Multivariable Robust Control

Lecture 6 (Meetings 13-14)

Chapter 8: Robust Stability and Performance Analysis for MIMO Systems

Eugenio Schuster



schuster@lehigh.edu Mechanical Engineering and Mechanics Lehigh University

General configuration with uncertainty [8.1]

For our robustness analysis we use a system representation in which the uncertain perturbations are "pulled out" into a block-diagonal matrix,

$$\Delta = \operatorname{diag}\{\Delta_i\} = \begin{bmatrix} \Delta_1 & & \\ & \ddots & \\ & & \Delta_i & \\ & & & \ddots \end{bmatrix}$$

where each Δ_i represents a specific source of uncertainty.

(6.1)





Figure 1: Rearranging an uncertain system into the $N\Delta$ -structure



Figure 2: $N\Delta$ -structure for robust performance analysis

If we also pull out the controller K, we get the generalized plant P, as shown in Figure 3. For analysis of the uncertain system, we use the $N\Delta$ -structure in Figure 2.



Figure 3: General control configuration (for controller synthesis)

Consider Figure 1 where it is shown how to pull out the perturbation blocks to form Δ and the nominal system N. N is related to P and K by a lower LFT

$$N = F_l(P, K) \stackrel{\Delta}{=} P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21}$$
(6.2)

Similarly, the uncertain closed-loop transfer function from w to $z,\,z=Fw,$ is related to N and Δ by an upper LFT,

$$F = F_u(N,\Delta) \stackrel{\Delta}{=} N_{22} + N_{21}\Delta(I - N_{11}\Delta)^{-1}N_{12}$$
(6.3)

To analyze robust stability of F, we can then arrange the system into the $M\Delta$ -structure of Figure 4, where $M = N_{11}$ is the transfer function from the output to the input of the perturbations.



Figure 4: $M\Delta$ -structure for robust stability analysis

Representing uncertainty [8.2]

As usual, each individual perturbation is assumed to be stable and is normalized,

$$\bar{\sigma}(\Delta_i(j\omega)) \le 1 \ \forall \omega \tag{6.4}$$

For a complex scalar perturbation we have $|\delta_i(j\omega)| \leq 1$, $\forall \omega$, and for a real scalar perturbation $-1 \leq \delta_i \leq 1$. Since the maximum singular value of a block diagonal matrix is equal to the largest of the maximum singular values of the individual blocks, it then follows for $\Delta = \text{diag}\{\Delta_i\}$ that

$$\bar{\sigma}(\Delta_i(j\omega)) \le 1 \ \forall \omega, \ \forall i \quad \Leftrightarrow \quad \left| \|\Delta\|_{\infty} \le 1 \right|$$
(6.5)

Note that Δ has *structure*, and therefore in the robustness analysis we do *not* want to allow all Δ s.t. (6.5) is satisfied.

Parametric uncertainty:

The representation of parametric uncertainty discussed for SISO systems carries straightforward over to MIMO systems.

Unstructured uncertainty:

We define *unstructured* uncertainty as the use of a "full" complex perturbation matrix Δ , usually with dimensions compatible with those of the plant, where at each frequency any $\Delta(j\omega)$ satisfying $\bar{\sigma}(\Delta(j\omega)) \leq 1$ is allowed.

Six common forms of unstructured uncertainty are shown in Figure 5. In Figure 5(a), (b) and (c) are shown three *feedforward* forms; additive uncertainty, multiplicative input uncertainty and multiplicative output uncertainty:

$$\Pi_A: \qquad G_p = G + E_A; \qquad E_a = w_A \Delta_a \tag{6.6}$$

$$\Pi_I: \qquad G_p = G(I + E_I); \qquad E_I = w_I \Delta_I \tag{6.7}$$

$$\Pi_O: \qquad G_p = (I + E_O)G; \qquad E_O = w_O \Delta_O \tag{6.8}$$

In Figure 5(d), (e) and (f) are shown three *feedback* or *inverse* forms; inverse additive uncertainty, inverse multiplicative input uncertainty and inverse multiplicative output uncertainty:

$$\Pi_{iA}: \qquad G_p = G(I - E_{iA}G)^{-1}; \qquad E_{iA} = w_{iA}\Delta_{iA}$$
(6.9)

$$\Pi_{iI}: \qquad G_p = G(I - E_{iI})^{-1}; \qquad E_{iI} = w_{iI}\Delta_{iI}$$
(6.10)

$$\Pi_{iO}: \qquad G_p = (I - E_{iO})^{-1}G; \qquad E_{iO} = w_{iO}\Delta_{iO}$$
(6.11)

The negative sign in front of the E's does not really matter here since we assume that Δ can have any sign. Δ denotes the normalized perturbation and E the "actual" perturbation. We have here used scalar weights w, so $E = w\Delta = \Delta w$, but sometimes one may want to use matrix weights, $E = W_2 \Delta W_1$ where W_1 and W_2 are given transfer function matrices.



Figure 5: (a) Additive uncertainty, (b) Multiplicative input uncertainty, (c) Multiplicative output uncertainty, (d) Inverse additive uncertainty, (e) Inverse multiplicative input uncertainty, (f) Inverse multiplicative output uncertainty

Obtaining P, N and M [8.3]



Figure 6: System with multiplicative input uncertainty and performance measured at the output

Example 1: System with input uncertainty (Figure 6). We want to derive the generalized plant P in Figure 3 which has inputs $\begin{bmatrix} u_{\Delta} & w & u \end{bmatrix}^{T}$ and outputs $\begin{bmatrix} y_{\Delta} & z & v \end{bmatrix}^{T}$. By writing down the equations or simply by inspecting Figure 6 (remember to break the loop before and after both K and Δ) we get

$$P = \begin{bmatrix} 0 & 0 & W_I \\ W_P G & W_P & W_P G \\ -G & -I & -G \end{bmatrix}$$
(6.12)

Next, we want to derive the matrix N corresponding to Figure 2. First, partition P to be compatible with K, i.e.

$$P_{11} = \begin{bmatrix} 0 & 0 \\ W_P G & W_P \end{bmatrix}, P_{12} = \begin{bmatrix} W_I \\ W_P G \end{bmatrix}$$
(6.13)
$$P_{21} = \begin{bmatrix} -G & -I \end{bmatrix}, P_{22} = -G$$
(6.14)

And then find $N = F_l(P, K)$ using (6.2). We get

$$N = \begin{bmatrix} -W_I K G (I + KG)^{-1} & -W_I K (I + GK)^{-1} \\ W_P G (I + KG)^{-1} & W_P (I + GK)^{-1} \end{bmatrix}$$
(6.15)

Alternatively, we can derive N directly from Figure 6 by evaluating the closed-loop transfer function from inputs $\begin{bmatrix} u_{\Delta} \\ w \end{bmatrix}$ to outputs $\begin{bmatrix} y_{\Delta} \\ z \end{bmatrix}$ (without breaking the loop before and after K).

For example, to derive N_{12} , which is the transfer function from w to y_{Δ} , we start at the output (y_{Δ}) and move backwards to the input (w) using the MIMO Rule (we first meet W_I , then -K and we then exit the feedback loop and get the term $(I + GK)^{-1}$).

The upper left block, N_{11} , in (6.15) is the transfer function from u_{Δ} to y_{Δ} . This is the transfer function M needed in Figure 4 for evaluating robust stability. Thus, we have $M = -W_I K G (I + K G)^{-1} = -W_I T_I$.

Robust stability & performance [8.4]

- Robust stability (RS) analysis: with a given controller K we determine whether the system remains stable for all plants in the uncertainty set.
- Obstitution of the second s

In Figure 2, w represents the exogenous inputs (normalized disturbances and references), and z the exogenous outputs (normalized errors). We have $z = F(\Delta)w$, where from (6.3)

$$F = F_u(N,\Delta) \stackrel{\Delta}{=} N_{22} + N_{21}\Delta(I - N_{11}\Delta)^{-1}N_{12}$$
(6.16)

We here use the \mathcal{H}_{∞} norm to define performance and require for RP that $||F(\Delta)||_{\infty} \leq 1$ for all allowed Δ 's. A typical choice is $F = w_P S_p$ (the weighted sensitivity function), where w_P is the performance weight (capital P for performance) and S_p represents the set of perturbed sensitivity functions (lower-case p for perturbed).

In terms of the $N\Delta\mbox{-structure}$ in Figure 2 our requirements for stability and performance are

$$\begin{array}{lll} \mathrm{NS} & \stackrel{\mathrm{def}}{\Leftrightarrow} & N \text{ is internally stable} & (6.17) \\ \mathrm{NP} & \stackrel{\mathrm{def}}{\Leftrightarrow} & \|N_{22}\|_{\infty} < 1; & \text{and NS} & (6.18) \\ \mathrm{RS} & \stackrel{\mathrm{def}}{\Leftrightarrow} & F = F_u(N, \Delta) \text{ is stable } \forall \Delta, \|\Delta\|_{\infty} \leq 1; & (6.19) \\ & & \text{and NS} \\ \mathrm{RP} & \stackrel{\mathrm{def}}{\Leftrightarrow} & \|F\|_{\infty} < 1, \quad \forall \Delta, \|\Delta\|_{\infty} \leq 1; & (6.20) \\ & & \text{and NS} \end{array}$$

Remark 1 Allowed perturbations. For simplicity below we will use the shorthand notation

$$\forall \Delta \quad \text{and} \quad \max_{\Delta}$$
 (6.21)

to mean "for all Δ 's in the set of allowed perturbations", and "maximizing over all Δ 's in the set of allowed perturbations". By *allowed perturbations* we mean that the \mathcal{H}_{∞} norm of Δ is less or equal to 1, $\|\Delta\|_{\infty} \leq 1$, and that Δ has a specified block-diagonal structure.

Robust stability of the $M\Delta$ -structure [8.5]

Consider the uncertain $N\Delta$ -system in Figure 2 for which the transfer function from w to z is, as in (6.16), given by

$$F_u(N,\Delta) = N_{22} + N_{21}\Delta(I - N_{11}\Delta)^{-1}N_{12}$$
(6.22)

Suppose that the system is nominally stable (with $\Delta = 0$), that is, N is stable (which means that the whole of N, and not only N_{22} , must be stable). We also assume that Δ is stable. We can see from (6.22) that the only potential source of instability is the feedback term $(I - N_{11}\Delta)^{-1}$. Thus, when we have nominal stability (NS), the stability of the system in Figure 2 is equivalent to the stability of the $M\Delta$ -structure in Figure 4 where $M = N_{11}$.

We need now to derive conditions for checking the stability of the $M\Delta$ -structure.

Theorem

Determinant stability condition (real or complex perturbations). Assume that the nominal system M(s) and the perturbations $\Delta(s)$ are stable. Consider the convex set of perturbations Δ , such that if Δ' is an allowed perturbation then so is $c\Delta'$ where c is any <u>real</u> scalar such that $|c| \leq 1$. Then the $M\Delta$ -system in Figure 4 is stable for all allowed perturbations (we have RS) if and only if

Nyquist plot of det
$$(I - M(s)\Delta(s))$$
 does not
encircle the origin, $\forall \Delta$ (6.23)

$$\Rightarrow \quad \det\left(I - M(j\omega)\Delta(j\omega)\right) \neq 0, \quad \forall \omega, \forall \Delta \tag{6.24}$$

$$\Leftrightarrow \quad \lambda_i(M\Delta) \neq 1, \quad \forall i, \forall \omega, \forall \Delta \tag{6.25}$$

Note that (6.23) is simply the generalization of the Nyquist theorem.

Theorem: Generalized (MIMO) Nyquist theorem. Let P_{ol} denote the number of open-loop unstable poles in L(s). The closed-loop system with loop transfer function L(s) and negative feedback is stable if and only if the Nyquist plot of det(I + L(s))

i) makes P_{ol} anti-clockwise encirclements of the origin, and

ii) does not pass through the origin.

Note

By "Nyquist plot of $\det(I+L(s))$ " we mean "the image of $\det(I+L(s))$ as s goes clockwise around the Nyquist D-contour" .

RS for unstructured uncertainty [8.6]

Theorem

RS for unstructured ("full") perturbations. Assume that the nominal system M(s) is stable (NS) and that the perturbation $\Delta(s)$ are stable ($\Delta(s)$ is allowed to be any (full) complex transfer function matrix). Then the $M\Delta$ -system in Figure 4 is stable for all perturbations Δ satisfying $\|\Delta\|_{\infty} \leq 1$ (i.e. we have RS) if and only if

$$\bar{\sigma}(M(j\omega)) < 1 \quad \forall w \qquad \Leftrightarrow \qquad \|M\|_{\infty} < 1 \qquad (6.26)$$

Remark 1: Condition (6.26) may be rewritten as

$$RS \qquad \Leftrightarrow \quad \bar{\sigma}(M(j\omega))\bar{\sigma}(\Delta(j\omega)) < 1 \quad \forall w, \forall \Delta$$
(6.27)

The sufficiency of (6.27) (\Leftarrow) follows directly from the small-gain theorem by choosing $L = M\Delta$. The small-gain theorem applies to any operator norm satisfying $||AB|| \leq ||A|| ||B||$. **Remark 2:** The \mathcal{H}_{∞} is one of such operators. This implies that the RS condition (6.27) is both necessary and sufficient.

Small Gain Theorem. Consider a system with a stable loop transfer function L(s). Then the closed-loop system is stable if

$$\|L(j\omega)\| < 1 \quad \forall \omega \tag{6.28}$$

where ||L|| denotes any matrix norm satisfying $||AB|| \le ||A|| \cdot ||B||$, for example the singular value $\bar{\sigma}(L)$.

Application of the unstructured RS-condition [8.6.1]:

We will now present necessary and sufficient conditions for robust stability (RS) for each of the six single unstructured perturbations in Figure 5 with

$$E = W_2 \Delta W_1, \quad \|\Delta\|_{\infty} \le 1 \tag{6.29}$$

To derive the matrix ${\cal M}$ we simply "isolate" the perturbation, and determine the transfer function matrix

$$M = W_1 M_0 W_2 (6.30)$$

from the output to the input of the perturbation, where M_0 for each of the six cases becomes (disregarding some negative signs which do not affect the subsequent robustness condition) is given by

$$G_p = G + E_A: \quad M_0 = K(I + GK)^{-1} = KS$$
 (6.31)

$$G_p = G(I + E_I): \quad M_0 = K(I + GK)^{-1}G = T_I$$
(6.32)

$$G_p = (I + E_O)G: \quad M_0 = GK(I + GK)^{-1} = T$$
 (6.33)

$$G_p = G(I - E_{iA}G)^{-1}: \quad M_0 = (I + GK)^{-1}G = SG$$
(6.34)
$$G_{iA} = G(I - E_{iA}G)^{-1}: \quad M_{iA} = (I + KG)^{-1}G = SG$$
(6.34)

$$G_p = G(I - E_{iI})^{-1} : \qquad M_0 = (I + KG)^{-1} = S_I$$

$$G_p = (I - E_{iQ})^{-1}G : \qquad M_0 = (I + GK)^{-1} = S$$
(6.36)
(6.36)

$$= (I - E_{iO})^{-1}G: \qquad M_0 = (I + GK)^{-1} = S$$
(6.36)

Theorem 2 then yields

$$\text{RS} \quad \Leftrightarrow \quad \|W_1 M_0 W_2(j\omega)\|_{\infty} < 1, \forall \ w \tag{6.37}$$

For instance, from second equation (6.32) and (6.37) we get for multiplicative input uncertainty with a scalar weight:

$$\operatorname{RS} \forall G_p = G(I + w_I \Delta_I), \ \|\Delta_I\|_{\infty} \le 1 \ \Leftrightarrow \ \|w_I T_I\|_{\infty} < 1$$
(6.38)

Note that the SISO-condition (5.15)

$$RS = |T| < 1/|w_I|, \quad \forall \omega$$
(6.39)

follows as a special case of (6.38). Similarly, (5.20)

$$RS \quad \Leftrightarrow \quad |S| < 1/|w_{oI}|, \quad \forall \omega$$
(6.40)

follows as a special case of the inverse multiplicative output uncertainty in (6.36):

$$\operatorname{RS} \forall G_p = (I - w_{iO} \Delta_{iO})^{-1} G,$$

$$\|\Delta_{iO}\|_{\infty} \leq 1 \Leftrightarrow \|w_{iO}S\|_{\infty} < 1$$
(6.41)

In general, the unstructured uncertainty descriptions in terms of a single perturbation are not "tight" (in the sense that at each frequency all complex perturbations satisfying $\bar{\sigma}(j\omega) \leq 1$ may not occur in practice). Thus, the above RS conditions are often conservative. In order to get tighter conditions we must use a tighter uncertainty description in terms of a block diagonal Δ .

RS with structured uncertainty [8.7]

Consider now the presence of structured uncertainty, where $\Delta = \text{diag}\{\Delta_i\}$ is block-diagonal. To test for robust stability we rearrange the system into the $M\Delta$ -structure and we have from (6.26)

RS if
$$\bar{\sigma}(M(j\omega)) < 1, \forall \omega$$
 (6.42)

We have here written "if" rather than "if and only if" since this condition is only necessary for RS when Δ has "no structure" (full-block uncertainty).

Can we take advantage of the fact that $\Delta = \text{diag}\{\Delta_i\}$ has structure to obtain tighter RS conditions? To reduce conservatism, we introduce the block-diagonal scaling matrix

$$D = \operatorname{diag}\{d_i I_i\} \tag{6.43}$$

where d_i is a scalar and I_i is an identity matrix of the same dimension as the *i*'th perturbation block, Δ_i (Figure 7). This clearly has no effect on stability.



Figure 7: Use of block-diagonal scalings, $\Delta D = D\Delta$

Note that with the chosen form for the scalings, we have for each perturbation block $\Delta_i = d_i \Delta_i d_i^{-1}$; that is, we have $\Delta = D \Delta D^{-1} \Rightarrow$ Same uncertainty!

RS if
$$\bar{\sigma}(DMD^{-1}) < 1, \forall \omega$$
 (6.44)

This applies for any D in (6.43), and therefore the "most improved" (least conservative) RS-condition is obtained by minimizing at each frequency the scaled singular value, and we have

RS if
$$\min_{D(\omega)\in\mathcal{D}} \bar{\sigma}(D(\omega)M(j\omega)D(\omega)^{-1}) < 1, \forall \omega$$
 (6.45)

where \mathcal{D} is the set of block-diagonal matrices whose structure is compatible to that of Δ , i.e, $\Delta D = D\Delta$. Note that when Δ is a full (unstructured) matrix, we must select D = dI and we have $\bar{\sigma}(DMD^{-1}) = \bar{\sigma}(M)$ (RS conditions for unstructured uncertainty). However, when Δ has structure, we get more degrees of freedom in D and $\bar{\sigma}(DMD^{-1})$ may be significantly smaller than $\bar{\sigma}(M)$.

This motivates the introduction of the structure singular value, $\mu(M)$ satisfying $\mu(M) \leq \min_D \bar{\sigma}(DMD^{-1})$.

The structured singular value [8.8]

The structured singular value (denoted Mu, mu, SSV or μ) is a function which provides a generalization of the singular value, $\bar{\sigma}$, and the spectral radius, ρ . We will use μ to get necessary and sufficient conditions for robust stability and also for robust performance. How is μ defined? A simple statement is:

Find the smallest structured Δ (measured in terms of $\bar{\sigma}(\Delta)$) which makes $\det(I - M\Delta) = 0$; then $\mu(M) = 1/\bar{\sigma}(\Delta)$.

Mathematically,

$$\mu(M)^{-1} \stackrel{\Delta}{=} \min_{\Delta} \{ \bar{\sigma}(\Delta) | \det(I - M\Delta) = 0 \text{ for structured } \Delta \}$$
(6.46)

Clearly, $\mu(M)$ depends not only on M but also on the allowed structure for Δ . This is sometimes shown explicitly by using the notation $\mu_{\Delta}(M)$.

Remark. For the case where Δ is "unstructured" (a full matrix), the smallest Δ which yields singularity has $\bar{\sigma}(\Delta) = 1/\bar{\sigma}(M)$, and we have $\mu(M) = \bar{\sigma}(M)$.

Remark. As one might guess, we have that $\mu(M) \leq \min_D \bar{\sigma}(DMD^{-1})$. In fact, for block-diagonal complex perturbations we generally have that $\mu(M)$ is very close to $\min_D \bar{\sigma}(DMD^{-1})$.

Example

Full perturbation (Δ *is unstructured*). Consider

$$M = \begin{bmatrix} 2 & 2 \\ -1 & -1 \end{bmatrix} = \\ = \begin{bmatrix} 0.894 & 0.447 \\ -0.447 & 0.894 \end{bmatrix} \begin{bmatrix} 3.162 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0.707 & -0.707 \\ 0.707 & 0.707 \end{bmatrix}^{H}$$
(6.47)

The perturbation

$$\Delta = \frac{1}{\sigma_1} v_1 u_1^H = \frac{1}{3.162} \begin{bmatrix} 0.707\\ 0.707 \end{bmatrix} \begin{bmatrix} 0.894 & -0.447 \end{bmatrix} = \\ = \begin{bmatrix} 0.200 & 0.200\\ -0.100 & -0.100 \end{bmatrix}$$
(6.48)

with $\bar{\sigma}(\Delta) = 1/\bar{\sigma}(M) = 1/3.162 = 0.316$ makes $\det(I - M\Delta) = 0$. Thus $\mu(M) = 3.162$ when Δ is a full matrix.

Note that the perturbation Δ in (6.48) is a full matrix. If we restrict Δ to be diagonal then we need a larger perturbation to make $\det(I - M\Delta) = 0$. This is illustrated next.

Example

Continued. Diagonal perturbation (Δ is structured). For the matrix M in (6.47), the smallest diagonal Δ which makes det $(I - M\Delta) = 0$ is

$$\Delta = \frac{1}{3} \begin{bmatrix} 1 & 0\\ 0 & -1 \end{bmatrix}$$
(6.49)

with $\bar{\sigma}(\Delta) = 0.333$. Thus $\mu(M) = 3$ when Δ is a diagonal matrix.

Definition

Structured Singular Value. Let M be a given complex matrix and let $\Delta = \operatorname{diag}\{\Delta_i\}$ denote a set of complex matrices with $\overline{\sigma}(\Delta) \leq 1$ and with a given block-diagonal structure (in which some of the blocks may be repeated and some may be restricted to be real). The real non-negative function $\mu(M)$, called the structured singular value, is defined by

$$\mu(M) \stackrel{\Delta}{=} \frac{1}{\min\{k_m | \det(I - k_m M \Delta) = 0, \bar{\sigma}(\Delta) \le 1\}}$$
(6.50)

If no such structured Δ exists then $\mu(M) = 0$.

A value of $\mu = 1$ means that there exists a perturbation with $\bar{\sigma}(\Delta) = 1$ which is just large enough to make $I - M\Delta$ singular. A larger value of μ is "bad" as it means that a smaller perturbation makes $I - M\Delta$ singular, whereas a smaller value of μ is "good".

Properties of the structured singular value:

Check Sections 8.8.1, 8.8.2 and 8.8.3 in the book.

RS - Structured uncertainty [8.9]

Consider stability of the $M\Delta$ -structure in Figure 4 for the case where Δ is a set of norm-bounded block-diagonal perturbations. From the determinant stability condition:

$$RS \Leftrightarrow \det \left(I - M(j\omega)\Delta(j\omega) \right) \neq 0, \quad \forall \omega, \forall \Delta, \bar{\sigma}(\Delta(j\omega)) \le 1 \quad \forall \omega$$
 (6.51)

This is just a "yes/no" condition. To find the factor k_m by which the system is robustly stable, we scale the uncertainty Δ by k_m , and look for the smallest k_m that yields "borderline instability," namely

$$\det\left(I - k_m M(j\omega)\Delta(j\omega)\right) = 0 \tag{6.52}$$

By definition, this value is $k_m = 1/\mu(M)$. We obtain the following necessary and sufficient condition for stability.
Theorem

RS for block-diagonal perturbations (real or complex). Assume that the nominal system M and the perturbations Δ are stable. Then the $M\Delta$ -system in Figure 4 is stable for all allowed perturbations with $\bar{\sigma}(\Delta) \leq 1, \forall \omega$, if and only if

$$\mu(M(j\omega)) < 1, \quad \forall \omega \tag{6.53}$$

Condition (6.53) for robust stability may be rewritten as

RS
$$\Leftrightarrow \mu(M(j\omega)) \ \bar{\sigma}(\Delta(j\omega)) < 1, \quad \forall \omega$$
 (6.54)

which may be interpreted as a "generalized small gain theorem" that also takes into account the *structure* of Δ .

Example: RS with diagonal input uncertainty

Consider robust stability of the feedback system in Figure 6 for the case when the multiplicative input uncertainty is diagonal. A nominal 2×2 plant and the controller (which represents PI-control of a distillation process using the DV-configuration) is given by

$$G(s) = \frac{1}{\tau s + 1} \begin{bmatrix} -87.8 & 1.4 \\ -108.2 & -1.4 \end{bmatrix};$$

$$K(s) = \frac{1 + \tau s}{s} \begin{bmatrix} -0.0015 & 0 \\ 0 & -0.075 \end{bmatrix}$$
(6.55)

(time in minutes). The controller results in a nominally stable system with acceptable performance. Assume there is complex multiplicative uncertainty in *each* manipulated input of magnitude

$$w_I(s) = \frac{s + 0.2}{0.5s + 1} \tag{6.56}$$

On rearranging the block diagram to match the $M\Delta$ -structure in Figure 4 we get $M = w_I K G (I + K G)^{-1} = w_I T_I$ (recall (6.15)), and the RS-condition $\mu(M) < 1$ in Theorem 4 yields

$$\operatorname{RS} \Leftrightarrow \mu_{\Delta_I}(T_I) < \frac{1}{|w_I(j\omega)|} \quad \forall \omega, \quad \Delta_I = \begin{bmatrix} \delta_1 & \\ & \delta_2 \end{bmatrix}$$
(6.57)

This condition is shown graphically in Figure 8 so the system is robustly stable. Also in Figure 8, $\bar{\sigma}(T_I)$ can be seen to be larger than $1/|w_I(j\omega)|$ over a wide frequency range. This shows that the system would be unstable for full-block input uncertainty (Δ_I full).



Figure 8: Robust stability for diagonal input uncertainty is guaranteed since $\mu_{\Delta_I}(T_I) < 1/|w_I|, \ \forall \omega$. The use of unstructured uncertainty and $\bar{\sigma}(T_I)$ is conservative.

Example: RS of Spinning Satellite [3.7.1]

Angular velocity control of a satellite spinning about one of its principal axes:

$$G(s) = \frac{1}{s^2 + a^2} \begin{bmatrix} s - a^2 & a(s+1) \\ -a(s+1) & s - a^2 \end{bmatrix}; \quad a = 10$$
(6.58)

A minimal, state-space realization, $G = C(sI - A)^{-1}B + D$, is

$$\begin{bmatrix} A & B \\ \hline C & D \end{bmatrix} = \begin{bmatrix} 0 & a & 1 & 0 \\ -a & 0 & 0 & 1 \\ \hline 1 & a & 0 & 0 \\ -a & 1 & 0 & 0 \end{bmatrix}$$
(6.59)

Poles at $s = \pm ja$ For stabilization:

$$K = I$$

$$T(s) = GK(I + GK)^{-1} = \frac{1}{s+1} \begin{bmatrix} 1 & a \\ -a & 1 \end{bmatrix}$$
(6.60)

Nominal stability (NS). Two closed loop poles at s = -1 and

$$A_{cl} = A - BKC = \begin{bmatrix} 0 & a \\ -a & 0 \end{bmatrix} - \begin{bmatrix} 1 & a \\ -a & 1 \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$$

Nominal performance (NP).



Figure 9: Singular values - Spinning satellite (6.58)

• $\underline{\sigma}(L) \leq 1 \quad \forall \omega \text{ poor performance in low gain direction}$ • g_{12}, g_{21} large \Rightarrow strong interaction

Prof. Eugenio Schuster

Robust stability (RS).

Check stability: one loop at a time.



Figure 10: Checking stability margins "one-loop-at-a-time"

$$\frac{z_1}{w_1} \stackrel{\Delta}{=} L_1(s) = \frac{1}{s} \Rightarrow GM = \infty, PM = 90^{\circ}$$
(6.61)

- Good Robustness? NO
- Consider perturbation in each feedback channel

$$u'_{1} = (1 + \epsilon_{1})u_{1}, \quad u'_{2} = (1 + \epsilon_{2})u_{2}$$

$$B' = \begin{bmatrix} 1 + \epsilon_{1} & 0\\ 0 & 1 + \epsilon_{2} \end{bmatrix}$$
(6.62)

Closed-loop state matrix:

$$A'_{cl} = A - B'KC = \begin{bmatrix} 0 & a \\ -a & 0 \end{bmatrix} - \begin{bmatrix} 1+\epsilon_1 & 0 \\ 0 & 1+\epsilon_2 \end{bmatrix} \begin{bmatrix} 1 & a \\ -a & 1 \end{bmatrix}$$

Characteristic polynomial:

$$det(sI - A'_{cl}) = s^2 + \underbrace{(2 + \epsilon_1 + \epsilon_2)}_{a_1} s + \underbrace{1 + \epsilon_1 + \epsilon_2 + (a^2 + 1)\epsilon_1\epsilon_2}_{a_0}$$

Stability for $(-1 < \epsilon_1 < \infty, \epsilon_2 = 0)$ and $(\epsilon_1 = 0, -1 < \epsilon_2 < \infty)$ (GM= ∞)

But only *small simultaneous changes* in the two channels: for example, let $\epsilon_1 = -\epsilon_2$, then the system is unstable $(a_0 < 0)$ for

$$|\epsilon_1| > \frac{1}{\sqrt{a^2 + 1}} \approx 0.1$$

Summary. Checking single-loop margins is inadequate for MIMO problems.

- $\mu(T) = \bar{\sigma}(T)$ irrespective of the structure of the COMPLEX multiplicative uncertainty perturbation (full block, diagonal, repeated scalar).
- We can tolerate more than 100% uncertainty above 10 rad/sec. At low frequencies we have $\mu(T)\sim 10$, so to guarantee RS we need less than 10% uncertainty. This confirms previous results showing that real perturbations $\delta_1=0.1$ and $\delta_2=-0.1$ yield instability. Then, use of complex rather than real perturbations is not conservative in this case, at least for diagonal uncertainty.
- For repeated scalar uncertainty, there is a difference between real and complex uncertainties. The characteristic polynomial shows that $\delta_1 = \delta_2 = -1$ (100% uncertainty) and $\delta_1 = \delta_2 = j0.1$ (10% uncertainty) yield instability.



Robust performance [8.10]

- With an \mathcal{H}_{∞} performance objective, the RP-condition is identical to a RS-condition with an additional perturbation block as shown in Figure 12.
- Step B in Figure 12 is the key step.
- Δ_P (where capital P denotes Performance) is always a full matrix. It is a fictitious uncertainty block representing the \mathcal{H}_{∞} performance specification.

Testing RP using μ [8.10.1]:

Theorem

Robust performance. Rearrange the uncertain system into the $N\Delta$ -structure of Figure 12. Assume nominal stability such that N is (internally) stable. Then

$$\begin{array}{ll} \operatorname{RP} & \stackrel{\text{def}}{\Leftrightarrow} & \|F\|_{\infty} = \|F_u(N,\Delta)\|_{\infty} < 1, \quad \forall \|\Delta\|_{\infty} \le 1 \\ & = & \boxed{\mu_{\widehat{\Delta}}(N(j\omega)) < 1, \quad \forall w} \end{array} \tag{6.63}$$

where μ is computed with respect to the structure

$$\widehat{\Delta} = \begin{bmatrix} \Delta & 0\\ 0 & \Delta_P \end{bmatrix}$$
(6.64)

and Δ_P is a full complex perturbation with the same dimensions as F^T .

NOTE: Recall that stability of the $M\Delta$ structure where Δ is a full complex matrix is equivalent to $||M||_{\infty} < 1$. From this theorem, the RP condition $||F||_{\infty} < 1$ is equivalent to the RS of the $F\Delta_P$ structure where Δ_P is a full complex matrix.



 $\mu_{\widehat{\Lambda}}(N) < 1, \ \forall w$

Figure 12: RP as a special case of structured RS.

Prof. Eugenio Schuster

Summary of μ -conditions for NP, RS, RP [8.10.2]: Rearrange the uncertain system into the $N\Delta$ - structure, where the blockdiagonal perturbations satisfy $\|\Delta\|_{\infty} \leq 1$. Introduce

$$F = F_u(N, \Delta) = N_{22} + N_{21}\Delta(I - N_{11}\Delta)^{-1}N_{12}$$

and let the performance requirement (RP) be $||F||_{\infty} \leq 1$ for all allowable perturbations. Then we have:

$$NS = N \text{ (internally) stable} \tag{6.65}$$

NP =
$$\bar{\sigma}(N_{22}) = \mu_{\Delta_P}(N_{22}) < 1, \ \forall \omega, \text{ and NS}$$
 (6.66)

$$RS = \mu_{\Delta}(N_{11}) < 1, \ \forall \omega, \text{ and } NS$$
(6.67)

$$RP = \mu_{\widetilde{\Delta}}(N) < 1, \ \forall \omega, \ \widetilde{\Delta} = \begin{bmatrix} \Delta & 0\\ 0 & \Delta_P \end{bmatrix},$$
(6.68)
and NS

Here Δ is a block-diagonal matrix (its detailed structure depends on the uncertainty we are representing), whereas Δ_P always is a full complex matrix. Note that nominal stability (NS) must be tested separately in all cases.

Prof. Eugenio Schuster

Application: RP - input uncertainty [8.11]:



Figure 13: Robust performance of system with input uncertainty

$$RP \Leftrightarrow ||w_P(I+G_PK)^{-1}||_{\infty} < 1, \quad \forall G_p$$
(6.69)

$$G_P = G(I + w_I \Delta_I), \quad \|\Delta_I\|_{\infty} \le 1$$
(6.70)

Interconnection matrix [8.11.1]:

On rearranging the system into the $N\Delta$ -structure, as shown in Figure 13, we get

$$N = \begin{bmatrix} w_I T_I & w_I KS \\ w_P SG & w_P S \end{bmatrix}$$
(6.71)

where $T_I = KG(I + KG)^{-1}$, $S = (I + GK)^{-1}$ and for simplicity we have omitted the negative signs in the 1,1 and 1,2 blocks of N, since $\mu(N) = \mu(UN)$ with unitary $U = \begin{bmatrix} -I & 0 \\ 0 & I \end{bmatrix}$.

For a given controller K we can now test for NS, NP, RS and RP using (6.65)-(6.68). Here $\Delta = \Delta_I$ may be a full or diagonal matrix (depending on the physical situation).

RP with input uncertainty for SISO system [8.11.2]:

For a SISO system, conditions (6.65)-(6.68) with N as in (6.71) become

$$NS = S, SG, KS$$
 and T_I are stable (6.72)

$$NP = |w_P S| < 1, \ \forall \omega \tag{6.73}$$

$$RS = |w_I T_I| < 1, \ \forall \omega \tag{6.74}$$

$$RP = |w_P S| + |w_I T_I| < 1, \ \forall \omega$$
(6.75)

Since Δ_I and Δ_P are scalars in this case, the RP conditions follows from (see Exercise 8.18) the fact that

$$\mu(N) = \mu \begin{bmatrix} w_I T_I & w_I KS \\ w_P SG & w_P S \end{bmatrix} = \mu \begin{bmatrix} w_I T_I & w_I T_I \\ w_P S & w_P S \end{bmatrix} = |w_I T_I| + |w_P S|$$

where $T_I = KSG$. For SISO systems, $T_I = T$.

RP for 2×2 distillation process [8.11.3]:

Consider again the distillation process example from Chapter 3 (Motivating Example No. 2) and the corresponding inverse-based controller:

$$G(s) = \frac{1}{75s+1} \begin{bmatrix} 87.8 & -86.4\\ 108.2 & -109.6 \end{bmatrix}; K(s) = \frac{0.7}{s} G(s)^{-1}$$
(6.76)

The controller provides a nominally decoupled system with

$$L = lI, S = \epsilon I \text{ and } T = tI$$
 (6.77)

where

$$l = \frac{0.7}{s}, \epsilon = \frac{1}{1+l} = \frac{s}{s+0.7},$$

$$t = 1 - \epsilon = \frac{0.7}{s+0.7} = \frac{1}{1.43s+1}$$

We have used ϵ for the nominal sensitivity in each loop to distinguish it from the Laplace variable s.

Prof. Eugenio Schuster

Weights for uncertainty and performance:

$$w_I(s) = \frac{s+0.2}{0.5s+1}; \quad w_P(s) = \frac{s/2+0.05}{s}$$
 (6.78)

The weight $w_I(s)$ may approximately represent a 20% gain error and a neglected time delay of 0.9 min (see Section 7.4.5). $|w_I(j\omega)|$ levels off at 2 (200% uncertainty) at high frequencies. The performance weight $w_P(s)$ specifies integral action, a closed-loop bandwidth of about 0.05 [rad/min] (which is relatively slow in the presence of an allowed time delay of 0.9 min) and a maximum peak for $\bar{\sigma}(S)$ of $M_s = 2$.



Figure 14: μ -plots for distillation process with decoupling controller

NS Yes.

NP With the decoupling controller we have

$$\bar{\sigma}(N_{22}) = \bar{\sigma}(w_P S) = \left| \frac{s/2 + 0.05}{s + 0.7} \right|$$

(dashed-dot line in Figure 14 \leftarrow NP is OK.)

RS Since in this case $w_I T_I = w_I T$ is a scalar times the identity matrix, we have, independent of the structure of Δ_I , that

$$\mu_{\Delta_I}(w_I T_I) = |w_I t| = \left| 0.2 \frac{5s+1}{(0.5s+1)(1.43s+1)} \right|$$

and we see from the dashed line in Figure 14 that RS is OK. $\ensuremath{\mathsf{RP}}$ Poor.

Table 1: MATLAB program for μ -analysis

```
% Uses the Mu toolbox
G0 = [87, 8-86, 4; 1068, 2 -109.6];
dyn = nd2sys(1,[75 1]);
Dyn-daug(dyn,dyn); G-mmult(Dyn,GO);
%
% Inverse-based control.
%
dynk=nd2sys([75 1],[1 1.e-5],0.7);
Dynk=daug(dynk,dynk); Kinv=mmult(Dynk,minv(GO));
%
% Weights.
%
wprnd2sys([10 1],[10 1.e-5],0.5); Wp=daug(wp,wp);
wi=nd2sys([1 0.2],[0.5 1]); Wi=daug(wi,wi);
%
```

Table 2: MATLAB program for μ -analysis

```
% Generalized plant P.
systemnames = 'G Wp Wi';
inputvar = '[ydel(2); w(2) ; u(2)]';
outputvar = '[Wi; Wp; -G-w]';
input_to_G = '[u+vdel]':
input_to_Wp = '[G+w]'; input_to_Wi = '[u]';
sysoutname = 'P':
cleanupsysic = 'yes'; sysic;
N = starp(P,Kinv); omega = logspace(-3,3,61);
Nf = frsp(N, omega);
%
% mu for RP.
blk = [1 1; 1 1; 2 2];
[mubnds,rowd,sens,rowp,rowg] = mu(Nf,blk,'c');
muRP = sel(mubnds,':',1); pkvnorm(muRP)
                                                   \% (ans = 5.7726).
```

Table 3: MATLAB program for μ -analysis

```
% Worst-case weighted sensitivity
%
[delworst,muslow,musup] = wcperf(Nf,blk,1); musup
                                                          % (musup = 44.93 for
%
                                                          %
                                                               delta=1).
% mu for RS.
Nrs=sel(Nf.1:2.1:2):
[mubnds,rowd,sens,rowp,rowg]=mu(Nrs,[1 1; 1 1],'c');
muRS = sel(mubnds,':',1); pkvnorm(muRS)
                                                         \% (ans = 0.5242).
%
% mu for NP (= max, singular value of Nnp),
Nnp=sel(Nf,3:4,3:4);
[mubnds,rowd,sens,rowp,rowg]=mu(Nnp,[2 2],'c');
muNP = sel(mubnds,':',1); pkvnorm(muNP)
                                                          \% (ans = 0.5000).
vplot('liv.m'.muRP.muRS.muNP):
```

μ -synthesis and DK-iteration [8.12]

The structured singular value μ is a very powerful tool for the analysis of robust performance with a given controller. However, one may also seek to find the controller that minimizes a given μ -condition: this is the μ -synthesis problem: $\min_K \mu(N)$

DK-iteration [8.12.1]:

At present there is no direct method to synthesize a μ -optimal controller. However, for complex perturbations a method known as DK-iteration is available. It combines \mathcal{H}_{∞} -synthesis and μ -analysis, and often yields good results. The starting point is the upper bound on μ in terms of the scaled singular value

$$\mu(N) \le \min_{D \in \mathcal{D}} \bar{\sigma}(DND^{-1})$$

• The structured singular value μ for *complex* perturbations is bounded by

$$\rho(M) \le \mu(M) \le \bar{\sigma}(M) \tag{6.79}$$

$$\Delta = \delta I \text{ (}\delta \text{ is a complex scalar}\text{): } \mu(M) = \rho(M) \tag{6.80}$$

$$\Delta$$
 is a full complex matrix: $\mu(M) = \bar{\sigma}(M)$ (6.81)

• Consider any matrix D which commutes with Δ : that is $\Delta D = D\Delta$. Then

$$\mu(DM) = \mu(MD) \text{ and } \mu(DMD^{-1}) = \mu(M)$$
 (6.82)

• Improved upper bound. Define D to be the set of matrices D which commute with Δ (i.e., satisfy $D\Delta = \Delta D$). Then

$$\mu(M) \le \min_{D \in \mathcal{D}} \bar{\sigma}(DMD^{-1}) \tag{6.83}$$

- This optimization is convex in *D*, i.e., has only one global minimum.
- $-\,$ The inequality is indeed an equality if there are three or fewer blocks in $\Delta.$
- Numerical evidence suggests that the bound is tight.

The idea is to find the controller that minimizes the peak value over frequency of this upper bound, namely

$$\min_{K} (\min_{D \in \mathcal{D}} \|DN(K)D^{-1}\|_{\infty})$$
(6.84)

by alternating between minimizing $||DN(K)D^{-1}||_{\infty}$ with respect to either K or D (while holding the other fixed).

- K-step. Synthesize an \mathcal{H}_{∞} controller for the scaled problem, $\min_{K} \|DN(K)D^{-1}\|_{\infty}$ with fixed D(s).
- O-step. Find D(jω) to minimize at each frequency σ̄(DND⁻¹(jω)) with fixed N.
- **③** Fit the magnitude of each element of $D(j\omega)$ to a stable and minimum phase transfer function D(s) and go to Step 1.

Example: μ -synthesis with DK-iteration [8.12.4]:

Simplified distillation process

$$G(s) = \frac{1}{75s+1} \begin{bmatrix} 87.8 & -86.4\\ 108.2 & -109.6 \end{bmatrix}$$
(6.85)

The uncertainty weight $w_I I$ and performance weight $w_P I$ are given in (6.78), and are shown graphically in Figure 15. The objective is to minimize the peak value of $\mu_{\widetilde{\Delta}}(N)$, where N is given in (6.71) and $\widetilde{\Delta} = \text{diag}\{\Delta_I, \Delta_P\}$. We will consider diagonal input uncertainty (which is always present in any real problem), so Δ_I is a 2×2 diagonal matrix. Δ_P is a full 2×2 matrix representing the performance specification.



Figure 15: Uncertainty and performance weights. Notice that there is a frequency range ("window") where both weights are less than one in magnitude.

Table 4: MATLAB program to perform *DK*-iteration

```
% Uses the Mu toolbox
G0 = [87.8 - 86.4; 108.2 - 109.6];
dyn = nd2sys(1,[75 1]); Dyn = daug(dyn,dyn);
G = mmult(Dvn,GO):
%
% Weights.
wp = nd2sys([10 1],[10 1.e-5],0.5);
                                                  % Approximated
wi = nd2svs([1 0.2], [0.5 1]);
                                                 % integrator.
Wp = daug(wp,wp); Wi = daug(wi,wi);
%
% Generalized plant P. %
systemnames = 'G Wp Wi':
inputvar = '[ydel(2); w(2) ; u(2)]';
outputvar = '[Wi; Wp; -G-w]';
input_to_G = '[u+vdel]':
input_to_Wp = '[G+w]'; input_to_Wi = '[u]';
sysoutname = 'P'; cleanupsysic = 'yes';
svsic:
```

Table 5: MATLAB program to perform *DK*-iteration

```
% Initialize.
%
omega = logspace(-3, 3, 61);
blk = [1 1; 1 1; 2 2];
nmeas=2; nu=2; gmin=0.9; gamma=2; tol=0.01; d0 = 1;
dsys1 = daug(d0,d0,eye(2),eye(2)); dsysr=dsys1;
% START ITERATION.
%
% STEP 1: Find H-infinity optimal controller
% with given scalings:
%
DPD = mmult(dsys1,P,minv(dsysr)); gmax=1.05*gamma;
[K,Nsc,gamma] = hinfsyn(DPD,nmeas,nu,gmin,gmax,tol);
Nf=frsp(Nsc,omega);
                                                          % (Remark:
%
                                                          % Without scaling:
%
                                                          % N=starp(P,K);).
% STEP 2: Compute mu using upper bound:
[mubnds,rowd,sens,rowp,rowg] = mu(Nf,blk,'c');
vplot('liv,m',mubnds); murp=pkvnorm(mubnds,inf)
% STEP 3: Fit resulting D-scales:
[dsys1,dsysr]=musynflp(dsys1,rowd,sens,blk,nmeas,nu);
                                                          % choose 4th order.
% New Version:
% [dsvsL.dsvsR]=msf(Nf.mubnds.rowd.sens.blk);
                                                          % order: 4.4.0.
% dsysl=daug(dsysL,eye(2)); dsysr=daug(dsysR,eye(2));
% GOTO STEP 1 (unless satisfied with murp).
```

Iteration No. 1.

Step 1: With the initial scalings, $D^0 = I$, the \mathcal{H}_{∞} software produced a 6 state controller (2 states from the plant model and 2 from each of the weights) with an \mathcal{H}_{∞} norm of $\gamma = 1.1823$.

Step 2: The upper μ -bound gave the μ -curve shown as curve "lter. 1" in Figure 16, corresponding to a peak value of μ =1.1818.

Step 3: The frequency-dependent $d_1(\omega)$ and $d_2(\omega)$ from Step 2 were each fitted using a 4th order transfer function. $d_1(w)$ and the fitted 4th-order transfer function (dotted line) are shown in Figure 17 and labelled "Iter. 1". *Iteration No. 2.*

Step 1: With the 8 state scaling $D^1(s)$ the \mathcal{H}_{∞} software gave a 22 state controller and $\|D^1N(D^1)^{-1}\|_{\infty} = 1.0238$.

Iteration No. 3.

Step 1: With the scalings $D^2(s)$ the \mathcal{H}_{∞} norm was only slightly reduced from 1.024 to 1.019.



Figure 16: Change in μ during *DK*-iteration



Figure 17: Change in *D*-scale d_1 during *DK*-iteration



Figure 18: Setpoint response for μ -"optimal" controller K_3 . Solid line: nominal plant. Dashed line: uncertain plant G'_3