 0$ implies that $\mathcal{X} > 0$. Conversely, (120) implies $\mathcal{A}^T\mathcal{X} + \mathcal{X}\mathcal{A} < 0$ for $\mathcal{X} > 0$. Hence $\mathcal{A}$ is stable and we arrive, again by Theorem 41, at (111).

Let us now suppose that (120) is valid. Partition $\mathcal{X}$ and $\mathcal{X}^{-1}$ in the same fashion as $\mathcal{A}$ to obtain

$$\mathcal{X} = \begin{pmatrix} X & U \\ U^T & \widehat{X} \end{pmatrix} \quad \text{and} \quad \mathcal{X}^{-1} = \begin{pmatrix} Y & V \\ V^T & \widehat{Y} \end{pmatrix}.$$

It is then obvious that

$$\mathcal{R} = \begin{pmatrix} X & U \\ I & 0 \end{pmatrix} \quad \text{and} \quad \mathcal{S} = \begin{pmatrix} I & 0 \\ Y & V \end{pmatrix} \quad \text{satisfy} \quad \mathcal{S}\mathcal{X} = \mathcal{R}.$$

We can assume without loss of generality that the size of A_K is not smaller than n. Hence the right upper block U of $\mathcal{X}$ has more columns than rows. This allows to assume that U is of full row rank; if not true one just needs to slightly perturb this block without violating the *strict* inequalities (120). Then we conclude that $\mathcal{R}$ has full row rank. Due to $\mathcal{S}\mathcal{X} = \mathcal{R}$, also $\mathcal{S}$ has full row rank.

Let us now left-multiply both inequalities in (120) with $\mathcal{S}$ and right-multiply with $\mathcal{S}^T$. Since $\mathcal{S}$ has full row rank and if we exploit $\mathcal{S}\mathcal{X} = \mathcal{R}$ or $\mathcal{X}\mathcal{S}^T = \mathcal{R}^T$, we arrive at

$$\mathcal{S}\mathcal{R}^T > 0, \quad \mathcal{S}\mathcal{A}^T\mathcal{R}^T + \mathcal{R}\mathcal{A}\mathcal{S}^T + \mathcal{R}\mathcal{B}\mathcal{B}^T\mathcal{R}^T + \mathcal{S}\mathcal{C}^T\mathcal{C}\mathcal{S}^T < 0. \tag{121}$$

The appearing blocks are most easily computed as follows:

$$\begin{aligned}
\mathcal{S}\mathcal{R}^T &= \begin{pmatrix} X & I \\ YX + VU^T & Y \end{pmatrix} \\
\mathcal{R}\mathcal{A}\mathcal{S}^T &= \begin{pmatrix} XA + UB_KC_2 & XAY + UB_KC_2Y + XB_2C_KV^T + UA_KV^T \\ A & AY + B_2C_KV^T \end{pmatrix} \\
\mathcal{R}\mathcal{B} &= \begin{pmatrix} XB_1 + UB_KD_{21} \\ B_1 \end{pmatrix} \\
\mathcal{C}\mathcal{S}^T &= \begin{pmatrix} C_1 & C_1Y + D_{12}C_KV^T \end{pmatrix}.
\end{aligned}$$

Let us now recall a relation between X, Y, U, V and define the new variables F and L as in

$$YX + VU^T = I, \quad L = X^{-1}UB_K \;\text{ and }\; F = C_KV^TY^{-1}. \tag{122}$$

Then the formulas simplify to

$$\begin{aligned}
\mathcal{S}\mathcal{R}^T &= \begin{pmatrix} X & I \\ I & Y \end{pmatrix} \\
\mathcal{R}\mathcal{A}\mathcal{S}^T &= \begin{pmatrix} X(A + LC_2) & X(A + LC_2 + B_2F)Y + UA_KV^T \\ A & (A + B_2F)Y \end{pmatrix} \\
\mathcal{R}\mathcal{B} &= \begin{pmatrix} X(B_1 + LD_{21}) \\ B_1 \end{pmatrix} \\
\mathcal{C}\mathcal{S}^T &= \begin{pmatrix} C_1 & (C_1 + D_{12}F)Y \end{pmatrix}.
\end{aligned}$$

We we conclude that (121) read as

$$\begin{pmatrix} X & I \\ I & Y \end{pmatrix} > 0$$

and

$$\begin{aligned}
&\begin{pmatrix} (A + LC_2)^TX + X(A + LC_2) & A^T + X(A + LC_2 + B_2F)Y + UA_KV^T \\ A + [X(A + LC_2 + B_2F)Y + UA_KV^T]^T & (A + B_2F)Y + Y(A + B_2F)^T \end{pmatrix} + \\
&+ \begin{pmatrix} X(B_1 + LD_{21})(B_1 + LD_{21})^TX & X(B_1 + LD_{21})B_1^T \\ B_1(B_1 + LD_{21})^TX & B_1B_1^T \end{pmatrix} + \\
&+ \begin{pmatrix} C_1^TC_1 & C_1^T(C_1 + D_{12}F)Y \\ Y(C_1 + D_{12}F)^TC_1 & Y(C_1 + D_{12}F)^T(C_1 + D_{12}F)Y \end{pmatrix} < 0.
\end{aligned} \tag{123}$$

If we pick out the diagonal blocks of the last inequality, we conclude

$$\begin{pmatrix} X & I \\ I & Y \end{pmatrix} > 0 \tag{124}$$

$$(A + LC_2)^T X + X(A + LC_2) + X(B_1 + LD_{21})(B_1 + LD_{21})^T X + C_1^T C_1 < 0 \tag{125}$$

$$(A + B_2F)Y + Y(A + B_2F)^T + B_1B_1^T + Y(C_1 + D_{12}F)^T(C_1 + D_{12}F)Y < 0. \tag{126}$$

We can apply Lemma 43 to (126) and a dual version to (125). This implies that X and Y satisfy (124) and the two algebraic Riccati inequalities

$$A^T X + XA + XB_1B_1^T X + C_1^T C_1 - C_2^T C_2 < 0 \tag{127}$$

$$AY + YA^T + B_1B_1^T - B_2B_2^T + YC_1^T C_1Y < 0. \tag{128}$$

We have shown: If there exists a controller that renders (111) satisfies, then there exist symmetric matrices X and Y that satisfy the two algebraic Riccati inequalities (127)-(128), and that these two matrices are coupled as (124). Note that these conditions are, again, formulated only in terms of the matrices defining the generalized plant; the controller parameters have been eliminated. It will turn out that one can reverse the arguments: If X and Y satisfy (124),(127)-(128), one can construct a controller that leads to (111).

Suppose X and Y satisfy (124),(127)-(128). Due to (124), X and Y are positive definite and hence nonsingular. If we apply Lemma 43 to (128) and a dual version to (127), we conclude that

$$L := -X^{-1}C_2^T \quad \text{and} \quad F := -B_2^T Y^{-1}$$

lead to (124)-(126). Again due to (124), $I - YX$ is non-singular as well. Hence we can find non-singular square matrices U and V satisfying $VU^T = I - YX$; take for example $U = I$ and $V = I - YX$. If we set

$$B_K = U^{-1}XL \quad \text{and} \quad C_K = FYV^{-T}, \tag{129}$$

we infer that the relations (122) are valid. If we now consider (123), we observe that the only undefined block on the left-hand side is A_K and this appears as UA_KV^T in the off-diagonal position. We also observe that the diagonal blocks of this matrix are negative definite. If we choose A_K to render the off-diagonal block zero, we infer that (123) is valid. This is clearly achieved for

$$A_K = -U^{-1}[A^T + X(A+LC_2+B_2F)Y + X(B_1+LD_{21})B_1^T + C_1^T(C_1+D_{12}F)Y]V^{-T}. \tag{130}$$

We arrive back to (121). Now $\mathcal{S}$ is square and non-singular. We can hence define $\mathcal{X}$ through $\mathcal{X} := \mathcal{S}^{-1}\mathcal{R}$. If we left-multiply both inequalities in (121) with $\mathcal{S}^{-1}$ and right-multiply with $\mathcal{S}^{-T}$, we arrive at (120). This shows that the constructed controller leads to (111) and the proof cycle is complete.

Theorem 46 *There exist A_K, B_K, C_K, D_K that solve the output-feedback H_∞ problem (111) if and only if there exist X and Y that satisfy the two ARIs*

$$A^T X + XA + XB_1B_1^T X + C_1^T C_1 - C_2^T C_2 < 0, \tag{131}$$

$$AY + YA^T + YC_1^T C_1Y + B_1B_1^T - B_2B_2^T < 0, \tag{132}$$

and the coupling condition

$$\begin{pmatrix} X & I \\ I & Y \end{pmatrix} > 0. \tag{133}$$

Suppose that X and Y satisfy (131)-(133). Let U and V be square and non-singular matrices with $UV^T = I - XY$, and set $L := -X^{-1}C_2^T$, $F := -B_2^T Y^{-1}$. Then A_K, B_K, C_K as defined in (130),(129) lead to (111).

Remarks. The necessity of the conditions (131)-(133) has been proved for a strictly proper controller only. In fact, the conclusion does not require this hypothesis. On the other hand, the controller as given in the construction is always strictly proper. In general, if $D_{11} = 0$, the existence of a proper controller solving the H_∞-problem implies the existence of a *strictly proper* controller that solves the problem. Note, however, that does in general not get strictly proper controller solving the H_∞-problem by simply removing the direct from a controller which is not proper and which solves the H_∞-problem!

Remark. If we recall (112), the formulas for the controller matrices can be simplified to

$$\begin{aligned} A_K &= -U^{-1}[A^T + XAY + X(B_1B_1^T - B_2B_2^T) + (C_1^T C_1 - C_2^T C_2)Y]V^{-T} \\ B_K &= -U^{-1}C_2^T, \\ C_K &= -B_2^T V^{-T}. \end{aligned} \tag{134}$$

For the particular choices $U = X$, $V = X^{-1} - Y$ or $U = Y^{-1} - X$, $V = Y$, one arrives at the specific formulas given in the literature. Note that all these constructions lead to controllers that have the *same order* as the generalized plant: the dimension of A_c is equal to the dimension of A.

We note again that (132)-(133) are equivalent to

$$\begin{pmatrix} A^T X + XA + C_1^T C_1 - C_2^T C_2 & XB_1 \\ B_1^T X & -I \end{pmatrix} < 0$$

and

$$\begin{pmatrix} AY + YA^T + B_1B_1^T - B_2B_2^T & YC_1^T \\ C_1Y & -I \end{pmatrix} < 0.$$

Hence testing the existence of solutions X and Y of (131)-(133) can be reduced to verifying the solvability of a system of linear matrix inequalities. In fact, numerical solvers provide solutions X, Y, and we have shown how to construct on the basis of these matrices a controller that satisfies (111).

6.7.2 Solution in Terms of Riccati Equations

As an alternative, Theorem 37 allows to go back to Riccati equations if $(A, B_1B_1^T)$ and $(A^T, C_1^TC_1)$ are controllable as described in the following Riccati equation solution of the H_∞ problem.

Theorem 47 *Suppose that*

$$(A, B_1) \ \text{ is controllable and } \ (A, C_1) \ \text{ is observable.} \tag{135}$$

There exist A_K, B_K, C_K, D_K that solves the output-feedback H_∞ problem (111) if and only if the Riccati equations

$$A^TX + XA + XB_1B_1^TX + C_1^TC_1 - C_2^TC_2 = 0, \tag{136}$$

$$AY + YA^T + YC_1^TC_1Y + B_1B_1^T - B_2B_2^T = 0,$$

have anti-stabilizing solutions X_+, Y_+, and these solutions satisfy the coupling condition

$$\begin{pmatrix} X_+ & I \\ I & Y_+ \end{pmatrix} > 0. \tag{137}$$

With any non-singular U and V satisfying $XY + UV^T = I$, the formulas (134) define a controller that satisfies (111).

Note that the conditions in this result are algebraically verifiable without relying on linear matrix inequalities. One can test for the existence of anti-stabilizing solutions by verifying whether the corresponding Hamiltonian matrix has no eigenvalues on the imaginary axis. If the test is passed, one can compute these anti-stabilizing solutions. Then one simply needs to check (137) what amounts to verifying whether the smallest eigenvalue of the matrix on the left-hand side is positive.

Proof. Let A_K, B_K, C_K, D_K satisfy (111). By Theorem 46, there exist X, Y with (131)-(133). If we apply Theorem 37 twice, we infer that the AREs (136)-(47) have anti-stabilizing solutions X_+, Y_+ with $X \leq X_+$, $Y \leq Y_+$. The last two inequalities clearly imply (137).

Let us now suppose that X_+, Y_+ exist and satisfy (137), and construct the controller in the same fashion as described in Theorem 46. As easily seen, the matrix $\mathcal{X}$ we constructed above will satisfy

$$\mathcal{X} > 0, \quad \mathcal{A}^T\mathcal{X} + \mathcal{X}\mathcal{A} + \mathcal{X}\mathcal{B}\mathcal{B}^T\mathcal{X} + \mathcal{C}^T\mathcal{C} = 0. \tag{138}$$

Let us prove that $\mathcal{A}$ is stable. For that purpose we assume that $\mathcal{A}x = \lambda x$ with $x \neq 0$. If we left-multiply the ARE in (138) with x^* and right-multiply with x, we arrive at

$$\text{Re}(\lambda)x^*\mathcal{X}x + x^*\mathcal{X}\mathcal{B}\mathcal{B}^T\mathcal{X}x + x^*\mathcal{C}^T\mathcal{C}x = 0.$$

Since $x^*\mathcal{X}x > 0$, we infer $\text{Re}(\lambda) \leq 0$. Let us show that $\text{Re}(\lambda) = 0$ cannot occur. In fact, if $\text{Re}(\lambda) = 0$, we conclude

$$x^*\mathcal{X}\mathcal{B} = 0 \ \text{ and } \ \mathcal{C}x = 0.$$

Right-multiplying the ARE in (138) leads (with $-\overline{\lambda} = \lambda$) to

$$x^*\mathcal{X}\mathcal{A} = \lambda x^*\mathcal{X} \ \text{ and, still, } \ \mathcal{A}x = \lambda x$$

Set $\widehat{x} = \mathcal{X}x$, and partition $\widehat{x}$ and x according to $\mathcal{A}$. Then we arrive at

$$\begin{pmatrix} \widehat{y}^* & \widehat{z}^* \end{pmatrix} \begin{pmatrix} A & B_2C_K \\ B_KC_2 & A_K \end{pmatrix} = \lambda \begin{pmatrix} \widehat{y}^* & \widehat{z}^* \end{pmatrix} \ \text{ and } \ \begin{pmatrix} \widehat{y}^* & \widehat{z}^* \end{pmatrix} \begin{pmatrix} B_1 \\ B_KD_{21} \end{pmatrix} = 0$$

as well as

$$\begin{pmatrix} A & B_2C_K \\ B_KC_2 & A_K \end{pmatrix} \begin{pmatrix} y \\ z \end{pmatrix} = \lambda \begin{pmatrix} y \\ z \end{pmatrix} \ \text{ and } \ \begin{pmatrix} C_1 & D_{12}C_K \end{pmatrix} \begin{pmatrix} y \\ z \end{pmatrix} = 0.$$

Right-multiplying with B_1 and left-multiplying with C_1^T imply that $\widehat{z}^*B_K = 0$ and $C_Kz = 0$. This reveals

$$\widehat{y}^*A = \lambda\widehat{y}^*, \ \widehat{y}^*B_1 = 0 \ \text{ and } \ Ay = \lambda y, \ C_1y = 0.$$

By controllability of (A, B_1) and observability of (A, C_1), we conclude $\widehat{y} = 0$ and $y = 0$. Finally,

$$\begin{pmatrix} 0 \\ \widehat{z} \end{pmatrix} = \begin{pmatrix} X_+ & U \\ U^T & * \end{pmatrix} \begin{pmatrix} 0 \\ z \end{pmatrix} \ \text{ and } \ \begin{pmatrix} 0 \\ z \end{pmatrix} = \begin{pmatrix} Y_+ & V \\ V^T & * \end{pmatrix} \begin{pmatrix} 0 \\ \widehat{z} \end{pmatrix}$$

lead to $0 = Uz$ and $0 = V\widehat{z}$ what implies $z = 0$ and $\widehat{z} = 0$ since U and V are non-singular. This is a contradiction to $x \neq 0$.

Since $\mathcal{A}$ is stable, the controller is stabilizing. Moreover, it is not difficult to verify that the Riccati equation in (138) implies $\|\mathcal{C}(sI - \mathcal{A})^{-1}\mathcal{B}\|_\infty \leq 1$. One can in fact show that the strict inequality holds true; since this is cumbersome and not really relevant for our considerations, we stop here.

■

6.7.3 Solution in Terms of Indefinite Riccati Equations

We observe that $Y > 0$ and

$$AY + YA^T + YC_1^TC_1Y + B_1B_1^T - B_2B_2^T = 0, \quad \lambda(A + YC_1^TC_1) \subset \mathbb{C}^+ \tag{139}$$

is equivalent to $Y_\infty > 0$ and

$$A^TY_\infty + Y_\infty A + Y_\infty(B_1B_1^T - B_2B_2^T)Y_\infty + C_1^TC_1 = 0, \ \lambda(A + (B_1B_1^T - B_2B_2^T)Y_\infty) \subset \mathbb{C}^- \tag{140}$$

with

$$Y_\infty = Y^{-1}.$$

Proof. Let us show that (139) implies (140). Left- and right-multiplying the ARE in (139) with $Y_\infty = Y^{-1}$ leads to the ARE in (140). Moreover, $Y > 0$ implies $Y_\infty = Y^{-1} > 0$. Finally, the ARE in (139) is easily rewritten to

$$(A + YC_1^TC_1)Y + Y(A^T + Y^{-1}[B_1B_1^T - B_2B_2^T]) = 0$$

what leads to

$$Y^{-1}(A + YC_1^TC_1)Y = -(A + [B_1B_1^T - B_2B_2^T]Y_\infty)^T.$$

Since $A + YC_1^TC_1$ is anti-stable, $A + [B_1B_1^T - B_2B_2^T]Y_\infty$ must be stable.

The converse implication (140) $\Rightarrow$ (139) follows by reversing the arguments.

■

Dually, we have $X > 0$ and

$$A^TX + XA + XB_1B_1^TX + C_1^TC_1 - C_2^TC_2 = 0, \quad \lambda(A + B_1B_1^TX) \subset \mathbb{C}^+$$

if and only if $X_\infty > 0$ and

$$AX_\infty + X_\infty A^T + X_\infty(C_1^TC_1 - C_2^TC_2)X_\infty + B_1B_1^T = 0, \ \lambda(A + X_\infty(C_1^TC_1 - C_2^TC_2)) \subset \mathbb{C}^-$$

with

$$X_\infty = X^{-1}.$$

Finally,

$$\begin{pmatrix} X & I \\ I & Y \end{pmatrix} > 0$$

is equivalent to

$$X_\infty > 0, \quad Y_\infty > 0, \quad \rho(X_\infty Y_\infty) < 1$$

with $X_\infty = X^{-1}$, $Y_\infty = Y^{-1}$.

Proof. The coupling condition is equivalent to $X > 0$, $Y > 0$, $Y - X^{-1} > 0$ (Schur) what is nothing but $X > 0$, $Y > 0$, $I - Y^{-1/2}X^{-1}Y^{-1/2} > 0$ or, equivalently, $X > 0$, $Y > 0$, $\rho(Y^{-1/2}X^{-1}Y^{-1/2}) < 1$ what can be rewritten (since $\rho(AB) = \rho(BA)$) as $X > 0$, $Y > 0$, $\rho(X^{-1}Y^{-1}) < 1$.

■

Hence, all conditions in Theorem 47 can be rewritten in terms of so-called indefinite algebraic Riccati equations. They are called indefinite since the matrices defining the quadratic terms are, in general, not positive or negative semi-definite.

For the particular choice of $U = Y^{-1} - X$, $V = Y$, the formulas for the controller can be rewritten in terms of $X_\infty = X^{-1}$, $Y_\infty = Y^{-1}$ as follows:

$$\begin{aligned} A_K &= A - (I - X_\infty Y_\infty)^{-1}X_\infty C_2^TC_2 + (B_1B_1^T - B_2B_2^T)Y_\infty, \\ B_K &= (I - X_\infty Y_\infty)^{-1}X_\infty C_2^T, \quad C_K = -B_2^TY_\infty. \end{aligned}$$

Proof. If we left-multiply (139) by Y^{-1}, we obtain

$$A^T + C_1^TC_1Y = -[Y^{-1}AY + Y^{-1}(B_1B_1^T - B_2B_2^T)].$$

Hence the formula for A_K in (134) can be rewritten to

$$A_K = -U^{-1}[(X - Y^{-1})AY - C_2^TC_2Y + (X - Y^{-1})(B_1B_1^T - B_2B_2^T)]V^{-T}$$

what is nothing but

$$A_K = A + (Y^{-1} - X)^{-1}C_2^TC_2 + (B_1B_1^T - B_2B_2^T)Y^{-1}.$$

or

$$A_K = A - (I - X^{-1}Y^{-1})^{-1}X^{-1}C_2^TC_2 + (B_1B_1^T - B_2B_2^T)Y^{-1}.$$

The formulas for B_K and C_K are obvious.

■

Why are the results in the literature usually formulated in terms of these indefinite AREs? The simple reason is the possibility to relax the artificial and strong hypotheses that (A, B_1) and (A, C_1) are controllable and observable to a condition on the non-existence of uncontrollable or unobservable modes on the imaginary axis. The exact formulation with a general bound γ and with an explicit controller formula is as follows.

Theorem 48 *Suppose that*

$$(A, B_1), (A, C_1) \ \textit{ have no uncontrollable, unobservable modes in } \ \mathbb{C}^0. \tag{141}$$

Then there exist A_K, B_K, C_K, D_K that solves the output-feedback H_∞ problem (111) if and only if the unique X_∞ and Y_∞ with

$$\begin{gathered} AX_\infty + X_\infty A^T + X_\infty(\frac{1}{\gamma^2}C_1^TC_1 - C_2^TC_2)X_\infty + B_1B_1^T = 0, \\ \lambda(A + X_\infty(\frac{1}{\gamma^2}C_1^TC_1 - C_2^TC_2)) \subset \mathbb{C}^- \end{gathered}$$

and

$$\begin{gathered} A^TY_\infty + Y_\infty A + Y_\infty(\frac{1}{\gamma^2}B_1B_1^T - B_2B_2^T)Y_\infty + C_1^TC_1 = 0, \\ \lambda(A + (\frac{1}{\gamma^2}B_1B_1^T - B_2B_2^T)Y_\infty) \subset \mathbb{C}^- \end{gathered}$$

exist, and they satisfy

$$X_\infty \geq 0, \quad Y_\infty \geq 0, \quad \rho(X_\infty Y_\infty) < \gamma^2.$$

If X_∞ and Y_∞ satisfy all these conditions, a controller with (111) is given by

$$\left[\begin{array}{c|c} A_K & B_K \\ \hline C_K & D_K \end{array}\right] = \left[\begin{array}{c|c} A - ZX_\infty C_2^T C_2 + \left[\frac{1}{\gamma^2} B_1 B_1^T - B_2 B_2^T\right] Y_\infty & ZX_\infty C_2^T \\ \hline -B_2^T Y_\infty & 0 \end{array}\right]$$

where $Z = (I - \frac{1}{\gamma^2} X_\infty Y_\infty)^{-1}$.

Remarks.

- X_∞ and Y_∞ are computed as for standard Riccati equations on the basis of the Hamiltonian matrices

  $$H_{X_\infty} = \begin{pmatrix} A^T & \frac{1}{\gamma^2} C_1^T C_1 - C_2^T C_2 \\ -B_1 B_1^T & -A \end{pmatrix} \text{ and } H_{Y_\infty} = \begin{pmatrix} A & \frac{1}{\gamma^2} B_1 B_1^T - B_2 B_2^T \\ -C_1^T C_1 & -A^T \end{pmatrix}$$

  as follows: Verify that H_{X_∞} and H_{Y_∞} do not have eigenvalues on the imaginary axis. Then compute (with Schur decompositions) $\begin{pmatrix} U_{X_\infty} \\ V_{X_\infty} \end{pmatrix}$, $\begin{pmatrix} U_{Y_\infty} \\ V_{Y_\infty} \end{pmatrix}$ and stable M_{X_∞}, M_{Y_∞} satisfying

  $$H_{X_\infty} \begin{pmatrix} U_{X_\infty} \\ V_{X_\infty} \end{pmatrix} = \begin{pmatrix} U_{X_\infty} \\ V_{X_\infty} \end{pmatrix} M_{X_\infty} \text{ and } H_{Y_\infty} \begin{pmatrix} U_{Y_\infty} \\ V_{Y_\infty} \end{pmatrix} = \begin{pmatrix} U_{Y_\infty} \\ V_{Y_\infty} \end{pmatrix} M_{Y_\infty}.$$

  Verify that U_{X_∞} nad U_{Y_∞} are non-singular. Then

  $$X_\infty = V_{X_\infty} U_{X_\infty}^{-1} \text{ and } Y_\infty = V_{Y_\infty} U_{Y_\infty}^{-1}$$

  exist and are the stabilizing solutions of the two indefinite AREs under considerations.

  After having verified that (the unique) X_∞ and Y_∞ exist, it remains to check whether they are both positive semi-definite, and whether the spectral radius of $X_\infty Y_\infty$ is smaller than γ^2.

- Note that X_∞ and Y_∞ are, in general, not invertible. That's why we insisted on deriving formulas in which no inverse of X_∞ or Y_∞ occurs. If X_∞ and Y_∞ exist, one can show:

  X_∞ has no kernel if and only if (A, B_1) has no uncontrollable modes in the open left-half plane, and Y_∞ has no kernel if and only if (A, C_1) has no unobservable modes in the open left-half plane.

- The optimal value

  $$\gamma_* = \inf_{K \text{ stabilizies } P} \|S(P, K)\|_\infty$$

  is the smallest of all γ for which the stabilizing solutions X_∞, Y_∞ of the indefinite AREs exist and satisfy $X_\infty \geq 0$, $Y_\infty \geq 0$, $\rho(X_\infty Y_\infty) < \gamma^2$. The optimal value γ_* can hence be computed by bisection.

- If $\gamma \leq \gamma_*$, it cannot be said a priori which of the conditions (existence of X_∞, Y_∞, positive semi-definiteness, coupling condition) fails.

  For $\gamma > \gamma_*$, but γ close to γ_*, it often happens that

  $$I - \frac{1}{\gamma^2} X_\infty Y_\infty \text{ is close to singular.}$$

  Hence computing the inverse of this matrix is ill-conditioned. This leads to an ill-conditioned computation of the controller matrices as given in the theorem. Therefore, it is advisable not to get too close to the optimum.

  Note, however, that this is only due to the specific choice of the controller formulas. Under our hypothesis, one can show that there always exists an *optimal* controller. Hence there is a possibility, even $\gamma = \gamma_*$, to compute an optimal controller a well-conditioned fashion.

- Let us consider the other extreme $\gamma = \infty$. Then one can *always find* $X_\infty \geq 0$ and $Y_\infty \geq 0$ that satisfy

  $$AX_\infty + X_\infty A^T - X_\infty C_2^T C_2 X_\infty + B_1 B_1^T = 0, \ \lambda(A - X_\infty C_2^T C_2) \subset \mathbb{C}^-$$

  and

  $$A^T Y_\infty + Y_\infty A - Y_\infty B_2 B_2^T Y_\infty + C_1^T C_1 = 0, \ \lambda(A - B_2 B_2^T Y_\infty) \subset \mathbb{C}^-.$$

  (Why?) Moreover, the controller formulas read as

  $$\left[\begin{array}{c|c} A_K & B_K \\ \hline C_K & D_K \end{array}\right] = \left[\begin{array}{c|c} A - X_\infty C_2^T C_2 - B_2 B_2^T Y_\infty & X_\infty C_2^T \\ \hline -B_2^T Y_\infty & 0 \end{array}\right].$$

  Clearly, this controller stabilizes P. In addition, however, it has even the additional property that it minimizes

  $$\|S(P, K)\|_2 \text{ among all controllers } K \text{ which stabilize } P.$$

  Here, $\|M\|_2$ is the so-called H_2-norm of the strictly proper and stable matrix M which is defined via

  $$\|M\|_2^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} \text{trace}(M(i\omega)^* M(i\omega)) \, d\omega.$$

  Hence the controller is a solution to the so-called H_2-control problem. Since the H_2-norm can be seen to be identical to the criterion in LQG-control, we have recovered the controller that solves the LQG problem as it is taught in an elementary course. All this will be discussed in more detail and generality in the LMI course.

6.8 What are the Weakest Hypotheses for the Riccati Solution?

The command `hinfys` of the μ-tools to design an H_∞-controller requires the following hypotheses for the system

$$\begin{pmatrix} z \\ y \end{pmatrix} = \left[\begin{array}{c|cc} A & B_1 & B_2 \\ \hline C_1 & D_{11} & D_{12} \\ C_2 & D_{21} & D_{22} \end{array}\right] \begin{pmatrix} w \\ u \end{pmatrix}$$

describing the interconnection:

- (A, B_2) is stabilizable, and (A, C_2) is detectable.
- D_{21} has full row rank, and D_{12} has full column rank.
- For all $\omega \in \mathbb{R}$, $\begin{pmatrix} A - i\omega I & B_1 \\ C_2 & D_{21} \end{pmatrix}$ has full row rank, and $\begin{pmatrix} A - i\omega I & B_2 \\ C_1 & D_{12} \end{pmatrix}$ has full column rank.

If note true, the second and the third hypotheses can be easily enforced as follows: With some $\epsilon > 0$, solve the problem for the perturbed matrices

$$\begin{pmatrix} C_1 & D_{12} \end{pmatrix} \to \begin{pmatrix} C_1 & D_{12} \\ \epsilon I & 0 \\ 0 & \epsilon I \end{pmatrix}, \quad \begin{pmatrix} B_1 \\ D_{21} \end{pmatrix} \to \begin{pmatrix} B_1 & \epsilon I & 0 \\ D_{21} & 0 & \epsilon I \end{pmatrix}, \quad D_{11} \to \begin{pmatrix} D_{11} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

Let us denote the resulting generalized plant by

$$\begin{pmatrix} z \\ z_1 \\ z_2 \\ y \end{pmatrix} = P_\epsilon \begin{pmatrix} w \\ w_1 \\ w_2 \\ u \end{pmatrix} = \left[\begin{array}{c|cccc} A & B_1 & \epsilon I & 0 & B_2 \\ \hline C_1 & D_{11} & 0 & 0 & D_{12} \\ \epsilon I & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \epsilon I \\ C_2 & D_{21} & 0 & \epsilon I & D_{22} \end{array}\right] \begin{pmatrix} w \\ w_1 \\ w_2 \\ u \end{pmatrix}.$$

The perturbation just amounts to introducing new disturbance signals w_1, w_2 and new controlled signals z_1, z_2 in order to render all the hypotheses for $\epsilon \neq 0$ satisfied.

Here are the precise conclusions that can be drawn for the relation of the H_∞ problem for the original interconnection P and for the perturbed interconnection P_ϵ.

- K stabilizes P if and only if K stabilizes P_ϵ. (Why?)
- For any K which stabilizes P and P_ϵ, the gain-interpretation of the H_∞ immediately reveals that
$$\|S(P, K)\|_\infty \le \|S(P_\epsilon, K)\|_\infty.$$

Hence, if the controller K stabilizes P_ϵ and achieves $\|S(P_\epsilon, K)\|_\infty < \gamma$, then the very same controller also stabilizes P and achieves $\|S(P, K)\|_\infty < \gamma$. **This property does not depend on the size of $\epsilon > 0$!**

- For any K stabilizing P and P_ϵ, one has
$$\|S(P_\epsilon, K)\|_\infty \to \|S(P, K)\|_\infty \quad \text{for} \quad \epsilon \to 0.$$
Hence, if there exists a K stabilizing P and rendering $\|S(P, K)\|_\infty < \gamma$ satisfied, the very same K stabilizes P_ϵ and achieves $\|S(P_\epsilon, K)\|_\infty < \gamma$ for some **sufficiently small $\epsilon > 0$.**

Note that there are other schemes to perturb the matrices in order to render the hypotheses satisfied. In general, however, it might not be guaranteed that the first of these two properties is true irrespective of the size of $\epsilon > 0$.

7 Robust Performance Synthesis

In the last Section we have dealt with designing a controller that achieves nominal performance. The related problem of minimizing the H_∞-norm of the controlled system has been the subject of intensive research in the 1980's which culminated in the very elegant solution of this problem in terms of Riccati equations.

In view of our analysis results in Section 5, the design of controllers that achieve robust stability and robust performance amounts to minimizing the SSV (with respect to a specific structure) of the controlled system over all frequencies. Although this problem has received considerable attention in the literature, the related optimization problem has, until today, not found any satisfactory algorithmic solution.

Instead, a rather heuristic method has been suggested how to attack the robust performance design problem which carries the name D/K-iteration or scalings/controller-iteration. Although it cannot be theoretically justified that this technique does lead to locally or even globally optimal controllers, it has turned out pretty successful in some practical applications. This is reason enough to describe in this section the pretty simple ideas behind this approach.

7.1 Problem Formulation

We assume that we have built the same set-up us for testing robust performance in Section 5: After fixing the performance signals, pulling out the uncertainties, and including all required uncertainty and performance weightings, one arrives at the controlled uncertain system as described by

$$\begin{pmatrix} z_\Delta \\ z \\ y \end{pmatrix} = P \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix} = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix} \begin{pmatrix} w_\Delta \\ w \\ u \end{pmatrix}, \ u = Ky, \ w_\Delta = \Delta z_\Delta, \ \Delta \in \boldsymbol{\Delta}$$

under the Hypotheses 32. Let us again use the notation $P_\Delta := S(\Delta, P)$. The goal in this section is to design a controller K which stabilizes P_Δ and which leads to

$$\|S(P_\Delta, K)\| \leq 1$$

for all uncertainties $\Delta \in \boldsymbol{\Delta}$.

In order to formulate again the robust performance analysis test, let us recall the **extended** block-structure

$$\boldsymbol{\Delta_e} := \left\{ \begin{pmatrix} \Delta_c & 0 \\ 0 & \hat{\Delta}_c \end{pmatrix} : \ \Delta_c \in \boldsymbol{\Delta_c}, \ \hat{\Delta}_c \in \mathbb{C}^{p_2 \times q_2}, \ \|\hat{\Delta}_c\| < 1 \right\}$$

where p_2/q_2 is the number of components of w/z respectively.

Then K achieves robust performance if it stabilizes the nominal system P and if it renders the inequality

$$\mu_{\boldsymbol{\Delta_e}}(S(P,K)(i\omega)) \leq 1 \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\} \tag{142}$$

satisfied.

Finding a K which achieves (142) cannot be done directly since not even the SSV itself can be computed directly. The main idea is to achieve (142) by guaranteeing that a computable upper bound on the SSV is smaller than one for all frequencies. Let us recall that the set of scalings $\boldsymbol{D}$ that corresponds to $\boldsymbol{\Delta_c}$ for computing an upper bound is given by all

$$D = \begin{pmatrix} D_1 & & & & & & & & 0 \\ & \ddots & & & & & & & \\ & & D_{n_r} & & & & & & \\ & & & D_{n_r+1} & & & & & \\ & & & & \ddots & & & & \\ & & & & & D_{n_r+n_c} & & & \\ & & & & & & d_1 I & & \\ & & & & & & & \ddots & \\ 0 & & & & & & & & d_{n_f} I \end{pmatrix}$$

where D_j are Hermitian positive definite matrices and d_j are real positive numbers. The class of scalings that corresponds to $\boldsymbol{\Delta_e}$ is then defined as

$$\boldsymbol{D_e} := \left\{ \begin{pmatrix} D & 0 \\ 0 & I \end{pmatrix} > 0 \mid D \in \boldsymbol{D} \right\}.$$

Remarks. With choosing this class of scalings, we recall that we ignore the fact that the uncertainty structure comprises real blocks. Moreover, the scaling block that corresponds to the full block included for the performance channel in the extension is set (without loss of generality) equal to the identity matrix.

With these class of scalings we have

$$\mu_{\boldsymbol{\Delta_e}}(S(P,K)(i\omega)) \leq \inf_{D \in \boldsymbol{D_e}} \|D^{-1} S(P,K)(i\omega) D\|.$$

We conclude that any stabilizing controller which achieves

$$\inf_{D \in \boldsymbol{D_e}} \|D^{-1} S(P,K)(i\omega) D\| \leq 1 \ \text{ for all } \ \omega \in \mathbb{R} \cup \{\infty\} \tag{143}$$

also guarantees the desired inequality (142). Hence instead of designing a controller that reduces the SSV directly, we design one that minimizes the upper bound of the SSV which is obtained with the class of scalings $\boldsymbol{D_e}$: SSV design is, actually, upper bound design!

Let us slightly re-formulate (143) equivalently as follows: There exists a frequency dependent scaling $D(\omega) \in \boldsymbol{D}_e$ such that

$$\|D(\omega)^{-1}S(P,K)(i\omega)D(\omega)\| < 1 \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}.$$

This leads us to the precise formulation of the problem that we intend to solve.

Robust performance synthesis problem. Minimize

$$\sup_{\omega \in \mathbb{R} \cup \{\infty\}} \|D(\omega)^{-1}S(P,K)(i\omega)D(\omega)\| \tag{144}$$

over all controllers K that stabilize P, and over all frequency dependent scalings $D(\omega)$ with values in the set $\boldsymbol{D_e}$.

If the minimal value that can be achieved is smaller than one, we are done: We guarantee (143) and hence also (142).

If the minimal value is larger than one, the procedure fails. Since we only consider the upper bound, it might still be possible to push the SSV below one by a suitable controller choice. Hence we cannot draw a definitive conclusion in this case. In practice, one concludes that robust performance cannot be achieved, and one tries to adjust the weightings in order to still be able to push the upper bound on the SSV below one.

7.2 The Scalings/Controller Iteration

Unfortunately, it is still not possible to minimize (144) over the controller K and the frequency dependent scalings $D(\omega)$ **together**. Therefore, it has been suggested to iterate the following two steps: 1) Fix the scaling function $D(\omega)$ and minimize (144) over all stabilizing controllers. 2) Fix the stabilizing controller K and minimize (144) over all scaling functions $D(\omega)$.

This procedure is called D/K-iteration and we use the more appropriate terminology scalings/controller iteration. It does not guarantee that we really reach a local or even a global minimum of (144). Nevertheless, in each step of this procedure the value of (144) is *reduced*. If it can be rendered smaller than one, we can stop since the desired goal is achieved. Instead, one could proceed until one cannot reduce the value of (144) by any of the two steps.

Let us now turn to the details of this iteration.

First Step. Set

$$D_1(\omega) = I$$

and minimize

$$\sup_{\omega \in \mathbb{R} \cup \{\infty\}} \|D_1(\omega)^{-1}S(P,K)(i\omega)D_1(\omega)\| = \|S(P,K)\|_\infty$$

over all K that stabilize P. This is nothing but a standard H_∞ problem! Let the optimal value be smaller than γ_1, and let the controller K_1 achieve this bound.

After Step k we have found a scaling function $D_k(\omega)$ and a controller K_k that stabilizes P and which renders

$$\sup_{\omega \in \mathbb{R} \cup \{\infty\}} \|D_k(\omega)^{-1}S(P,K_k)(i\omega)D_k(\omega)\| < \gamma_k \tag{145}$$

for some bound γ_k satisfied.

Scalings optimization to determine $D_{k+1}(\omega)$. Given K_k, perform an SSV robust performance analysis test. This amounts to calculating at each frequency $\omega \in \mathbb{R} \cup \{\infty\}$ the upper bound

$$\inf_{D \in \boldsymbol{D}_e} \|D^{-1}S(P,K_k)(i\omega)D\| \tag{146}$$

on the SSV. Typical algorithms also return an (almost) optimal scaling $D_{k+1}(\omega)$. This step leads to a scaling function $D_{k+1}(\omega)$ such that

$$\sup_{\omega \in \mathbb{R} \cup \{\infty\}} \|D_{k+1}(\omega)^{-1}S(P,K_k)(i\omega)D_{k+1}(\omega)\| < \hat{\gamma}_k$$

for some new bound $\hat{\gamma}_k$.

Controller optimization to determine K_{k+1}. We cannot optimize (144) over K for an arbitrary scaling function $D(\omega) = D_{k+1}(\omega)$. This is the reason why one first has to fit this scaling function by a real rational $\hat{D}(s)$ that is proper and stable, that has a proper and stable inverse, and that is chosen close to $D(\omega)$ in the following sense: For a (small) error bound $\epsilon > 0$, it satisfies

$$\|D_{k+1}(\omega) - \hat{D}(i\omega)\| \leq \epsilon \quad \text{for all} \quad \omega \in \mathbb{R} \cup \{\infty\}.$$

With $\hat{D}$, one then solves the H_∞-control problem

$$\inf_{K \text{ stabilizes } P} \|\hat{D}^{-1}S(P,K)\hat{D}\|_\infty$$

to find an almost optimal controller K_{k+1}. This step leads to a K_{k+1} such that

$$\sup_{\omega \in \mathbb{R} \cup \{\infty\}} \|D_{k+1}(\omega)^{-1}S(P,K_k)(i\omega)D_{k+1}(\omega)\| < \gamma_{k+1} \tag{147}$$

holds for some new bound γ_{k+1}.

We have arrived at (145) for $k \to k+1$ and can iterate.

Let us now analyze the improvements that can be gained during this iteration. During the scalings iteration, we are guaranteed that the new bound $\hat{\gamma}_k$ can be chosen with

$$\hat{\gamma}_k < \gamma_k.$$

However, it might happened that the value of (146) cannot be made significantly smaller than γ_k at some frequency. Then the new bound $\hat{\gamma}_k$ is close to γ_k and the algorithm is stopped. In the other case, $\hat{\gamma}_k$ is significantly smaller than γ_k and the algorithm proceeds.

During the controller iteration, one has to perform an approximation of the scaling function $D_{k+1}(\omega)$ by $\hat{D}(i\omega)$ uniformly over all frequencies with a real rational $\hat{D}(s)$. If the approximation error is small, we infer that

$$\sup_{\omega\in\mathbb{R}\cup\{\infty\}} \|\hat{D}^{-1}(i\omega)S(P,K)(i\omega)\hat{D}(i\omega)\| \approx \sup_{\omega\in\mathbb{R}\cup\{\infty\}} \|D_{k+1}^{-1}(\omega)S(P,K)(i\omega)D_{k+1}(\omega)\|$$

for both $K = K_k$ and $K = K_{k+1}$. For a sufficiently good approximation, we can hence infer from (147) that

$$\sup_{\omega\in\mathbb{R}\cup\{\infty\}} \|\hat{D}^{-1}(i\omega)S(P,K_k)(i\omega)\hat{D}(i\omega)\| < \hat{\gamma}_k.$$

Since K_{k+1} is obtained by solving an H_∞-optimization problem, it can be chosen with

$$\|\hat{D}^{-1}S(P,K_{k+1})\hat{D}\|_\infty \leq \|\hat{D}^{-1}S(P,K_k)\hat{D}\|_\infty.$$

This implies

$$\sup_{\omega\in\mathbb{R}\cup\{\infty\}} \|\hat{D}^{-1}(i\omega)S(P,K_{k+1})(i\omega)\hat{D}(i\omega)\| < \hat{\gamma}_k.$$

Again, if the approximation of the scalings is good enough, this leads to

$$\sup_{\omega\in\mathbb{R}\cup\{\infty\}} \|D_{k+1}^{-1}(\omega)S(P,K_{k+1})(i\omega)D_{k+1}(\omega)\| < \hat{\gamma}_k.$$

Hence the bound γ_{k+1} can be taken **smaller** than $\hat{\gamma}_k$. Therefore, we can conclude

$$\gamma_{k+1} < \gamma_k.$$

Note that this inequality requires a good approximation of the scalings. In practice it can very well happen that the new bound γ_{k+1} cannot be made smaller than the previous bound γ_k! In any case, if γ_{k+1} can be rendered significantly smaller than γ_k, the algorithm proceeds, and in the other cases it stops.

Under ideal circumstances, we observe that the sequence of bounds γ_k is monotonically decreasing and, since bounded from below by zero, hence convergent. This is the **only convergence conclusion that can be drawn.** There are no general implications about the convergence of K_k or of the scaling functions $D_k(\omega)$, and no conclusions can be drawn about optimality of the limiting value of γ_k.

Remarks.

- The μ-tools support the fitting of $D(\omega)$ with rational transfer matrices $\hat{D}(i\omega)$. This is done with GUI support on an element by element basis of the function $D(\omega)$, where the user has control over the McMillan degree of the rational fitting function. In addition, automatic fitting routines are available as well.

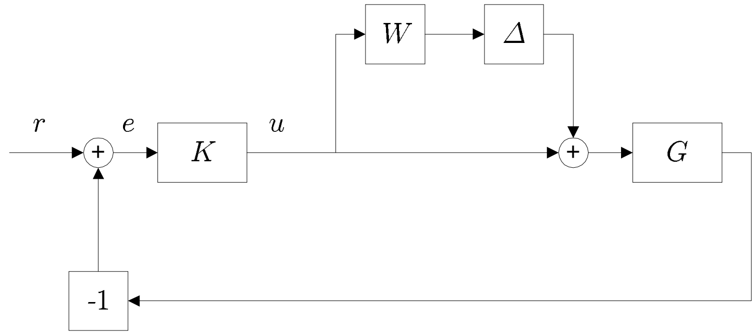


Figure 40: Tracking interconnection of simplified distillation column.

- Since $\hat{D}$ and $\hat{D}^{-1}$ are both proper and stable, minimizing $\|\hat{D}^{-1}S(P,K)\hat{D}\|_\infty$ over K amounts to solving a standard weighted H_∞-problem. The McMillan degree of an (almost) optimal controller is given by

$$2 * \text{McMillan degree of } \hat{D} + \text{McMillan degree of } P.$$

  Keeping the order of K small requires to keep the order of $\hat{D}$ small. Note that this might be only possible at the expense of an large approximation error during the fitting of the scalings. Again, no general rules can be given here and it remains to the user to find a good trade-off between these two aspects.

- If the order of the controller is too large, one should perform a reduction along the lines as described in the chapters 7 and 9 in [ZDG] and chapter 11 in [SP].

To learn about the practice of applying the scalings/controller we recommend to run the `himat`-demo around the design of a pitch axis controller for the simple model of an airplane which is included in the μ-Toolbox. This examples comprises a detailed description of how to apply the commands for the controller/scalings iteration. Moreover, it compares the resulting μ-controller with a simple loop-shaping controller and reveals the benefits of a robust design.

Exercise

1) Consider the following simplified model of a distillation column

$$G(s) = \frac{1}{75s+1}\begin{pmatrix} 87.8 & -86.4 \\ 108.2 & -109.6 \end{pmatrix}$$

(with time expressed in minutes) in the tracking configuration of Figure 40. The uncertainty weighting is given as

$$W(s) = \begin{pmatrix} \frac{s+0.1}{0.5s+1} & 0 \\ 0 & \frac{s+0.1}{0.5s+1} \end{pmatrix}$$

and the real rational proper and stable Δ with $\|\Delta\|_\infty < 1$ is structured as

$$\Delta(s) = \begin{pmatrix} \Delta_1(s) & 0 \\ 0 & \Delta_2(s) \end{pmatrix}.$$

a) Provide an interpretation of this uncertainty structure, and discuss how the uncertainty varies with frequency.

b) Choose the decoupling controllers

$$K_\beta(s) = \frac{\beta}{s} G(s)^{-1}, \quad \beta \in \{0.1, 0.3, 0.5, 0.7\}$$

Discuss in terms of step responses in how far these controller lead to a good closed-loop response! Now choose the performance weightings

$$W_p(s) = \alpha \frac{s+\beta}{s+10^{-6}} I, \quad \alpha \in [0,1], \ \beta \in \{0.1, 0.3, 0.5, 0.7\}$$

with a small perturbation to render the pure intergrator stable. Test robust stability, nominal performance, and robust performance of K_β for $\alpha = 1$ and discuss.

Reveal that K_β does not lead to good robust performance in the time-domain by determining a simple *real* uncertainty which leads to bad step responses in $r \to e$.

c) Perform a two step scalings/controller iteration to design a controller that enforces robust peformance, possibly by varying α to render the SSV for robust performance of the controlled system close to one. Discuss the resulting controller in the frequency-domain and the time-domain, and compare it with the decoupling controllers K_β. Show that this controller exhibits a much better time-response for the 'bad' disturbance constructed in the previous exercise.

Remark. You should make a sensible selection of all the plots that you might collect during performing this exercise in order to nicely display in a non-repetitive fashion all the relevant aspects of your design!

8 A Brief Summary and Outlooks

We have seen that the **generalized plant framework** is very general and versatile to capture a multitude of interconnection structures. This concept extends to much larger classes of uncertainties, and it can be also generalized to some extent to non-linear systems where it looses, however, its generality.

The **structured singular value** offered us computable tests for robust stability and robust performance against structured linear time-invariant uncertainties. It is possible to include parametric uncertainties which are, however, computationally more delicate.

Nominal controller synthesis, formulated as reducing the H_∞-norm of the performance channel, found a very satisfactory and complete solution in the celebrated Riccati approach to H_∞-control.

Robust controller synthesis is, from a theoretical point of view and despite intensive efforts, still in its infancy. The scaling/controller iteration and variations thereof form - to date - the only possibility to design robustly peforming controllers. It offers no guarantee of optimality, but it has proven useful in practice.

These notes were solely concerned with LTI controller analysis/synthesis, with LTI uncertainties, and with H_∞-norm bounds as performance specifications. **L**inear **M**atrix **I**nequalities (LMIs) techniques offer the possibilities for extensions in the following directions:

- There is a much greater flexibility in choosing the performance specification, such as taking into account H_2-norm constraints (stochastic noise reduction), positive real conditions and amplitude constraints.
- The LMI framework allows the extension to multi-objective design in which the controller is built to guarantee various performance specs on different channels.
- It is possible to include time-varying parametric, non-linear static and non-linear dynamic uncertainties in the robustness tests. The uncertainties will be described in this framework by **I**ntegral **Q**uadratic **C**onstraints (IQCs) which are generalizations of the scalings techniques developed in these notes.
- Finally, LMI techniques allow to perform a systematic design of gain-scheduling controller to attack certain class of non-linear control problems.

A Bisection

At several places we encountered the problem to compute a critical value γ_{critical}, such as in computing the upper bound for the SSV or the optimal value in the H_∞ problem. However, the algorithms we have developed only allowed to test whether a given number γ satisfies $\gamma_{\text{critical}} < \gamma$ or not. How can we compute γ_{critical} just by exploiting the possibility to perform such a test?

The most simple technique is bisection. Fix a level of accuracy $\epsilon > 0$.

- Start with an interval $[a_1, b_1]$ such that $a_1 \leq \gamma_{\text{critical}} \leq b_1$.
- Suppose one has constructed $[a_j, b_j]$ with $a_j \leq \gamma_{\text{critical}} \leq b_j$.

  Then one tests whether
  $$\gamma_{\text{critical}} < \frac{a_j + b_j}{2}.$$
  We assume that this test can be performed and leads to either yes or no as an answer.

  If the answer is **yes**, set $[a_{j+1}, b_{j+1}] = [a_j, \frac{a_j+b_j}{2}]$.

  If the answer is **no**, set $[a_{j+1}, b_{j+1}] = [\frac{a_j+b_j}{2}, b_j]$.
- If $b_{j+1} - a_{j+1} > \epsilon$ then proceed with the second step for j replaced by $j+1$.

  If $b_{j+1} - a_{j+1} \leq \epsilon$ then stop with $a_{j+1} \leq \gamma_{\text{critical}} \leq a_{j+1} + \epsilon$.

Since the length of $[a_{j+1}, b_{j+1}]$ is just half the length of $[a_j, b_j]$, there clearly exists an index for which the length of the interval is smaller than ϵ. Hence the algorithm **always stops**. After the algorithm has stopped, we have calculated γ_{critical} up to the absolute accuracy ϵ.

B Proof of Theorem 37

Note that
$$A^TX + XA + XRX + Q = (-A)^T(-X) + (-X)(-A) + (-X)R(-X) + Q$$
and
$$A + RX = -((-A) + R(-X)).$$
Hence we can apply Theorem 38 to the ARE/ARI
$$(-A)^TY + Y(-A) + YRY + Q = 0, \quad (-A)^TY + Y(-A) + YRY + Q < 0$$
if $(-A, R)$ is stabilizable. This leads to the following result.

Corollary 49 *Suppose that all hypothesis in Theorem 38 hold true but that $(-A, R)$ is only stabilizable. Then the following statements are equivalent:*

(a) H has no eigenvalues on the imaginary axis.

(b) $A^TX + XA + XRX + Q = 0$ has a (unique) anti-stabilizing solution X_+.

(c) $A^TX + XA + XRX + Q < 0$ has a symmetric solution X.

If one and hence all of these conditions are satisfied, then

$$\text{any solution } X \text{ of the ARE or ARI satisfies } \; X \leq X_+.$$

Combining this corollary with Theorem 38 implies Theorem 37.

C Proof of Theorem 38

Let us first show the inequality $X_- \leq X$ if X_- is the stabilizing solution of the ARE (existence assumed) and X is any other solution of the ARE or ARI.

The key is the easily proved identity

$$\begin{aligned}(A^TZ + ZA + ZRZ + Q) - (A^TY + YA + YRY + Q) \quad &= \\ = (A + RY)^T(Z - Y) + (Z - Y)(A + RY) + (Z - Y)R(Z - Y).& \quad (148)\end{aligned}$$

If we set $Z = X$ and $Y = X_-$, and if we exploit $R \geq 0$, we obtain

$$0 \geq A^TX + XA + XRX + Q \geq (A + RX_-)^T(X - X_-) + (X - X_-)(A + RX_-).$$

Since $A + RX_-$ is stable, we infer that $X - X_- \geq 0$.

Minimality of X_- implies that there is *at most one* stabilizing solution. In fact, if X_1 and X_2 are two stabilizing solutions of the ARE, we can infer $X_1 \leq X_2$ (since X_2 is smallest) and $X_2 \leq X_1$ (since X_1 is smallest); this leads to $X_1 = X_2$.

Before we can start the proof, we have to establish an important property of the Hamiltonian matrix H. First we observe that the particular structure of H can be expressed as follows. Defining
$$J := \begin{pmatrix} 0 & -I \\ I & 0 \end{pmatrix},$$
the matrix JH is symmetric! It is a pretty immediate consequence of this fact that the eigenvalues of any Hamiltonian matrix are located symmetrically with respect to the imaginary axis in the complex plane.

Lemma 50 *Suppose H is a matrix such that JH is symmetric. If H has k eigenvalues in $\mathbb{C}^-$ then it has also k eigenvalues in $\mathbb{C}^+$ (counted with their algebraic multiplicity) and vice versa.*

Proof. By $JH = (JH)^T = H^T J^T = -H^T J$ we infer $JHJ^{-1} = -H^T$. Hence H and $-H^T$ are similar and, thus, their characteristic polynomials are identical: $\det(H - sI) = \det(-H^T - sI)$. Since H has even size, we infer $\det(-H^T - sI) = \det(H^T + sI) = \det(H + sI) = \det(H - (-s)I)$. The resulting equation $\det(H - sI) = \det(H - (-s)I)$ is all what we need: If $\lambda \in \mathbb{C}^-$ is a zero of $\det(H - sI)$ (of multiplicity k), $-\lambda$ is a zero (of multiplicity k) of the same polynomial.

■

Now we can start the stepwise proof of Theorem 38.

Proof of (a) $\Rightarrow$ (b). Since H has no eigenvalues in $\mathbb{C}^0$, it has n eigenvalues in $\mathbb{C}^-$ and in $\mathbb{C}^+$ respectively (Lemma 50). Then there exists a unitary matrix T with

$$T^*HT = \begin{pmatrix} M & M_{12} \\ 0 & M_{22} \end{pmatrix}$$

where M of size $n \times n$ is stable and M_{22} of size $n \times n$ is antistable. Let us denote the first n columns of T by Z to infer

$$HZ = ZM.$$

Now partition $Z = \begin{pmatrix} U \\ V \end{pmatrix}$ with two square blocks U and V of size n. The difficult step is now to prove that U is invertible. Then it is not so hard to see that $X_- := VU^{-1}$ is indeed a real Hermitian stabilizing solution of the ARE.

We proceed in several steps. We start by showing

$$V^*U = U^*V.$$

Indeed, $HZ = ZM$ implies $Z^*JHZ = Z^*JZM$. Since the left-hand side is symmetric, so is the right-hand side. This implies $(Z^*JZ)M = M^*(Z^*J^*Z) = -M^*(Z^*JZ)$ by $J^* = -J$. Since M is stable, we infer from $M^*(Z^*JZ) + (Z^*JZ)M = 0$ that $Z^*JZ = 0$[4] what is indeed nothing but $V^*U = U^*V$. Next we show that

$$Ux = 0 \Rightarrow RVx = 0 \Rightarrow UMx = 0.$$

Indeed, $Ux = 0$ and the first row of $HZ = ZM$ imply $UMx = (AU + RV)x = RVx$ and thus $x^*V^*UMx = x^*V^*RVx$. Since $x^*V^*U = x^*U^*V = 0$, the left-hand side and hence the right-hand side vanish. By $R \geq 0$, we conclude $RVx = 0$. From $UMx = RVx$ we infer $UMx = 0$. Now we can establish that

$$U \text{ is invertible.}$$

[4] Recall that $AX - XB = 0$ has no nonzero solution iff A and B have no eigenvalues in common.

It suffices to prove $\ker(U) = \{0\}$. Let us assume that $\ker(U)$ is nontrivial. We have just shown $x \in \ker(U) \Rightarrow Ux = 0 \Rightarrow UMx = 0 \Rightarrow Mx \in \ker(U)$. Hence $\ker(U)$ is a nonzero M-invariant subspace. Therefore, there exists an eigenvector of M in $\ker(U)$, i.e., an $x \neq 0$ with $Mx = \lambda x$ and $Ux = 0$. Now the second row of $HZ = ZM$ yields $(-QU - A^T V)x = VMx$ and thus $A^T Vx = -\lambda Vx$. Since $Ux = 0$, we have $RVx = 0$ (second step) or $R^T Vx = 0$. Since (A, R) is stabilizable and $\mathrm{Re}(-\lambda) > 0$, we infer $Vx = 0$. Since $Ux = 0$, this implies $Zx = 0$ and hence $x = 0$ because Z has full column rank. However, this contradicts the choice of x as a nonzero vector.

Since U is nonsingular we can certainly define

$$X_- := VU^{-1}.$$

X_- is Hermitian since $V^*U = U^*V$ implies $U^{-*}V^* = VU^{-1}$ and hence $(VU^{-1})^* = VU^{-1}$. X_- is a stabilizing solution of the ARE. Indeed, from $HZ = ZM$ we infer $HZU^{-1} = ZMU^{-1} = ZU^{-1}(UMU^{-1})$. This leads to

$$H \begin{pmatrix} I \\ X_- \end{pmatrix} = \begin{pmatrix} I \\ X_- \end{pmatrix} (UMU^{-1}).$$

The first row of this identity shows $A + RX_- = UMU^{-1}$ such that $A + RX_-$ is stable. The second row reads as $-Q - A^T X_- = X_-(A + RX_-)$ what is nothing but the fact that X_- satisfies the ARE.

So far, X_- might be complex. Since the data matrices are real, we have

$$\overline{A^T X + XA + XRX + Q} = A^T \bar{X} + \bar{X}A + \bar{X}R\bar{X} + Q, \quad \overline{A + RX} = A + R\bar{X}.$$

Consequently, with X_-, also its complex conjugate $\bar{X}_-$ is a stabilizing solution of the ARE. Since we have already shown that there is at most one such solution, we infer $X = \bar{X}_-$ such that X_- must be necessarily real.

Proof of (b) $\Rightarrow$ (a). Just evaluating both sides gives

$$H \begin{pmatrix} I & 0 \\ X_- & I \end{pmatrix} = \begin{pmatrix} I & 0 \\ X_- & I \end{pmatrix} \begin{pmatrix} A + RX_- & R \\ 0 & -(A + RX_-)^T \end{pmatrix}.$$

Hence

$$H \text{ is similar to } \begin{pmatrix} A + RX_- & R \\ 0 & -(A + RX_-)^T \end{pmatrix}. \tag{149}$$

Therefore, any eigenvalue of H is an eigenvalue of $A + RX_-$ or of $-(A + RX_-)^T$ such that H cannot have eigenvalues in $\mathbb{C}^0$.

Proof of (a) $\Rightarrow$ (c). We perturb Q to $Q + \epsilon I$ and denote the corresponding Hamiltonian as H_ϵ. Since the eigenvalues of a matrix depend continuously on its coefficients, H_ϵ

has no eigenvalues in $\mathbb{C}^0$ for all small $\epsilon > 0$. By (b), there exists a symmetric X with $A^T X + XA + XRX + Q + \epsilon I = 0$ what implies (c).

Proof of (c) $\Rightarrow$ (b): Suppose Y satisfies the strict ARI and define $P := A^T Y + YA + YRY + Q > 0$. If we can establish that

$$(A + RY)^T \Delta + \Delta(A + RY) + \Delta R \Delta + P = 0 \tag{150}$$

has a stabilizing solution Δ, we are done: Due to (148), $X = Y + \Delta$ satisfies the ARE and renders $A + RX = (A + RY) + R\Delta$ stable. The existence of a stabilizing solution of (150) is assured as follows: Clearly, $(A + RY, R)$ is stabilizable and (A, P) is observable (due to $P > 0$). By Lemma 39, the Hamiltonian matrix corresponding to (150) does not have eigenvalues on the imaginary axis. Hence we can apply the already proved implication (a) $\Rightarrow$ (b) to infer that (150) has a stabilizing solution.

■

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