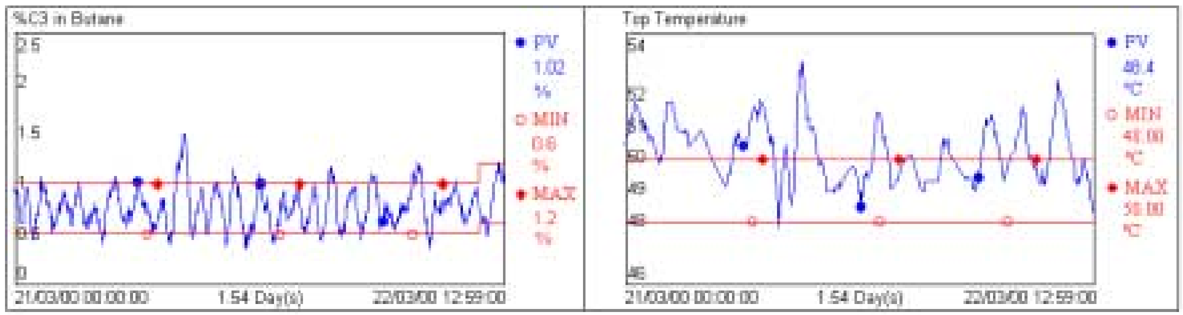
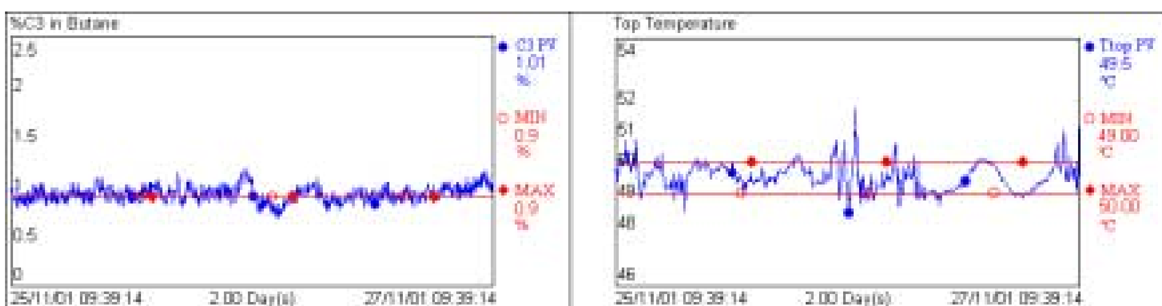
Robust Model Predictive Control

Motivation: An industrial C3/C4 splitter:

MPC assuming ideal model:



MPC considering model uncertainty



Robust Model Predictive Control

Nominal model of the plant: $G_0(z) = D_0(z)^{-1} N_0(z)$

Norm-bounded uncertainty:

$$G(z) = G_0(z) + \Delta$$

$$G(z) = G_0(z)\left[1 + \Delta\right]$$

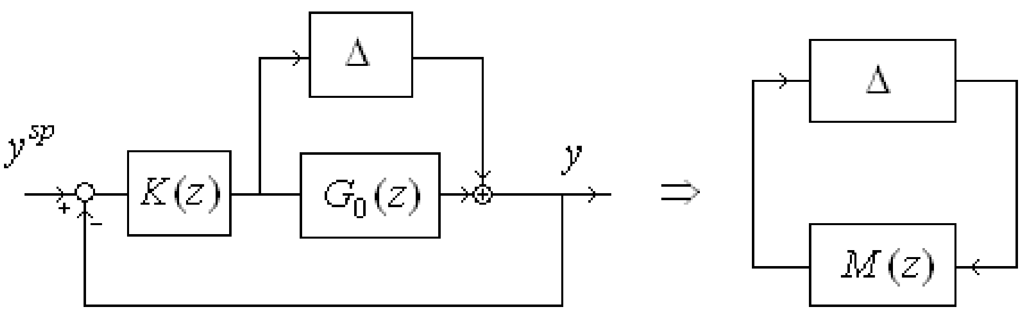
$$G(z) = \left[D_0(z) + \Delta_D\right]^{-1}\left[N_0(z) + \Delta_N\right]$$

Uncertainty is measured through the *H infinity* norm $\|\Delta\|_\infty$

Closed Loop with Model Uncertainty

$K(z)$ stabilizes the nominal plant $G_0(z)$

Additive uncertainty: $G(z) = G_0(z) + \Delta$



$$M(z) = K(z)\left(I + G_0(z)K(z)\right)^{-1}$$

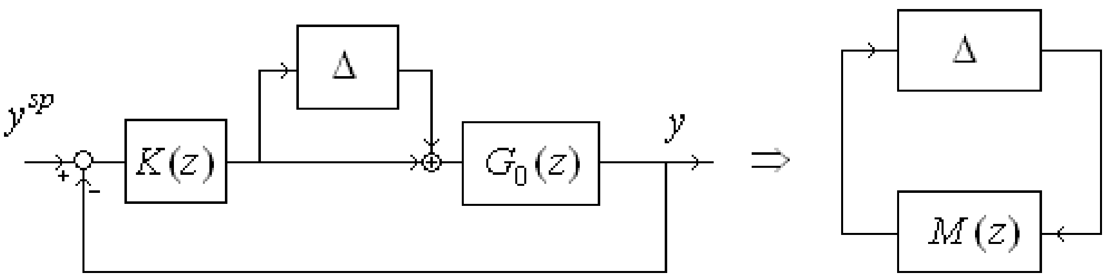
Small gain theorem:

$$\bar{\sigma}\left(M(e^{j\omega T})\right)\|\Delta\|_\infty < 1$$

$$\bar{\sigma}\left[K(e^{j\omega T})\left(I + K(e^{j\omega T})G_0(e^{j\omega T})\right)^{-1}\right]\|\Delta\|_\infty < 1$$

Closed Loop Stability – Multiplicative Uncertainty

Multiplicative uncertainty: $G(z) = G_0(z)\left[1+\Delta\right]$



$$M(z) = K(z)G_0(z)\left(I + KG_0(Z)\right)^{-1}$$

Small gain theorem:

$$\bar{\sigma}\left(M(e^{j\omega T})\right)\left\|\Delta\right\|_\infty < 1$$

$$\bar{\sigma}\left[K(e^{j\omega T})G_0(e^{j\omega T})\left(I + K(e^{j\omega T})G_0(e^{j\omega T})\right)^{-1}\right]\left\|\Delta\right\|_\infty < 1$$

Robust Stability of DMC

Question:

How much model uncertainty a well tuned DMC can tolerate?

Robust Stability of the Unconstrained DMC

Predicting Model

$$[y]_{k/k} = A[y]_{k-1/k-1} + B\Delta u(k-1) + K_F\left\{\bar{y}_k - C[y]_{k/k-1}\right\}$$

$$[y]_{k/k-1} = A[y]_{k-1/k-1} + B\Delta u(k-1)$$

$$y = \begin{bmatrix} y(k)^T & y(k+1)^T & \cdots & y(k+n_h)^T \end{bmatrix}^T$$

$$A = \begin{bmatrix} 0 & I_{ny} & 0 & \cdots & 0 \\ 0 & 0 & I_{ny} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & I_{ny} \\ 0 & 0 & 0 & \cdots & I_{ny} \end{bmatrix}, \quad B = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_{n_h} \\ S_{n_h+1} \end{bmatrix}, \quad K_F = \begin{bmatrix} I_{ny} \\ I_{ny} \\ \vdots \\ I_{ny} \\ I_{ny} \end{bmatrix}, \quad S_i = \begin{bmatrix} S_{1,1,i} & S_{1,2,i} & \cdots & S_{1,nu,i} \\ S_{2,1,i} & S_{2,2,i} & \cdots & S_{2,nu,i} \\ \vdots & \vdots & \ddots & \vdots \\ S_{ny,1,i} & S_{ny,2,i} & \cdots & S_{ny,nu,i} \end{bmatrix}$$

$$\bar{y}(k) = \bar{C}[\bar{y}]_{k/k} \qquad \bar{C} = C = \begin{bmatrix} I_{ny} & 0 & \cdots & 0 \end{bmatrix}$$

Robust Stability of the Unconstrained DMC

True Plant Model

$$\left[\bar{y}\right]_{k/k} = A\left[\bar{y}\right]_{k-1/k-1} + \bar{B}\Delta u(k)$$

DMC control law

$$\left[\Delta u\right]_k = N_s\left\{\left(S_n^m\right)^T Q^T Q S_n^m + R^T R\right\}^{-1}\left(S_n^m\right)^T Q^T Q N\left\{y^{sp} - \left[y\right]_{k/k}\right\} = K_{MPC}\left\{y^{sp} - \left[y\right]_{k/k}\right\}$$

$$\left[\Delta u\right]_k = \left[\begin{matrix}\Delta u(k)^T & \Delta u(k+1)^T & \cdots & \Delta u(k+m-1)^T\end{matrix}\right]^T$$

$$N = \left[\begin{matrix}I_{ny.n} & 0_{(ny.n)\times(ny.(nh-1))}\end{matrix}\right]$$

$$N_s = \left[\begin{matrix}I_{nu} & 0_{(nu)\times(nu.(m-1))}\end{matrix}\right]$$

$$S_n^m = \begin{bmatrix} S_1 & 0 & \cdots & 0 \\ S_2 & S_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ S_m & S_{m-1} & \cdots & S_1 \\ \vdots & \vdots & & \vdots \\ S_n & S_{n-1} & \cdots & S_{n-m+1} \end{bmatrix}$$

Robust Stability of the Unconstrained DMC

Combining predicting model and plant

$$\begin{bmatrix} \bar{y} \\ y \end{bmatrix}_{k/k} = \begin{bmatrix} A & 0 \\ K_F C A & (I - K_F C)A \end{bmatrix} \begin{bmatrix} \bar{y} \\ y \end{bmatrix}_{k-1/k-1} + \begin{bmatrix} \bar{B} \\ B + K_F C(\bar{B} - B) \end{bmatrix} \Delta u(k-1)$$

$$\Delta u(k) = \begin{bmatrix} 0 & K_{MPC} \end{bmatrix} \begin{bmatrix} y^{sp} - \bar{y} \\ y^{sp} - y \end{bmatrix}_{k/k} = K \begin{bmatrix} y^{sp} - \bar{y} \\ y^{sp} - y \end{bmatrix}_{k/k}$$

Additive uncertainty $\bar{B} = B + \Delta_S$ $\Delta_S = \begin{bmatrix} \Delta_{S_1}^T & \Delta_{S_2}^T & \cdots & \Delta_{S_{nh+1}}^T \end{bmatrix}^T$

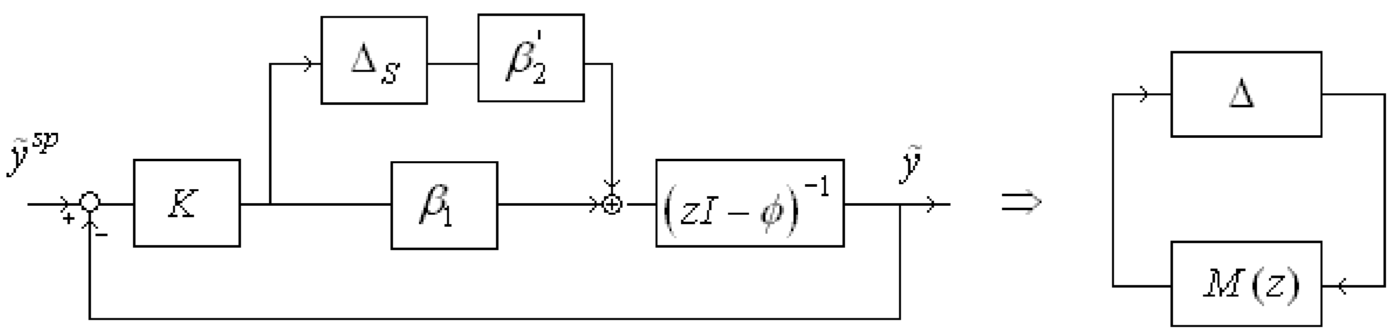
Robust Stability of the Unconstrained DMC

Closed loop with DMC

$$[\tilde{y}]_{k+1/k+1} = \phi[\tilde{y}]_{k/k} + \beta_1 \Delta u(k) + \beta_2 \Delta u(k)$$

$$\Delta u(k) = K \begin{bmatrix} y^{sp} - \overline{y} \\ y^{sp} - y \end{bmatrix}_{k/k}$$

$$\phi = \begin{bmatrix} A & 0 \\ K_F CA & (I - K_F C)A \end{bmatrix} \qquad \beta_1 = \begin{bmatrix} B \\ B \end{bmatrix} \qquad \beta_2 = \begin{bmatrix} I \\ K_F C \end{bmatrix} \Delta_S = \beta_2' \Delta_S$$



$$M(z) = -K\left[I + (zI - \phi)^{-1}\beta_1 K\right]^{-1}(zI - \phi)^{-1}\beta_2'$$

Robust Stability of the Unconstrained DMC

Example 1

$$G(s) = \begin{bmatrix} \dfrac{1.77+\Delta_{11}}{60s+1} & \dfrac{5.88+\Delta_{12}}{50s+1} \\ \dfrac{4.41+\Delta_{21}}{44s+1} & \dfrac{7.2+\Delta_{22}}{19s+1} \end{bmatrix}$$

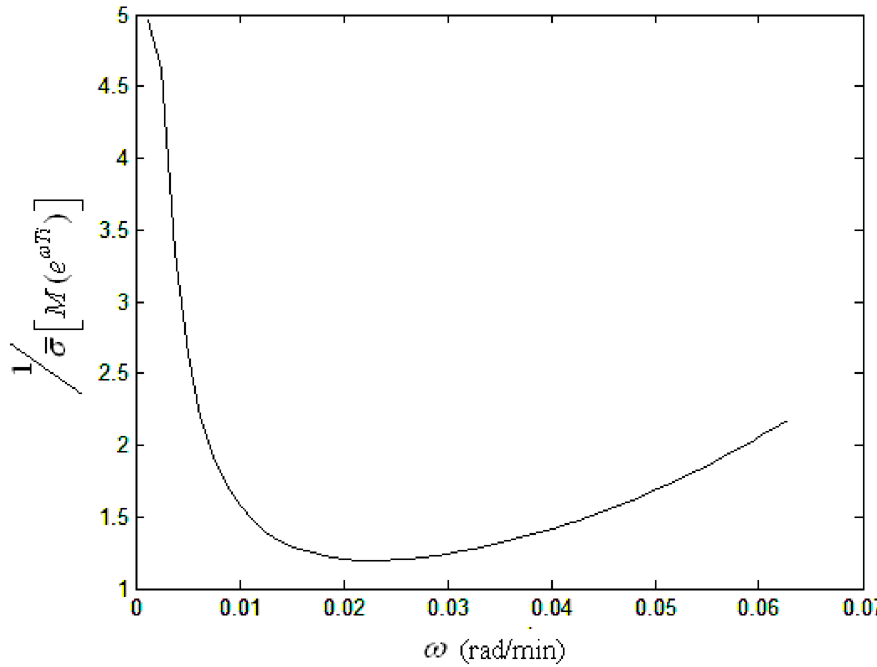
DMC parameters: T=5, n=12, m=5, Q=diag(1,1), R=diag(0.3,0.3)

Question: What is the max size of Δ_{11}, Δ_{12}, Δ_{21} and Δ_{22} such that DMC will remain stable?

Response: DMC will be stable for Δ_S not larger than

$$\bar{\sigma}(\Delta_S) = \min_{\omega} 1 \Big/ \bar{\sigma}\left[M(e^{\omega Ti})\right] \qquad M(z) = -K\left[I + (zI-\phi)^{-1}\beta_1 K\right]^{-1}(zI-\phi)^{-1}\beta_2'$$

Example 1 DMC with: T=5, n=12, m=5, Q=diag(1,1), R=diag(0.3,0.3)



$$\min_{\omega} \frac{1}{\bar{\sigma}\left[M(e^{\omega Ti})\right]} = 1.195$$

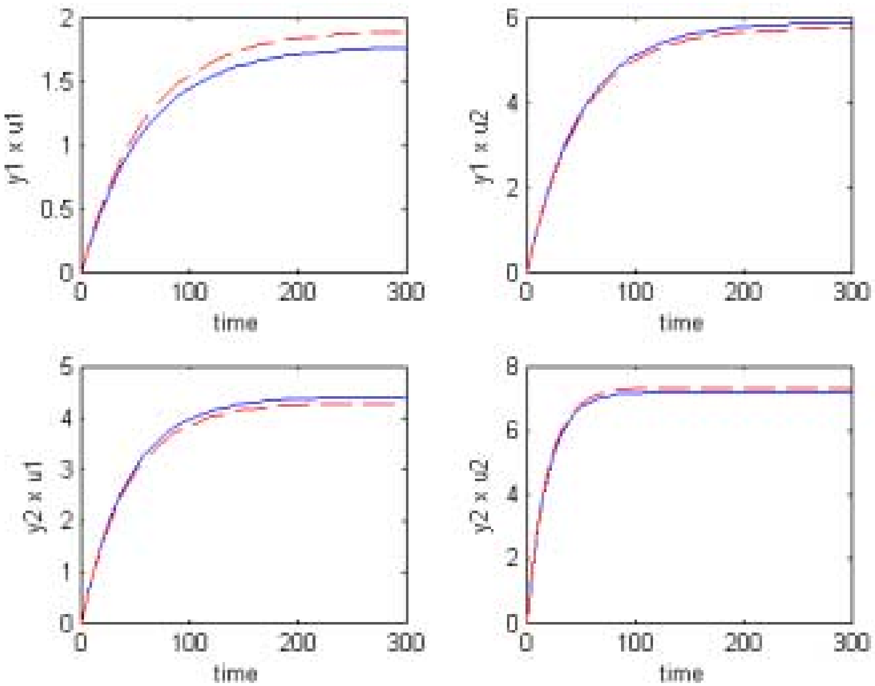
The approximate bounds are:

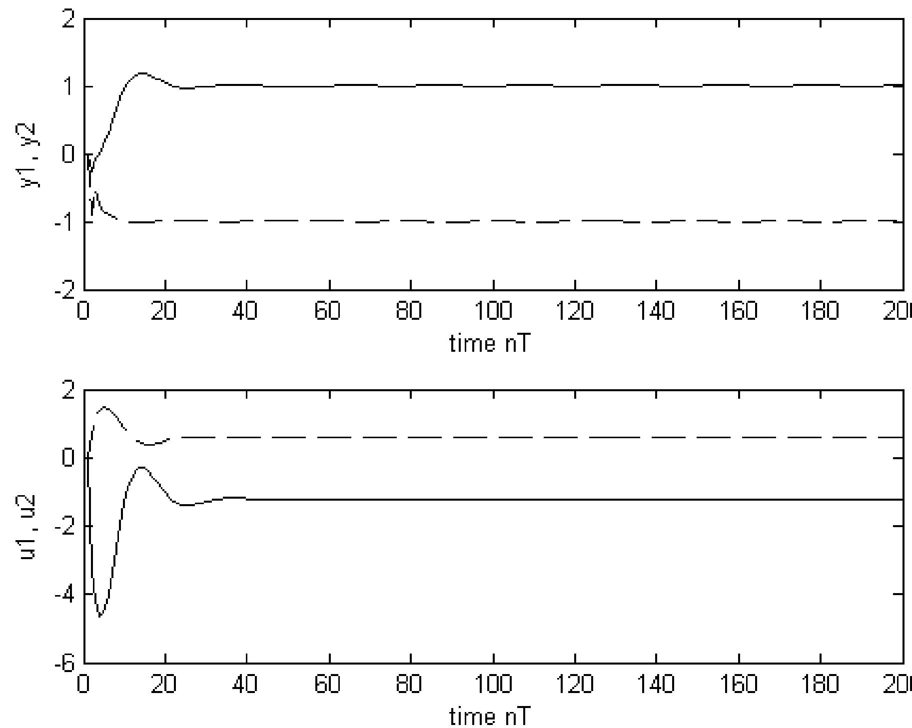
$$S_{i,j,l} - 0.13 \le \bar{S}_{i,j,l} \le S_{i,j,l} + 0.13 \quad i = 1,2; \quad j = 1,2; \quad l = 1,\ldots,12$$

Or: $$-0.13 \le \Delta_{i,j} \le +0.13 \quad i = 1,2; \quad j = 1,2$$

Example 1 Stability bounds are very conservative

$$S_{i,j,l} - 0.13 \le \bar{S}_{i,j,l} \le S_{i,j,l} + 0.13 \quad i = 1,2; \quad j = 1,2; \quad l = 1,\ldots,12$$

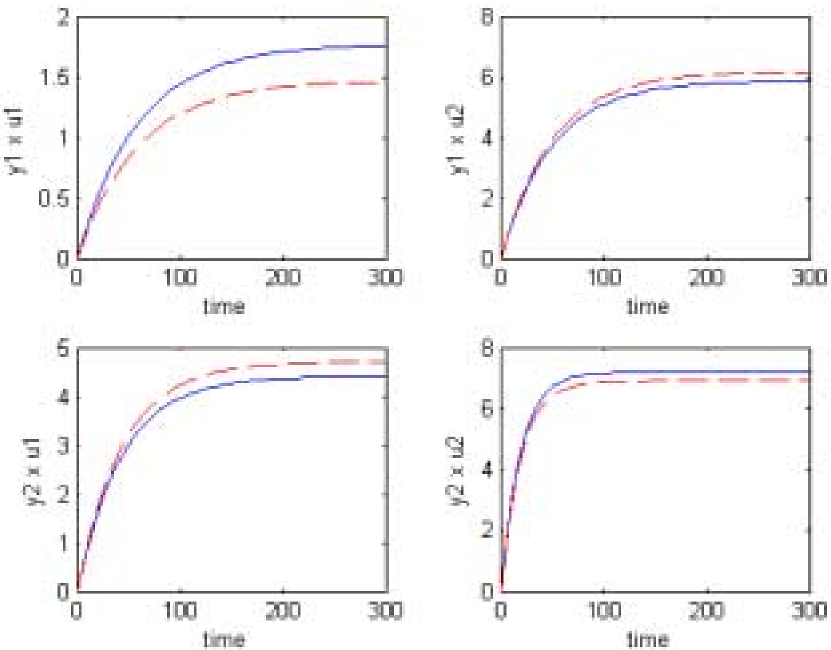


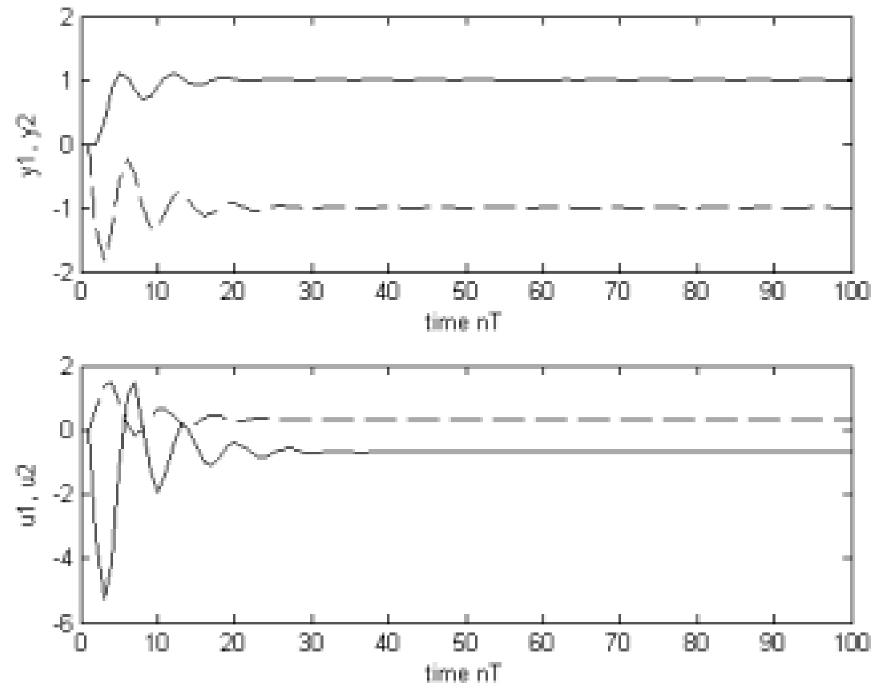


$$G(s) = \begin{bmatrix} \dfrac{1.77+0.13}{60s+1} & \dfrac{5.88-0.13}{50s+1} \\ \dfrac{4.41-0.13}{44s+1} & \dfrac{7.2+0.13}{19s+1} \end{bmatrix}$$

Example 1 Stability bounds are very conservative

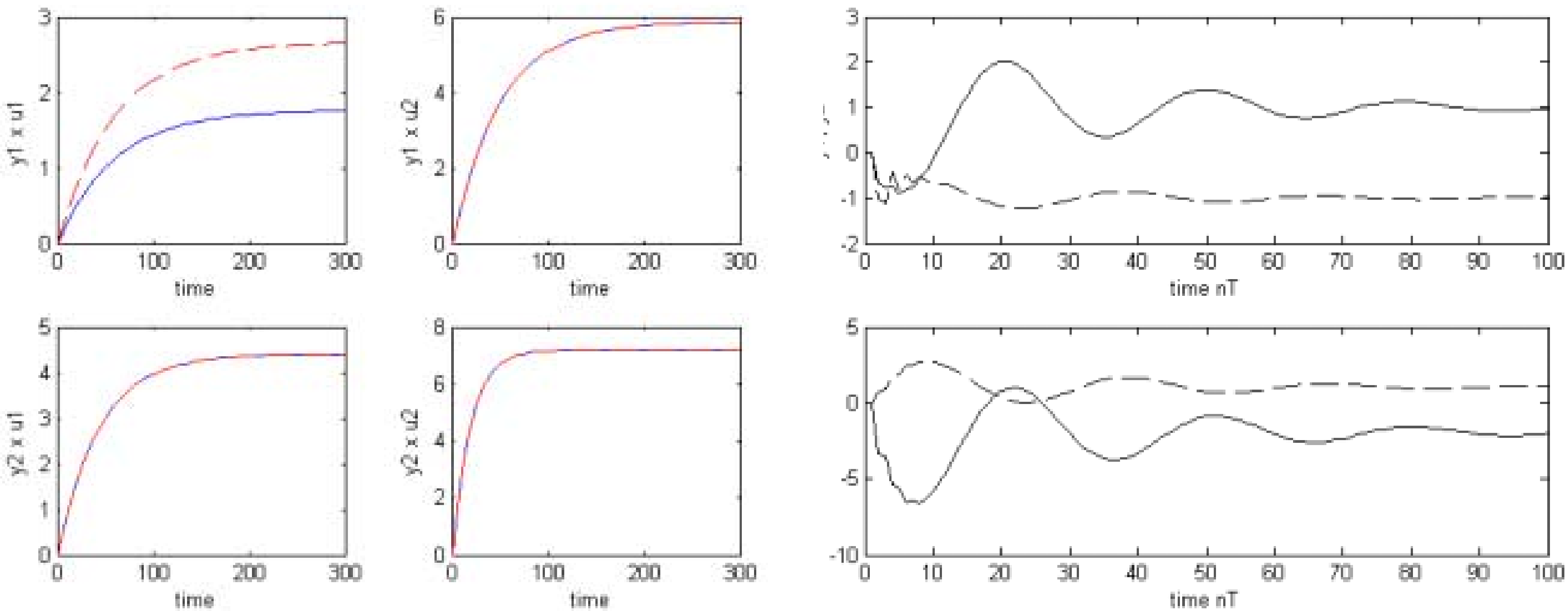
$$S_{i,j,l} - 0.30 \leq \bar{S}_{i,j,l} \leq S_{i,j,l} + 0.30 \qquad i = 1,2; \quad j = 1,2; \quad l = 1,\ldots,12$$





$$G(s) = \begin{bmatrix} \dfrac{1.77+0.3}{60s+1} & \dfrac{5.88-0.3}{50s+1} \\ \dfrac{4.41-0.3}{44s+1} & \dfrac{7.2+0.3}{19s+1} \end{bmatrix}$$

Example 1 Stability bounds are very conservative



$$G(s) = \begin{bmatrix} \dfrac{1.77 - 0.9}{60s+1} & \dfrac{5.88}{50s+1} \\ \dfrac{4.41}{44s+1} & \dfrac{7.2}{19s+1} \end{bmatrix}$$

Robust Stability - Multiplicative gain uncertainty

$$\begin{bmatrix} \bar{y} \\ y \end{bmatrix}_{k/k} = \begin{bmatrix} A & 0 \\ K_F CA & (I - K_F C)A \end{bmatrix} \begin{bmatrix} \bar{y} \\ y \end{bmatrix}_{k-1/k-1} + \begin{bmatrix} \bar{B} \\ B + K_F C(\bar{B} - B) \end{bmatrix} \Delta u(k-1)$$

$$\bar{B}_{ij} = B_{ij}\left(1 + \Delta_{i,j}\right) \qquad \bar{B} = B + \Delta_S$$

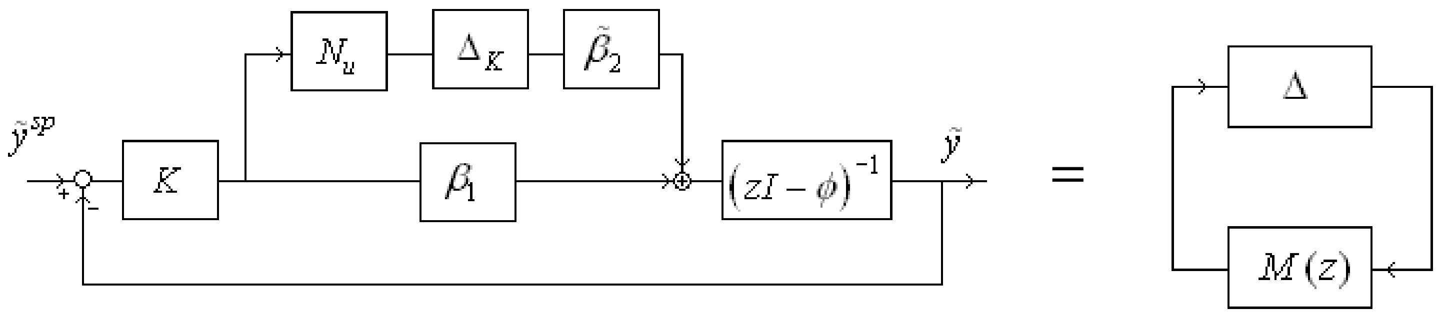
$$\Delta_S = \begin{bmatrix} S_{1,1} & 0 & \cdots & 0 & S_{1,2} & 0 & \cdots & 0 & \cdots & S_{1,nu} & 0 & \cdots & 0 \\ 0 & S_{2,1} & \cdots & 0 & 0 & S_{2,2} & \cdots & 0 & \cdots & 0 & S_{2,nu} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & S_{ny,1} & 0 & 0 & \cdots & S_{ny,2} & \cdots & 0 & 0 & \cdots & S_{ny,nu} \end{bmatrix} \times \begin{bmatrix} \Delta_{1,1} & & & & & & 0 \\ & \ddots & & & & & \\ & & \Delta_{ny,1} & & & & \\ & & & \ddots & & & \\ & & & & \Delta_{1,nu} & & \\ & 0 & & & & \ddots & \\ & & & & & & \Delta_{ny,nu} \end{bmatrix} \begin{bmatrix} \underbrace{\begin{matrix} 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & 0 \\ 1 & 0 & \cdots & \vdots \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 1 & \cdots & 0 \\ 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1 \end{matrix}}_{nu} \end{bmatrix}$$

$$\Delta_S = \tilde{S}\,\Delta_K\,N_u$$

$$[\tilde{y}]_{k+1/k+1} = \phi[\tilde{y}]_{k/k} + \beta_1 \Delta u(k) + \beta_2 \Delta u(k)$$

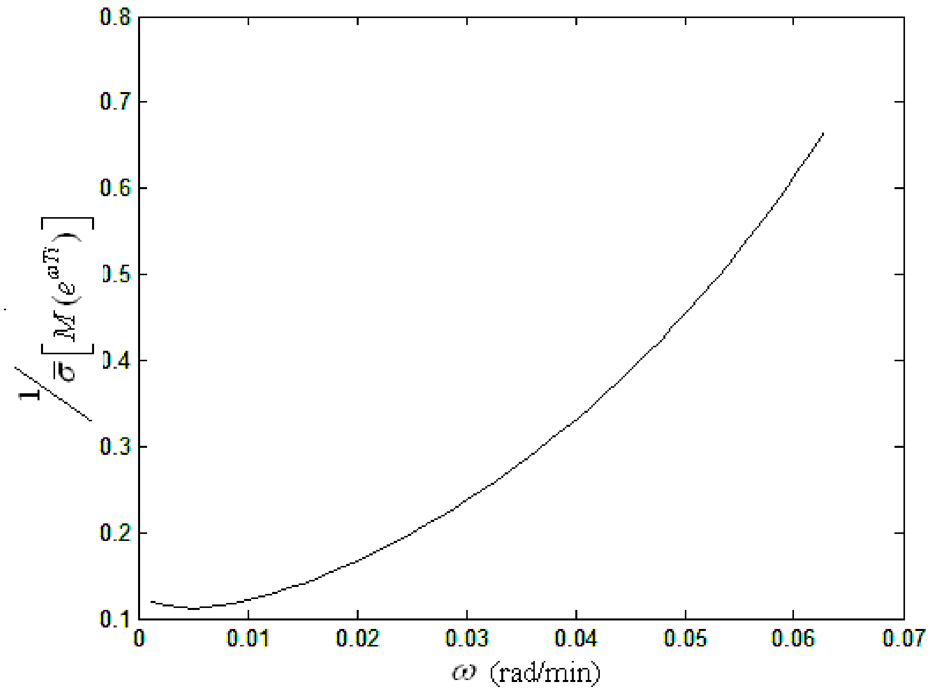
$$\phi = \begin{bmatrix} A & 0 \\ K_F CA & (I - K_F C)A \end{bmatrix} \qquad \beta_1 = \begin{bmatrix} B \\ B \end{bmatrix} \qquad \beta_2 = \begin{bmatrix} \tilde{B} \\ K_F C\tilde{B} \end{bmatrix} \Delta_K N_u = \tilde{\beta}_2 \Delta_K N_u$$

Robust Stability - Multiplicative gain uncertainty



$$M(z) = -N_u K\left[I + (zI-\phi)^{-1}\beta_1 K\right]^{-1}(zI-\phi)^{-1}\tilde{\beta}_2$$

Example 1 DMC with: T=5, n=12, m=5, Q=diag(1,1), R=diag(0.3,0.3)



$$G(s)=\begin{bmatrix} \dfrac{1.77(1+\Delta_{11})}{60s+1} & \dfrac{5.88(1+\Delta_{12})}{50s+1} \\ \dfrac{4.41(1+\Delta_{21})}{44s+1} & \dfrac{7.2(1+\Delta_{22})}{19s+1} \end{bmatrix}$$

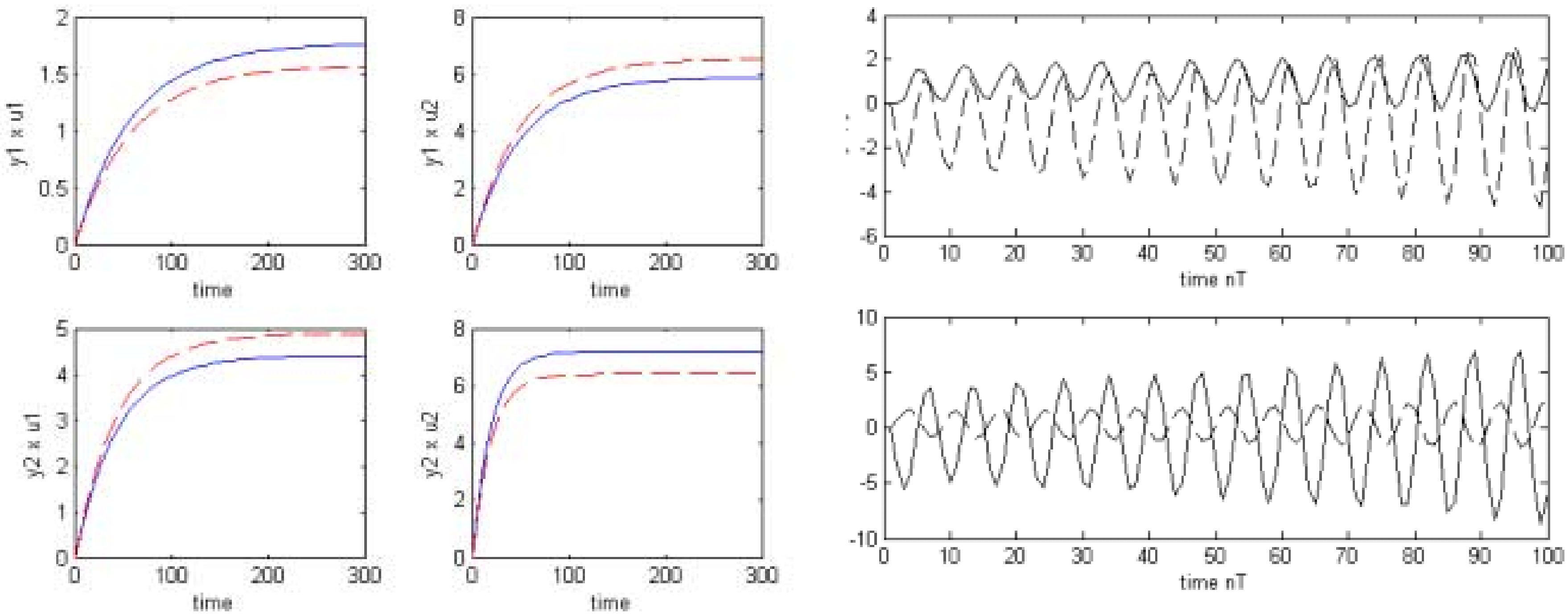
$$\min_{\omega} 1 \Big/ \bar{\sigma}\left[M(e^{\omega Ti})\right] = 0.112$$

The approximate bounds are:

$$-0.112 \le \Delta_{i,j} \le +0.112 \quad i=1,2; \quad j=1,2$$

Example 1 Gain uncertainty - Stability bounds are not so conservative

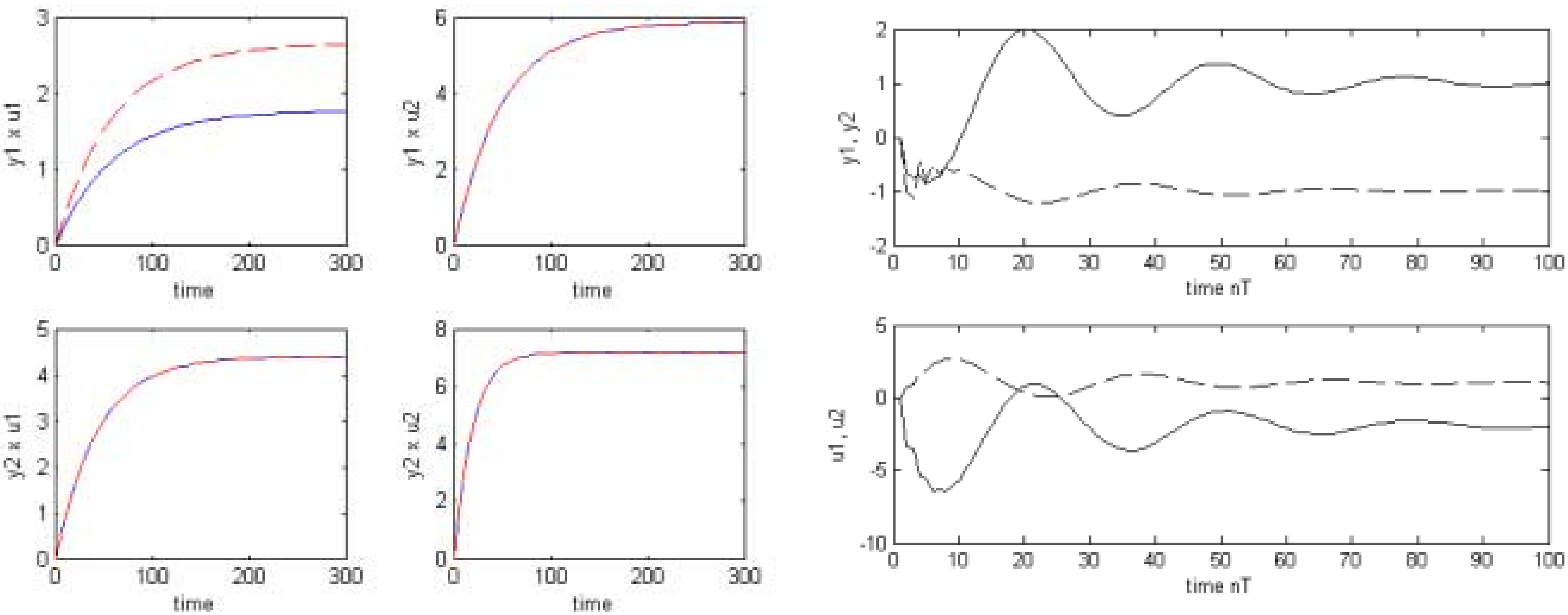
$$-0.112 \leq \Delta_{i,j} \leq +0.112 \qquad i=1,2; \quad j=1,2$$



$$G(s)=\begin{bmatrix} \dfrac{1.77(1-0.11)}{60s+1} & \dfrac{5.88(1+0.11)}{50s+1} \\ \dfrac{4.41(1+0.11)}{44s+1} & \dfrac{7.2(1-0.11)}{19s+1} \end{bmatrix}$$

Example 1 Gain uncertainty - Stability bounds are not so conservative but misses some particular systems

$$-0.112 \le \Delta_{i,j} \le +0.112 \quad i = 1,2; \quad j = 1,2$$



$$G(s) = \begin{bmatrix} \dfrac{1.77(1+0.5)}{60s+1} & \dfrac{5.88}{50s+1} \\ \dfrac{4.41}{44s+1} & \dfrac{7.2}{19s+1} \end{bmatrix}$$

Robust Stability with H_∞ Approach

-The ranges of general unstructured model uncertainties where DMC is guaranteed to be stable are quite conservative. Less conservative bounds can be obtained by taking into account the structure of the uncertainty. However, the results are still not useful for practical applications.

-The procedure does not account for constraints on the inputs and input moves. When a constraint becomes active, the closed loop system may become unstable, even if uncertainty is smaller than the maximum uncertainty tolerated by the unconstrained DMC controller.

Robust MPC with Infinite Horizon

IHMPC (regulator case):

$$x(k+1) = Ax(k) + Bu(k)$$

$$y(k) = Cx(k)$$

Control objective: $\min\limits_{u(k),u(k+1),\ldots,u(k+m-1)} J_k$

$$J_k = \sum_{i=0}^{\infty} x(k+i)^T \; Q \; x(k+i) + \sum_{j=0}^{m-1} u(k+j)^T \; R \, u(k+j)$$

$$u^{\min} \le u(k+j) \le u^{\max}; \; j = 0,1,\cdots,m-1$$

Robust MPC with Infinite Horizon

IHMPC (regulator case) for stable systems:

$$\min_{u(k),u(k+1),\ldots,u(k+m-1)} J_k$$

$$J_k = \sum_{j=0}^{m} x(k+j)^T Q\, x(k+j) + x(k+m)^T P x(k+m) + \sum_{j=0}^{m-1} u(k+j)^T R u(k+j)$$

$$A^T P A - P = -Q$$

$$u^{\min} \le u(k+j) \le u^{\max};\ j = 0,1,\cdots,m-1$$

Advantage: The closed-loop is stable for any set of tuning parameters

Drawback: Cannot be applied to the set point tracking case

Model is written in terms of $u - u_{ss}$ and $y - y_{ss}$

Robust MPC with Infinite Horizon

Robust IHMPC (regulator case):

$$x(k+1) = Ax(k) + Bu(k) \qquad \theta = (A, B)$$

$$y(k) = Cx(k)$$

Multi plant system: $\Omega \triangleq \{\theta_1, \theta_2, \ldots, \theta_L\}$

True plant: $\theta_T = (A_T, B_T) \qquad \theta_T \in \Omega$

Nominal plant: $\theta_N = (A_N, B_N) \qquad \theta_N \in \Omega$

$$J_{k,\theta_i} = \sum_{j=0}^{m} x(k+j)_{\theta_i}^T Q\, x(k+j)_{\theta_i} + x(k+m)_{\theta_i}^T P_{\theta_i} x(k+m)_{\theta_i} + \sum_{j=0}^{m-1} u(k+j)^T R u(k+j)$$

$$A_{\theta_i}^T P_{\theta_i} A_{\theta_i} - P_{\theta_i} = -Q$$

Robust MPC with Infinite Horizon

Robust IHMPC (regulator case) is obtained from the solution to:

$$\min_{u(k),u(k+1),\ldots,u(k+m-1)} J_{k,\theta_N}$$

Subject to:

$$\Rightarrow \quad u_k = \begin{bmatrix} u^*(k) & u^*(k+1) & \cdots & u^*(k+m-1) \end{bmatrix}_k$$

$$J_{k,\theta_i} \le \hat{J}_{k,\theta_i} \qquad \theta_i \in \Omega$$

$$u^{\min} \le u(k+j) \le u^{\max}; \; j = 0,1,\cdots,m-1$$

$\hat{J}_{k,\theta_i}\ (i = 1,\ldots,L)$ is obtained with the following control sequence:

$$\hat{u}_k = \begin{bmatrix} u^*(k) & \cdots & u^*(k+m-2) & 0 \end{bmatrix}_{k-1}$$

Robust IHMPC (regulator) cannot be applied to the set-point tracking:

$\hat{J}_{k,\theta_i}$ is not bounded for all plants $\theta_i \in \Omega$ with different gains.

Extended Infinite Horizon MPC

Process model in the incremental form:

$$\begin{bmatrix} x^s(k+1) \\ x^d(k+1) \end{bmatrix} = \begin{bmatrix} I_{ny} & 0 \\ 0 & F \end{bmatrix} \begin{bmatrix} x^s(k) \\ x^d(k) \end{bmatrix} + \begin{bmatrix} B^s \\ B^d \end{bmatrix} \Delta u(k)$$

$$y(k) = \begin{bmatrix} I_{ny} & \Psi \end{bmatrix} \begin{bmatrix} x^s(k) \\ x^d(k) \end{bmatrix} \qquad \Delta u(k) = u(k) - u(k-1)$$

Control objective:

$$V_k = \sum_{j=0}^{\infty} (e(k+j) - \delta_k)^T Q (e(k+j) - \delta_k) + \sum_{j=0}^{m-1} \Delta u(k+j)^T R \Delta u(k+j) + \delta_k{}^T S \delta_k$$

$$e(k+j) = y(k+j) - y^{sp}$$

Extended IHMPC

Problem P2: $\min\limits_{\Delta u_k, \delta_k} \quad V_k$

Subject to:

$$V_k = \sum_{j=0}^{m} \left(e(k+j) - \delta_k\right)^T Q \left(e(k+j) - \delta_k\right) + x^d(k+m)^T \bar{Q}\, x^d(k+m)$$

$$+ \sum_{j=0}^{m-1} \Delta u(k+j)^T R \Delta u(k+j) + \delta_k^T S\, \delta_k$$

$$\bar{Q} - F^T \bar{Q} F = F^T \Psi^T Q \Psi F \qquad \Delta u_k = \begin{bmatrix} \Delta u(k) & \Delta u(k+1) & \cdots & \Delta u(k+m-1) \end{bmatrix}$$

$$e^s(k) + \tilde{B}^s \Delta u_k - \delta_k = 0 \qquad \tilde{B}^s = \underbrace{\begin{bmatrix} B^s & \cdots & B^s \end{bmatrix}}_{m}$$

$$-\Delta u^{\max} \le \Delta u(k+j) \le \Delta u^{\max}$$

$$u^{\min} \le u(k-1) + \sum_{i=0}^{j} \Delta u(k+i) \le u^{\max}; \quad j = 0, 1, \cdots, m-1$$

Extended Robust IHMPC

Problem P3: $$\min_{\Delta u_k, \delta_{k,\theta_i}, i=1,\dots,L} V_{k,\theta_N}$$

Subject to: $$e^s(k) + \tilde{B}_i^s \Delta u_k - \delta_{k,\theta_i} = 0 \qquad i = 1,\dots,L$$

$$-\Delta u^{\max} \le \Delta u(k+j) \le \Delta u^{\max}$$

$$u^{\min} \le u(k-1) + \sum_{i=0}^{j} \Delta u(k+i) \le u^{\max}; \quad j = 0,1,\cdots,m-1$$

$$V_{k,\theta_i} \le \hat{V}_{k,\theta_i} \qquad i = 1,\dots,L$$

$\hat{V}_{k,\theta_i}$ is computed with: $\Delta \hat{u}_k$ and $\hat{\delta}_{k,\theta_i}$

$$\Delta \hat{u}_k = \begin{bmatrix} \Delta u^*(k) & \cdots & \Delta u^*(k+m-2) & 0 \end{bmatrix}_{k-1}$$

$$e^s(k) + \tilde{B}_i^s \Delta \hat{u}_k - \hat{\delta}_{k,\theta_i} = 0 \qquad i = 1,\dots,L$$

Robust Extended IHMPC

Example 2 : The high purity distillation column

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \frac{1}{22.98s+1} \begin{bmatrix} 0.7868(1+\gamma_1) & -0.6147(1+\gamma_2) \\ 0.8098(1+\gamma_1) & -0.982(1+\gamma_2) \end{bmatrix} \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix}$$

$$\Omega \quad \Rightarrow \quad -0.4 \le \gamma_1, \gamma_2 \le 0.4$$

$$\Omega \;\cong\; \left[(0,0) \quad (-0.4,-0.4) \quad (-0.4,0.4) \quad (0.4,-0.4) \quad (0.4,0.4) \right]$$

Tuning parameters of *RE-IHMPC*: $T = 2$, $m = 3$, $Q = \text{diag}(1, 1)$, $R = \text{diag}(10^{-2}, 10^{-2})$,

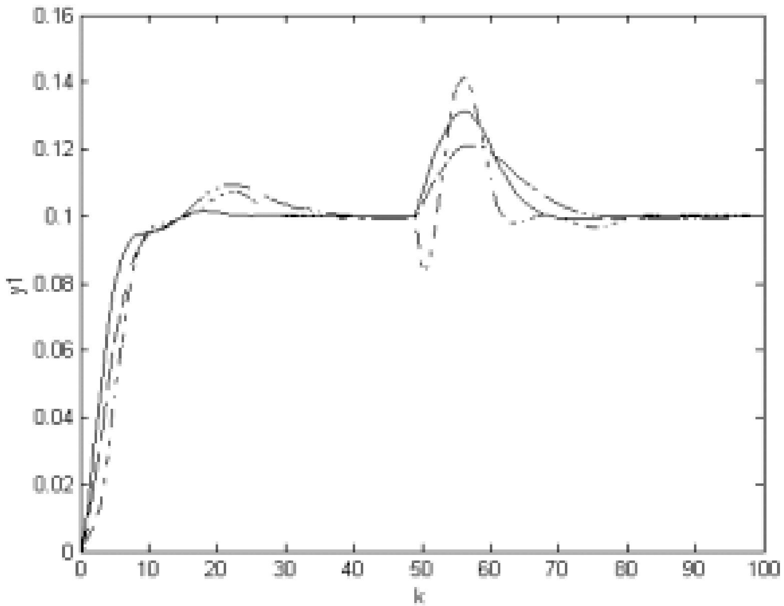
$S = \text{diag}(10^2, 10^2)$, $\Delta u_{max} = 0.25$, $u_{max} = 1.5$, $u_{min} = -1.5$

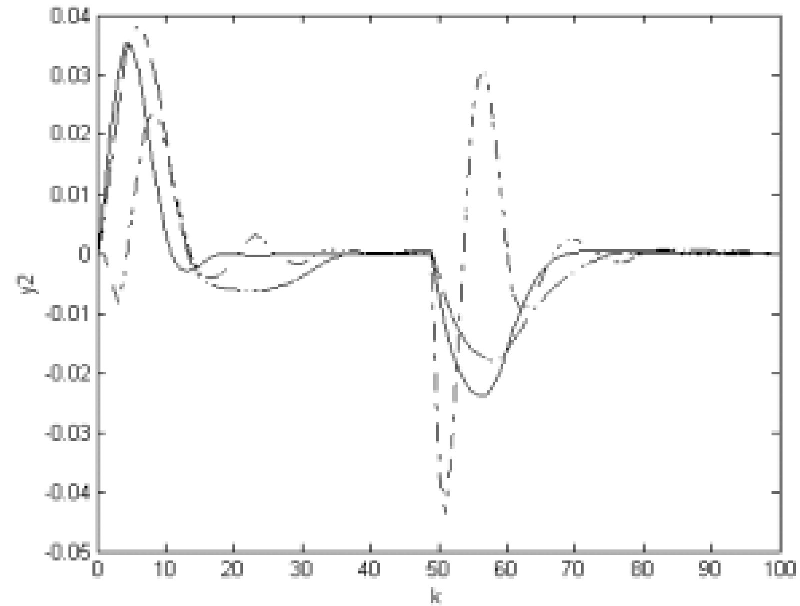
Example 2 Nominal model: $(\gamma_1, \gamma_2) = (0, 0)$

Case 1: true plant is $(\gamma_1, \gamma_2) = (0, 0)$ (——)

Case 2: true plant is $(\gamma_1, \gamma_2) = (-0.4, -0.4)$ (- - - -)

Case 3: true plant is $(\gamma_1, \gamma_2) = (-0.4, 0.4)$ (— · — ·)



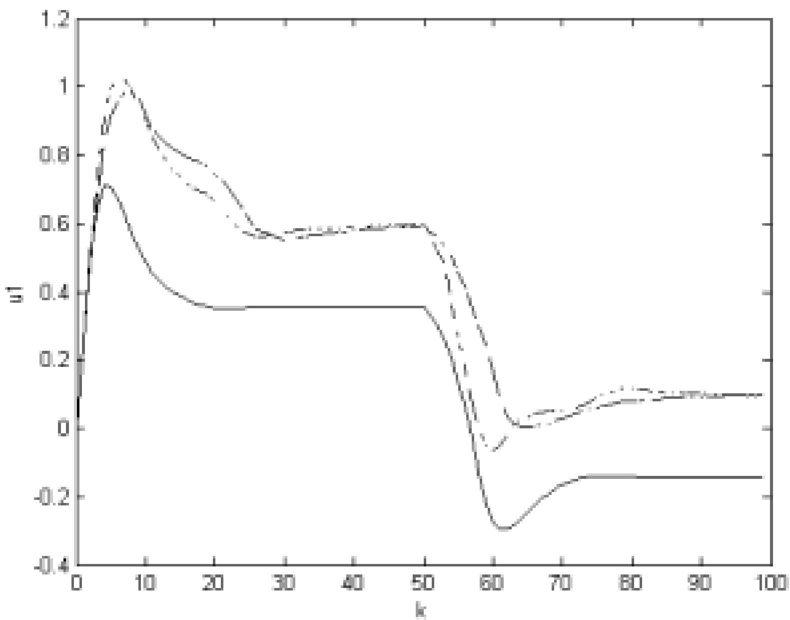


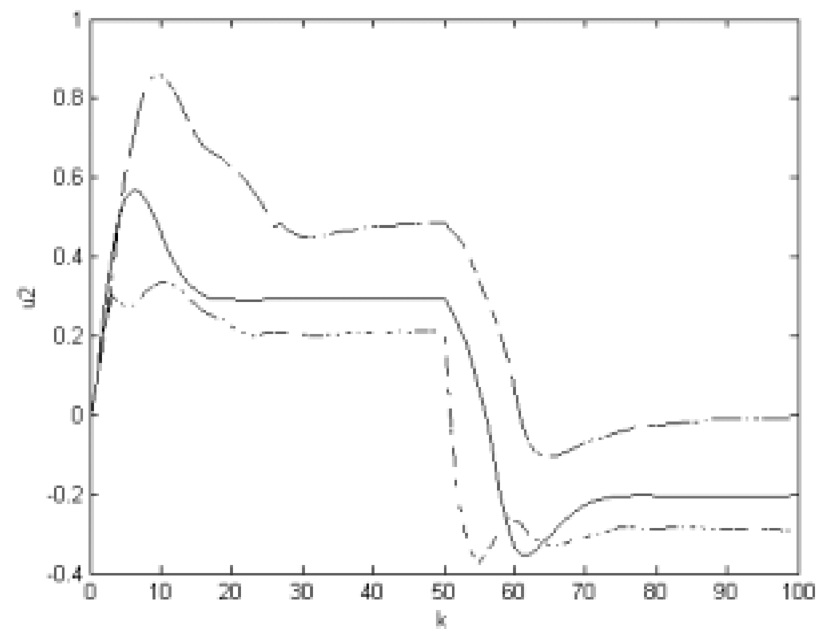
Example 2 Nominal model: $(\gamma_1, \gamma_2) = (0,0)$

Case 1: true plant is $(\gamma_1, \gamma_2) = (0,0)$ (———)

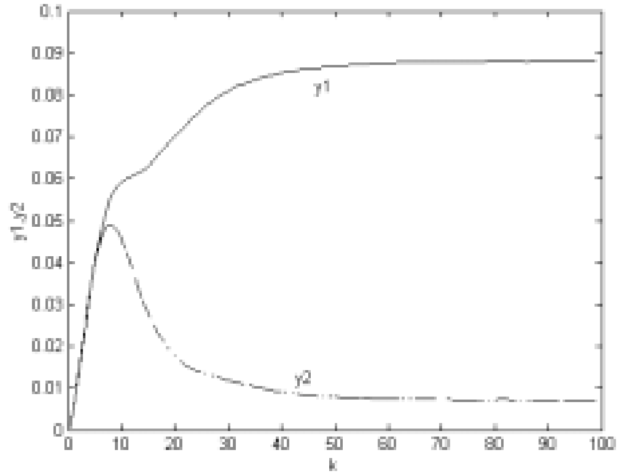
Case 2: true plant is $(\gamma_1, \gamma_2) = (-0.4, -0.4)$ (- - - -)

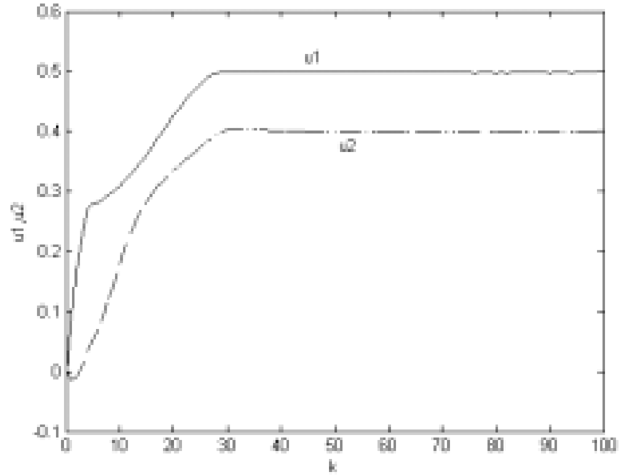
Case 3: true plant is $(\gamma_1, \gamma_2) = (-0.4, 0.4)$ (— · — ·)

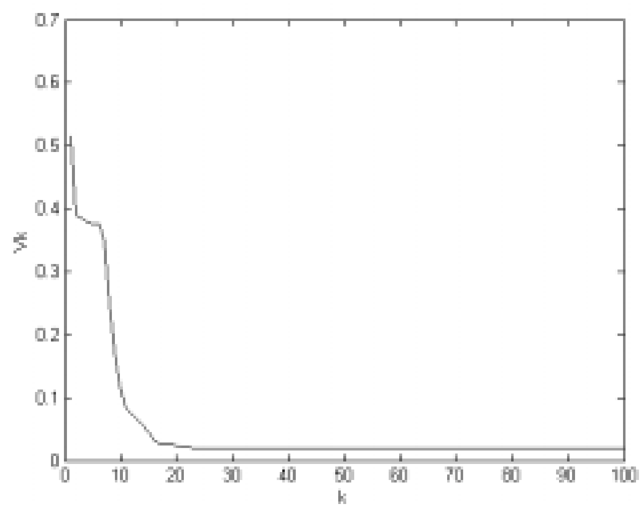




Example 2 RE-IHMPC with input saturation: Case 2: with u_{max} = 0.5







Robust Stability with IHMPC

Advantages:

-Quite large ranges of model uncertainties can be considered in the MPC control law computation.

-The structure of MPC is preserved (constraints are included) and can be implemented in practice.

-Performance is expected to deteriorate if uncertainty is too large but better than the controller with nominal model.

Disadvantages:

-Computer effort tends to be larger than in the nominal MPC. Should be applied only in subsystems where uncertainty is critical.

-Still lacking a practical solution to integrating and unstable systems.