



# Robust output feedback MPC using interval observers

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International Online Seminar on Interval Methods in Control Engineering

*May 7th, 2021* 

#### Outline

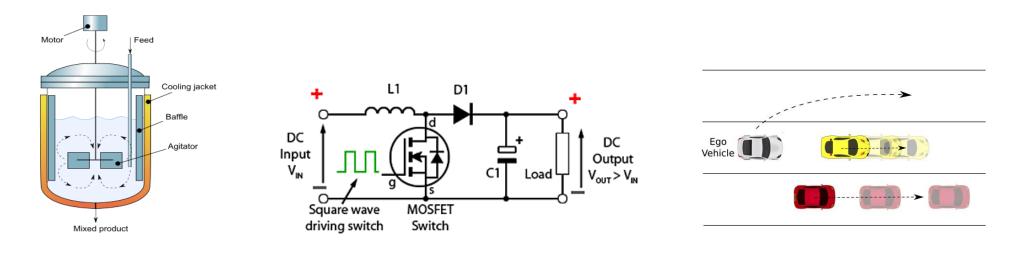
- 1 Motivation
- 2 Problem statement
- 3 Design of interval observer and predictor
- 4 Interval MPC
- 5 Numerical example

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#### Motivation

• Constrained systems are recurrent: physical limitations, performance and safety;



Chemical reactors [Wikipedia]

Power electronics [Elprocus]

Vehicle control [MPC and VDL Labs]

ullet Usual feedback solutions based on Lyapunov methods often fail to ensure constraint satisfaction  $\to$  Model Predictive Control

#### Motivation

- What about robustness?
  - Model uncertainties and noises → discrepancies between prediction and real system;
  - Unavailable states  $\rightarrow$  state estimation;
  - How to ensure constraint satisfaction and feasibility?

Classical solutions: Tubes (rigid, homothetic), error set-membership estimation, moving-horizon estimation (MHE), minmax optimization, multi-stage MPC, ...

#### Motivation

• What about *robustness*?

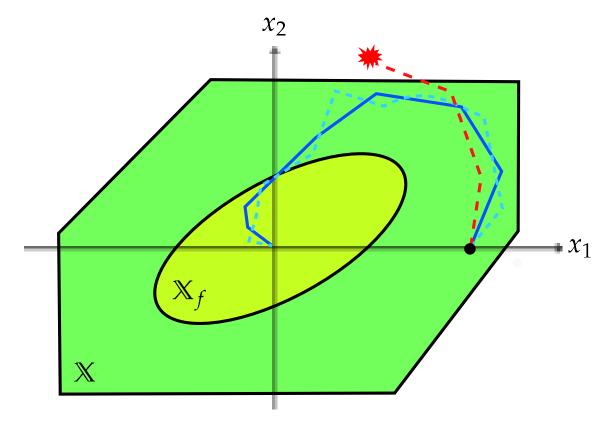


Illustration of loss of feasibility due to uncertainty

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#### Problem statement

Consider the following discrete-time LPV system:

$$x_{k+1} = A(\theta_k)x_k + B(\theta_k)u_k + w_k$$
  

$$y_k = Cx_k + v_k$$
(1)

where  $x_k$  is the state vector,  $u_k$  is the control input,  $y_k$  is the measurement vector,  $w_k$  and  $v_k$  are process and measurement noises, respectively.

Assumption 1: The additive perturbations  $w_k \in [\underline{w}_k, \overline{w}_k]$  and  $v_k \in [\underline{v}_k, \overline{v}_k]$  for all  $k \in \mathbb{Z}_+$ , where  $\underline{w}, \overline{w} \in \ell_{\infty}^n$  and  $\underline{v}, \overline{v} \in \ell_{\infty}^p$  are known signals. The scheduling parameter is unmeasured, but takes values in a known bounded set  $\Theta$ .

Assumption 2: Initial conditions of (1) are bounded such as  $\underline{x}_0 \leq x_0 \leq \overline{x}_0$ , for some known  $\underline{x}_0, \overline{x}_0 \in \mathbb{R}^n$ .

#### Problem statement

Assumption 3: There exist matrices  $A_0 \in \mathbb{R}^{n \times n}$ ,  $B_0 \in \mathbb{R}^{n \times m}$  and  $\Delta A_i \in \mathbb{R}^{n \times n}$ ,  $\Delta B_i \in \mathbb{R}^{n \times m}$ ,  $i = 1, ..., \nu$  for some  $\nu \in \mathbb{Z}_+$ , such that the following relations are satisfied for all  $\theta \in \Theta$ :

$$A(\theta) = A_0 + \sum_{i=1}^{\nu} \lambda_i(\theta) \Delta A_i, \quad B(\theta) = B_0 + \sum_{i=1}^{\nu} \lambda_i(\theta) \Delta B_i,$$
$$\sum_{i=1}^{\nu} \lambda_i(\theta) = 1, \quad \lambda_i(\theta) \in [0, 1].$$

Assumption 4: Let  $C \geq 0$ .

#### Problem statement

Problem 1 (Robust constrained control) Design an output feedback control that stabilizes (1) while respecting the following constraints

$$x_k \in \mathbb{X}$$
,  $u_k \in \mathbb{U}$ ,  $\forall k \in \mathbb{Z}_+$ 

having X and U as known convex bounded sets, for any possible realization of disturbances  $w_k$  and  $v_k$ , and of the scheduling parameter  $\theta_k$ .

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#### **Preliminaries**

For our developments, we will need the following lemmas:

Lemma 1: [Efimov et al. 2013] Let  $x \in \mathbb{R}^n$  be a vector variable,  $\underline{x} \leq x \leq \overline{x}$  for some  $\underline{x}, \overline{x} \in \mathbb{R}^n$ . Then,

(1) if  $A \in \mathbb{R}^{m \times n}$  is a constant matrix, then

$$A^{+}\underline{x} - A^{-}\overline{x} \le Ax \le A^{+}\overline{x} - A^{-}\underline{x} \tag{2}$$

(2) if  $A \in \mathbb{R}^{m \times n}$  is a matrix variable and  $\underline{A} \leq A \leq \overline{A}$  for some  $\underline{A}, \overline{A} \in \mathbb{R}^{m \times n}$ , then

$$\underline{A}^{+}\underline{x}^{+} - \overline{A}^{+}\underline{x}^{-} - \underline{A}^{-}\overline{x}^{+} + \overline{A}^{-}\overline{x}^{-} \le Ax \le \overline{A}^{+}\overline{x}^{+} - \underline{A}^{+}\overline{x}^{-} - \overline{A}^{-}\underline{x}^{+} + \underline{A}^{-}\underline{x}^{-}$$

$$\tag{3}$$

#### **Preliminaries**

Lemma 2: [Smith, 1995] For  $A \in \mathbb{R}^{n \times n}_+$ , the system

$$x_{k+1} = Ax_k + \omega_k$$
,  $\omega : \mathbb{Z}_+ \to \mathbb{R}_+^n$ ,  $\omega \in \mathcal{L}_{\infty}^n$ ,  $k \in \mathbb{Z}_+$ 

has a non-negative solution  $x_k \in \mathbb{R}^n_+$  for all  $k \in \mathbb{Z}_+$  provided that  $x_0 \geq 0$ .

Lemma 3: [Farina and Rinaldi, 2000] A matrix  $A \in \mathbb{R}^{n \times n}$  is Schur stable iff there exists a diagonal matrix  $P \in \mathbb{R}^{n \times n}$ , P > 0, such that  $A^{\top}PA - P \prec 0$ .

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IO-MPC

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An *interval observer* is a two-point set-membership estimator, with stability guarantees. Under *cooperativity conditions*, they produce the following bounds:

$$\underline{x}_k \leq x_k \leq \overline{x}_k$$

Main idea: use the relation above to check constraints, since

$$[\underline{x}_k, \overline{x}_k] \subset \mathbb{X} \implies x_k \in \mathbb{X}.$$

Main features: low computation complexity and ease of design (LMIs).

Using the measurement  $y_k$ :

$$x_{k+1} = (A_0 - LC)x_k + \sum_{i=1}^{\nu} \lambda_i(\theta) \Delta A_i x_k + Ly_k + (B_0 + \sum_{i=1}^{\nu} \lambda_i(\theta) \Delta B_i) u_k - Lv_k + w_k$$

the following IO can be proposed:

$$\overline{x}_{k+1} = (A_0 - L_o C)\overline{x}_k + \Delta A_+ \overline{x}_k^+ + \Delta A_- \underline{x}_k^- + B_0 u_k + \Delta B u_k^+ + L_o y_k - L_o^+ \underline{v}_k + L_o^- \overline{v}_k + \overline{w}_k 
\underline{x}_{k+1} = (A_0 - L_o C)\underline{x}_k - \Delta A_+ \underline{x}_k^- - \Delta A_- \overline{x}_k^+ + B_0 u_k - \Delta B u_k^- + L_o y_k - L_o^+ \overline{v}_k + L_o^- \underline{v}_k + \underline{w}_k$$
(4)

where  $L_o$  is the observer gain to be designed. Define the observer estimation errors  $e_k = x_k - \underline{x}_k$  and  $e_k = \overline{x}_k - x_k$ .

Lemma 4: Let assumptions 1–3 be satisfied. Then, provided that  $A_0 - L_o C$  is non-negative, the estimation errors are non-negative, i.e.,  $\underline{e}_k$ ,  $\overline{e}_k \geq 0$  for all k > 0.

In order to derive stability conditions for IO (4), let us rewrite it as:

$$\chi_{k+1} = \left(\mathcal{A}_0 - \tilde{L}_o C_1\right) \chi_k + \mathcal{A}_+ \chi_k^+ + \mathcal{A}_- \chi_k^- + \delta_k$$

where  $A_0 = \operatorname{diag}(A_0, A_0) \in \mathbb{R}^{2n \times 2n}$ ,  $\tilde{L}_o = \operatorname{diag}(L_o, L_o) \in \mathbb{R}^{2n \times 2p}$ ,  $C_1 = \operatorname{diag}(C, C) \in \mathbb{R}^{2p \times 2n}$ ,  $\delta_k = \operatorname{vec}(\overline{\delta}_k, \underline{\delta}_k)$ , and

$$\mathcal{A}_{+} = \begin{bmatrix} \Delta A_{+} & 0 \\ -\Delta A_{-} & 0 \end{bmatrix}, \quad \mathcal{A}_{-} = \begin{bmatrix} 0 & \Delta A_{-} \\ 0 & -\Delta A_{+} \end{bmatrix},$$

$$\overline{\delta}_{k} = B_{0}u_{k} + \Delta Bu_{k}^{+} + L_{o}y_{k} - L_{o}^{+}\underline{v}_{k} + L_{o}^{-}\overline{v}_{k} + \overline{w}_{k},$$

$$\underline{\delta}_{k} = B_{0}u_{k} - \Delta Bu_{k}^{-} + L_{o}y_{k} - L_{o}^{+}\overline{v}_{k} + L_{o}^{-}\underline{v}_{k} + \underline{w}_{k}.$$

The next result verifies stability:

Theorem 1: Let assumptions 1–3 be satisfied. If there exist diagonal matrices  $\tilde{P}, Q_1, Q_2, Q_3, \Omega_+, \Omega_-, \Psi \in \mathbb{R}^{2n \times 2n}$ , matrices  $\Gamma \in \mathbb{R}^{2n \times 2n}$  and  $\tilde{U} \in \mathbb{R}^{2n \times p}$ , such that the following LMIs are verified:

$$ilde{P}\mathcal{A}_0 - ilde{U}C_1 \geq 0$$
 
$$\begin{bmatrix} ilde{P} - Q_1 & -\Omega_+ & -\Omega_- & 0 & \mathcal{A}_0^{ op} ilde{P} - C_1^{ op} ilde{U}^{ op} \\ ilde{\star} & -Q_2 & -\Psi & 0 & \mathcal{A}_+^{ op} ilde{P} \\ ilde{\star} & \star & -Q_3 & 0 & \mathcal{A}_-^{ op} ilde{P} \\ ilde{\star} & \star & \star & \Gamma & ilde{P} \\ ilde{\star} & \star & \star & \star & ilde{P} \end{bmatrix} \succeq 0$$
 
$$ilde{P} > 0, \quad \Gamma \succ 0, \quad Q_1, Q_2, Q_3, \Omega_+, \Omega_- \geq 0,$$
 
$$Q_1 + \min\{Q_2, Q_3\} + 2\min\{\Omega_+, \Omega_-\} > 0$$

then system (4) with a gain  $L_o = P^{-1}U$  is an IO for system (1), *i.e.*, relation  $\underline{x}_k \leq x_k \leq \overline{x}_k$  is satisfied for all  $k \in \mathbb{Z}_+$  and, in addition,  $\chi \in \ell_{\infty}^{2n}$  provided that  $\delta \in \ell_{\infty}^{2n}$ .

To better illustrate the developments of this section, consider the following prototype model:

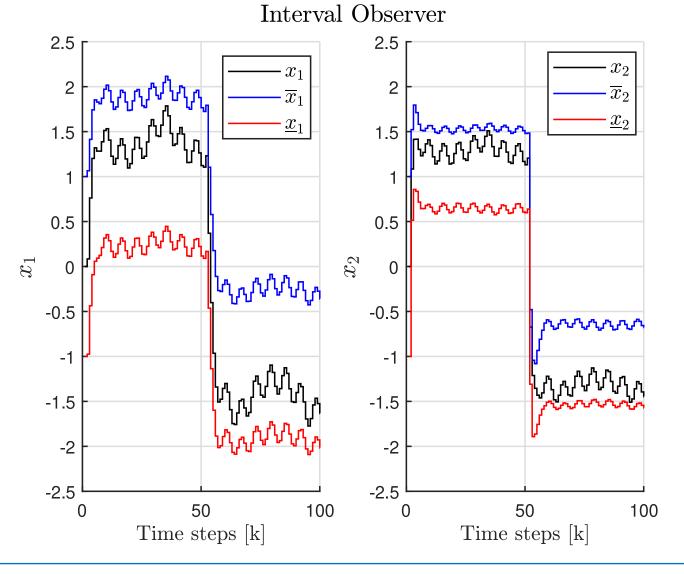
$$x_{k+1} = \begin{bmatrix} 0.5 & 0.6 + \theta_k \\ \theta_k & 0.3 \end{bmatrix} x_k + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u_k + w_k$$
$$y_k = \begin{bmatrix} 0 & 1 \end{bmatrix} x_k + v_k$$

$$W = [-0.1, 0.1] \times [-0.1, 0.1], \quad V = [-0.1, 0.1], \quad \text{and } \Theta = [0, -0.3].$$

Interpolating functions  $\lambda_1 = \frac{\theta_k - \underline{\theta}_k}{\overline{\theta}_k - \underline{\theta}_k}$  and  $\lambda_2 = \frac{\overline{\theta}_k - \theta_k}{\overline{\theta}_k - \underline{\theta}_k}$ .

#### Simulate the IO

$$u_k = 1$$
, for  $k = [0, ... 49]$   
 $u_k = -1$ , for  $k = [50, ... 100]$   
 $\theta_k = -|0.3 \sin(0.1k)|$   
 $w_k = 0.1 \sin(k)$ ,  $v_k = 0.1 \sin(k)$ 



As seen in (4), the IO requires the measurement  $y_k \to \text{unsuitable}$  for prediction.

**Solution**: propose an *interval predictor*  $\rightarrow$  an open-loop *framer*, *i.e.*, independent of  $y_k$ .

Recalling that  $y_k = Cx_k + v_k$ , we can write the following relation under Lemma 1 and Assumption 4:

$$L_p^+ C \underline{z}_k - L_p^- C \overline{z}_k \le L_p C z_k \le L_p^+ C \overline{z}_k - L_p^- C \underline{z}_k.$$
 (5)

then the terms  $L_p y_k - L_p v_k = L_p C x_k$  can be replaced by the bounding relations above.

The proposed IP:

$$\overline{z}_{k+1} = (A_0 - L_p C)\overline{z}_k + \Delta A_+ \overline{z}_k^+ + \Delta A_- \underline{z}_k^- + L_p^+ C \overline{z}_k - L_p^- C \underline{z}_k + B_0 u_k + \Delta B u_k^+ + \overline{w}_k 
\underline{z}_{k+1} = (A_0 - L_p C)\underline{z}_k - \Delta A_+ \underline{z}_k^+ - \Delta A_- \overline{z}_k^- + L_p^+ C \underline{z}_k - L_p^- C \overline{z}_k + B_0 u_k - \Delta B u_k^- + \underline{w}_k 
(6)$$

Define the prediction estimation errors  $\underline{\epsilon}_k = x_k - \underline{z}_k$  and  $\overline{\epsilon}_k = \overline{z}_k - x_k$ .

Lemma 5: Let assumptions 1–4 be satisfied. Then, provided that  $A_0 - L_pC$  is non-negative, the prediction errors are non-negative, i.e.,  $\underline{\epsilon}_k, \overline{\epsilon}_k \geq 0$  for all  $k \in \mathbb{Z}_+$ .

In order to derive stability conditions for IP (6), let us rewrite it as:

$$\mathcal{Z}_{k+1} = \left(\mathcal{A}_0 + \tilde{L}_p C_2\right) \mathcal{Z}_k + \mathcal{A}_+ \mathcal{Z}_k^+ + \mathcal{A}_- \mathcal{Z}_k^- + \varrho_k,$$

where  $A_0$ ,  $A_+$  and  $A_-$  are the same as for IO (4),  $\tilde{L}_p = \operatorname{diag}(L_p^-, L_p^-) \in \mathbb{R}^{2n \times 2p}$ ,  $\varrho_k = \operatorname{vec}(\overline{\rho}_k, \rho_k)$  and

$$C_2 = \begin{bmatrix} C & -C \\ -C & C \end{bmatrix},$$

$$\overline{\rho}_k = B_0 u_k + \Delta B u_k^+ + \overline{w}_k, \quad \underline{\rho}_k = B_0 u_k - \Delta B u_k^- + \underline{w}_k.$$

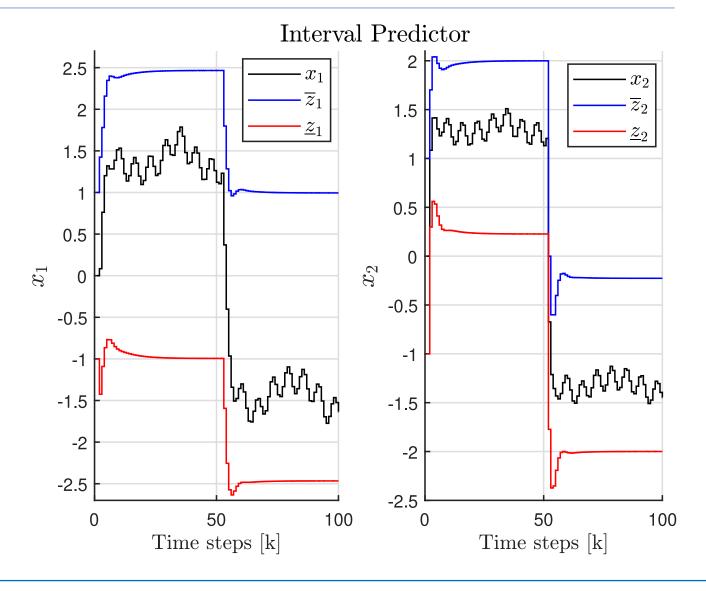
Theorem 2: Let assumptions 1–4 be satisfied. If there exist diagonal matrices  $\tilde{P}_2$ ,  $Q_1, Q_2, Q_3, \Omega_+, \Omega_-, \Psi$ ,  $\Gamma \in \mathbb{R}^{2n \times 2n}$  and  $U^+, U^- \in \mathbb{R}^{n \times p}$ , such that

$$\begin{split} \tilde{P}_{2}\mathcal{A}_{0} - \tilde{U}^{+}C_{1} + \tilde{U}^{-}C_{1} &\geq 0 \\ \begin{bmatrix} \tilde{P}_{2} - Q_{1} & -\Omega_{+} & -\Omega_{-} & 0 & (\tilde{P}_{2}\mathcal{A}_{0} + \tilde{U}^{-}C_{2})^{\top} \\ \star & -Q_{2} & -\Psi & 0 & (\tilde{P}_{2}\mathcal{A}_{+})^{\top} \\ \star & \star & -Q_{3} & 0 & (\tilde{P}_{2}\mathcal{A}_{-})^{\top} \\ \star & \star & \star & \Gamma & \tilde{P}_{2} \\ \star & \star & \star & \star & \tilde{P}_{2} \end{bmatrix} &\geq 0 \\ Q_{1}, Q_{2}, Q_{3}, \Omega_{+}, \Omega_{-}, U^{+}, U^{-} &\geq 0, \quad \Gamma > 0, \quad P_{2} > 0 \\ \tilde{P}_{2} &= \operatorname{diag}(P_{2}, P_{2}), \quad \tilde{U}^{+} &= \operatorname{diag}(U^{+}, U^{+}), \quad \tilde{U}^{-} &= \operatorname{diag}(U^{-}, U^{-}), \\ Q &= Q_{1} + \min\{Q_{2}, Q_{3}\} + 2\min\{\Omega_{+}, \Omega_{-}\} > 0 \end{split}$$

then (6) with gains  $L_p^- = P_2^{-1}U^-$  and  $L_p^+ = P_2^{-1}U^+$  is an IP for system (1), *i.e.*,  $\underline{z}_k \leq x_k \leq \overline{z}_k$  holds for all  $k \in \mathbb{Z}_+$ , and (6) is ISS with respect to the input  $\varrho \in \ell_{\infty}^{2n}$ .

#### Simulate the IP

$$u_k = 1$$
, for  $k = [0, ... 49]$   
 $u_k = -1$ , for  $k = [50, ... 100]$   
 $\theta_k = -|0.3 \sin(0.1k)|$   
 $w_k = 0.1 \sin(k)$ ,  $v_k = 0.1 \sin(k)$ 



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#### Recall on MPC

How to prove stability  $\rightarrow$  stabilizing ingredients:

- Terminal set  $X_f$ : the set that the endpoint of the prediction must reach;
- Terminal gain  $\kappa_f$ : there exists a stabilizing controller;
- Terminal cost  $V_f$ .

#### Recall on MPC

How to prove stability  $\rightarrow$  stabilizing ingredients. Recall the classic axioms of Mayne et al.:

**Definition 1** The stabilizing ingredients are such that the following axioms are verified:

- 1.  $X_f \subset X$ , closed and  $0 \in X_f$ : the state constraint is satisfied in  $X_f$ ;
- 2.  $\kappa_f(x) \in \mathbb{U}, \ \forall x \in \mathbb{X}_f$ : the control constraint is satisfied in  $\mathbb{X}_f$ ;
- 3.  $f(x, \kappa_f(x)) \in \mathbb{X}_f$ ,  $\forall x \in \mathbb{X}_f$ :  $\mathbb{X}_f$  is positively invariant under  $\kappa_f(x)$ ;
- 4.  $[V_f + \ell](x, \kappa_f(x)) \leq 0$ ,  $\forall x \in X_f : V_f \text{ is a local Lyapunov function.}$

#### IP: Control design

How to design a feedback controller for the IP? Let us consider:

$$u_k = K\mathcal{Z}_k + K_+\mathcal{Z}_k^+ + K_-\mathcal{Z}_k^- + R\mathcal{W} \tag{7}$$

where  $W_k = \text{vec}(\underline{w}_k, \overline{w}_k)$ . This control leads to the following closed-loop:

$$\mathcal{Z}_{k+1} = \mathcal{K}\mathcal{Z}_k + \mathcal{K}_+\mathcal{Z}_k^+ + \mathcal{K}_-\mathcal{Z}_k^- + \tilde{D}\mathcal{W}$$
 (8)

where 
$$K = A_0 + \tilde{L}_p C_2 + \mathcal{B}_0 K$$
,  $K_* = A_* + \mathcal{B}_0 K_*$   $\tilde{D} = \mathbb{I}_{2n} + \mathcal{B}_0 R$  and  $\mathcal{B}_0 = [B_0^\top, B_0^\top]$ .

#### IP: Control design

This brings us to the following result:

Theorem 3: Let assumptions 1–4 be satisfied. If there exist matrices P,  $Q_1$ ,  $Q_2$ ,  $Q_3$ ,  $\Gamma$ ,  $\Omega_+$ ,  $\Omega_-$ ,  $\Psi \in \mathbb{R}^{2n \times 2n}$  and  $W_1$ ,  $W_2$ ,  $W_3$ ,  $W_4 \in \mathbb{R}^{m \times 2n}$  such that

$$\begin{bmatrix} P - Q_{1} & -\Omega_{+} & -\Omega_{-} & 0 & W_{1}^{\top} \mathcal{B}_{0}^{\top} + P D_{z}^{\top} \\ \star & -Q_{2} & -\Psi & 0 & W_{2}^{\top} \mathcal{B}_{0}^{\top} + P \mathcal{A}_{+}^{\top} \\ \star & \star & -Q_{3} & 0 & W_{3}^{\top} \mathcal{B}_{0}^{\top} + P \mathcal{A}_{-}^{\top} \\ \star & \star & \star & \Gamma & W_{4}^{\top} \mathcal{B}_{0}^{\top} + P \end{bmatrix} \succ 0$$

$$P > 0, \quad \Gamma > 0, \quad Q_{1}, Q_{2}, Q_{3}, \Omega_{+}, \Omega_{-} \geq 0,$$

$$Q = Q_{1} + \min\{Q_{2}, Q_{3}\} + 2\min\{\Omega_{+}, \Omega_{-}\} > 0,$$

then IP (6) under control (7) with gains  $K = W_1 P^{-1}$ ,  $K_+ = W_2 P^{-1}$ ,  $K_- = W_3 P^{-1}$ ,  $R = W_4 P^{-1}$  is ISS with respect to the inputs  $\mathcal{W} \in \ell_{\infty}^{2n}$ .

#### IP: Control design

How to ensure that  $u_k \in \mathbb{U}$ ?

Corollary 1: Let there exist symmetric and positive definite matrices  $S \in \mathbb{R}^{m \times m}$  and  $Z \in \mathbb{R}^{2n \times 2n}$  such that  $\mathbb{U} = \{u \in \mathbb{R}^m : u^\top Su \leq 1\}$  and  $\mathcal{W}_k \in \{\mathcal{W} \in \mathbb{R}^{2n} : \mathcal{W}^\top Z\mathcal{W} \leq 1\}$ , and the conditions of Theorem 4 be satisfied with additional inequalities:

$$\frac{\eta}{\alpha\kappa}\Gamma \leq \min\{\kappa^{-1}Z, P\}, \ P \geq \kappa Z^{-1},$$

$$\begin{bmatrix} \frac{\eta}{3}P & 0 & 0 & W_1^\top + W_2^\top \\ 0 & \frac{\eta}{3}P & 0 & W_3^\top - W_1^\top \\ 0 & 0 & \frac{\kappa}{3}P & W_4^\top \\ W_1 + W_2 & W_3 - W_1 & W_4 & S^{-1} \end{bmatrix} \geq 0$$

for some constants  $\eta > 0$  and  $\kappa > 0$ , then control (7) satisfies the constraint  $u_k \in \mathbb{U}$  for all  $\mathcal{Z}_k \in \mathbb{X}_f \times \mathbb{X}_f$ .

Determine  $S_n = \{s_0, \ldots, s_{N-1}\}$  solving the OCP

$$\mathcal{S}_N^k := \arg\min_{\mathcal{S}_N} V_N(\mathcal{Z}_{k,0}, \dots, \mathcal{Z}_{k,N}, \mathcal{S}_N)$$

with a cost function  $V_N(\mathcal{Z}_{k,0},\ldots,\mathcal{Z}_{k,N},\mathcal{S}_N) = V_f(\mathcal{Z}_{k,N}) + \sum_{i=0}^{N-1} \ell(\mathcal{Z}_{k,i},s_i).$ 

under the following constraints:

$$\underline{z}_{k,0} = \min\{\overline{x}_k, \overline{z}_{k-1,1}\}, \quad \overline{z}_{k,0} = \max\{\underline{x}_k, \underline{z}_{k-1,1}\}$$
 (9a)  $\rightarrow$  intialization  $\mathcal{Z}_{k,i+1}$  computed by X (9b)  $\rightarrow$  prediction using the IP

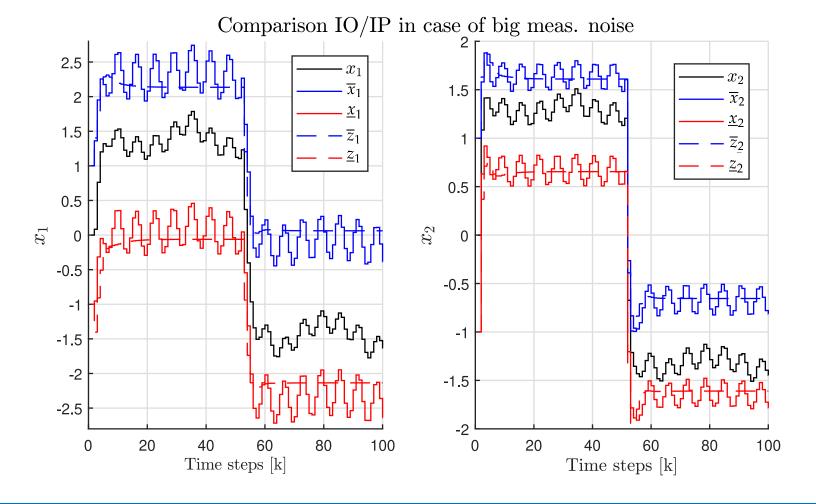
$$\mathcal{Z}_{k,i+1} \subset \mathbb{X} \times \mathbb{X}$$
,  $s_i \subset \mathbb{U}$ , (9c)  $\rightarrow$  state and input constraint

$$\mathcal{Z}_{k,N} \in \mathbb{X}_f \times \mathbb{X}_f$$
 (9d)  $\rightarrow$  terminal constraint

IO-MPC

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Why initialize using information from both IO and IP? Let  $\mathbb{V} = [-0.5, 0.5]$ .



#### Algorithm 1: IO-MPC

**Offline:** Solve LMIs, estimate  $X_f$  and select  $\Psi_1 = P^{-1}$ ,  $\Psi_2 \leq \frac{\alpha}{2}P^{-1}$  and  $\Psi_3 \leq \frac{\alpha}{8}P^{-1}$ .

**Input:** Initial conditions  $\underline{x}_0$ ,  $\overline{x}_0$  and prediction horizon N.

#### Online:

- 1. for each decision instant  $k \in \mathbb{Z}_+$  do
- 2. Measure  $y_k$  and update IO (4).
- 3. Initialize IP (6).
- 4. Solve OCP (17) under constraints (9a)-(9d).
- 5. Assign  $u_k = s_0^k$  and apply to the system.
- 6. end for

Theorem 4: Let  $[\underline{x}_0, \overline{x}_0] \subset X$  and assumptions 1–4 be satisfied with  $[\underline{w}_{k+1}, \overline{w}_{k+1}] \subseteq [\underline{w}_k, \overline{w}_k]$  for all  $k \in \mathbb{Z}_+$ . Then, following Algorithm 1, the closed-loop system composed by (1), (4) and (6) has the following features:

- 1. Recursive feasibility of reaching the terminal set in N steps;
- 2. ISS of dynamics (8) in  $X_f$  and practical ISS for (1);
- 3. Constraint satisfaction.

#### The LTI and the TD case

The same ideas were applied to linear time-invariant (LTI) and time-delayed systems (TD):

$$x_{k+1} = A_0 x_k + A_1 x_{k-h} + B u_k + w_k, \quad k \in \mathbb{Z}_+$$
  
 $x_k = \phi_k, \quad k \in [-h, ..., 0]$   
 $y_k = C x_k + v_k$ 

#### Main differences:

- Optimization of gains made through the interval width  $\delta x_k = \overline{x}_k \underline{x}_k$ .
- Control design made regarding the interval center  $x_k^* = \frac{\overline{x_k} + \underline{x_k}}{2}$ .
- For the TD case, the Lyapunov-Krasovskii framework is required;

#### Complexity

One of the main advantages of using IO/IP is their fixed complexity.

Assume that the number of hyperplanes needed to define X, U and  $X_f$  depends linearly on n, and that m = n. Therefore, the worst-case number of variables for solving the constrained OCP is 10Nn (8Nn for the linear cases).

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## Numerical example (LPV)

Recall the LPV prototype example:

$$x_{k+1} = \begin{bmatrix} 0.5 & 0.6 + \theta_k \\ \theta_k & 0.3 \end{bmatrix} x_k + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u_k + w_k$$
$$y_k = \begin{bmatrix} 0 & 1 \end{bmatrix} x_k + v_k$$

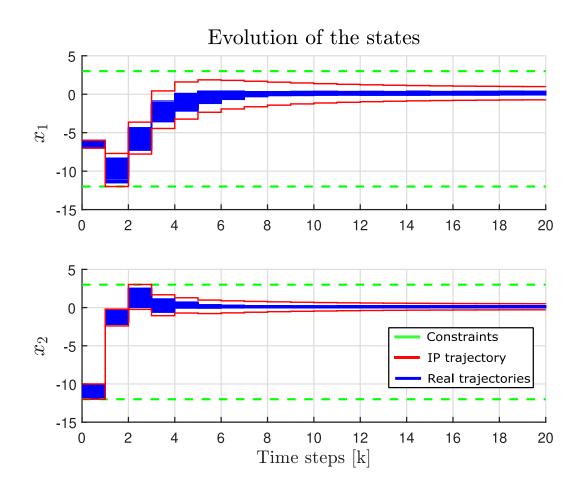
Constraints:  $X = [-12, 3] \times [-12, 3], \ \mathbb{U} = [-2, 2]$ 

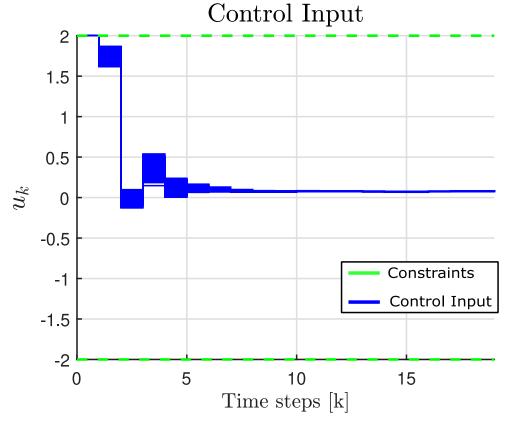
Disturbances:  $W = [-0.1, 0.1]^2$ , V = [-0.1, 0.1]

Interpolating functions  $\lambda_1 = \frac{\theta_k - \underline{\theta}_k}{\overline{\theta}_k - \underline{\theta}_k}$  and  $\lambda_1 = \frac{\overline{\theta}_k - \theta_k}{\overline{\theta}_k - \underline{\theta}_k}$ ,  $\Theta = [-0.1, 0.1]$ 

Select  $\underline{x}_0 = \text{vec}(-7, -12)$  and  $\overline{x}_0 = \text{vec}(-6, -10)$ . Prediction horizon N = 20, simulation time span T = 20 steps  $\times$  100 runs.

# Numerical example (LPV)

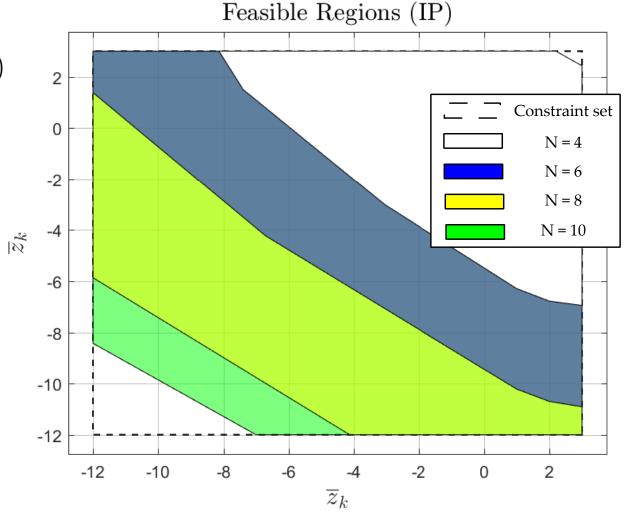




# Numerical example (LPV)

Solver: fmincon (active set method)

For N = 10, computation time  $0.22 \pm 0.0313$  second/step with a maximum of 0.7725 second.



## Numerical example (LTI)

Consider the (linearized) CSTR model, given by the following matrices:

$$A = \begin{bmatrix} 0.745 & -0.002 \\ 5.610 & 0.780 \end{bmatrix}$$
,  $B = \begin{bmatrix} 5.6 \times 10^{-6} \\ 0.464 \end{bmatrix}$ ,  $C = \begin{bmatrix} 0 & 1 \end{bmatrix}$ 

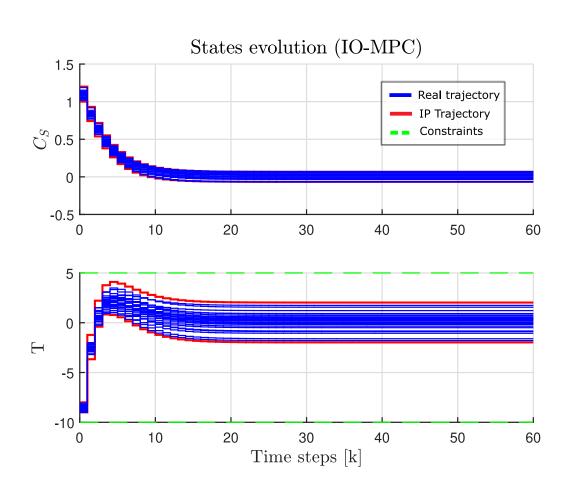
Constraints:  $X = [-2, 2] \times [-10, 5]$  and U = [-4.5, 4.5]

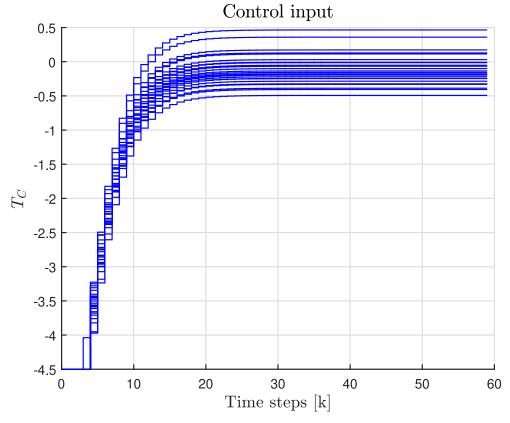
Disturbances:  $W = [-0.02, 0.02] \times [-0.2, 0.2]$  and V = [-0.3, 0.3]

For a later comparison, the Tube-MPC from [Mayne et al, 2009] will be implemented, taking an LQR controller for its design with matrices  $Q_{LQ} = 0.1\mathbb{I}_2$  and  $R_{LO} = 0.1$ .

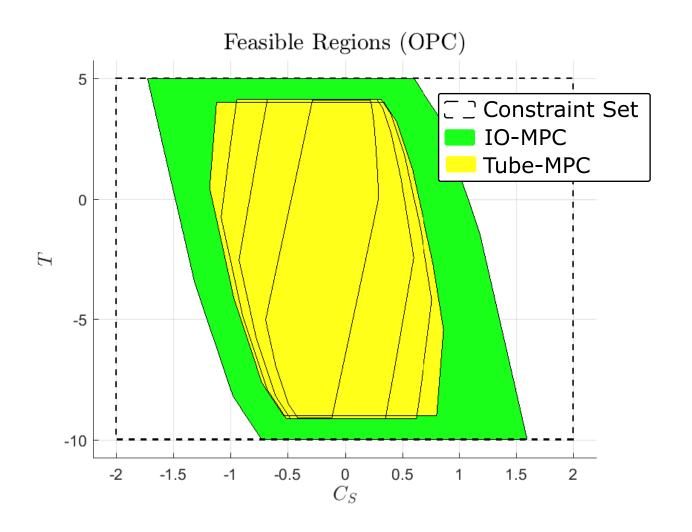
Solver: quadprog, computation time:  $0.0032 \pm 0.0021$  second/step, maximum of 0.1358.

# Numerical example (LTI)





# Numerical example (LTI)



## Numerical example (TD)

Consider the following TD system:

$$x_{k+1} = \begin{bmatrix} 0.5 & -0.1 \\ 0.5 & 0.2 \end{bmatrix} x_k + \begin{bmatrix} 0.1 & -0.3 \\ 0 & -0.1 \end{bmatrix} x_{k-h} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u_k + w_k$$
$$y_k = \begin{bmatrix} 0 & 1 \end{bmatrix} x_k + v_k$$

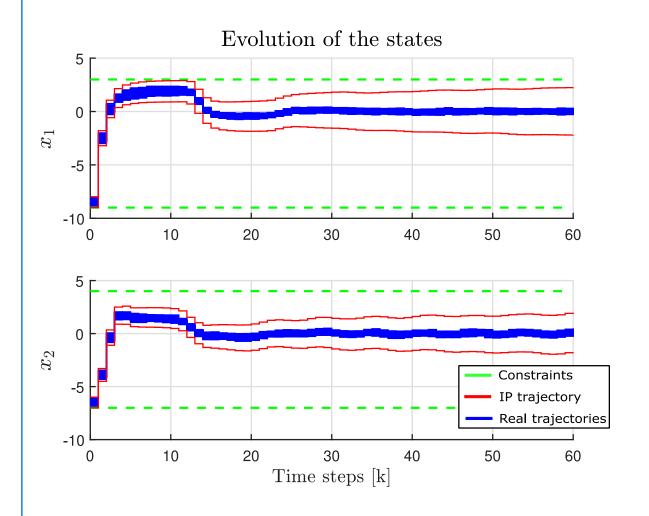
Constraints:  $\mathbb{X} = [-9,3] \times [-7,4]$  and  $\mathbb{U} = [-1,1]$ 

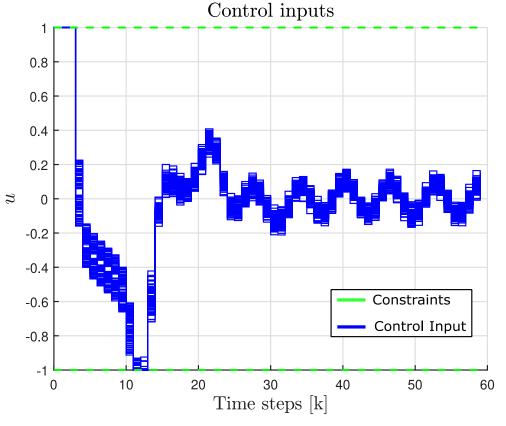
Disturbances:  $W = [-0.2, 0.2]^2$  and V = [-0.5, 0.5]

and a known time-delay h = 10.

Solver: quadprog, computation time:  $0.0032 \pm 0.0021$  second/step, maximum of 0.1358.

# Numerical example (TD)





#### Conclusions & perspectives

#### Conclusions:

- Developed new interval estimators for LTI, LPV and TD systems, as well as their respective state feedback controllers;
- Proposed new robust output feedback MPC algorithms;
- Illustrated the methodologies with numerical experiments;
- Advantages: low fixed complexity, ease of design, low conservativeness.

#### Perspectives:

- Enhance the interval estimators and the proposed MPC algorithms aiming to reduce conservativeness;
- Test their efficiency in practical scenarios.

# Thank you for your attention



Feel free to ask questions or contact me by e-mail: alex.dos-reis-de-souza@inria.fr