

# Model Predictive Control for Linear and Hybrid Systems Robust Constrained Optimal Control

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- 4 Min-Max Constrained Robust Optimal Control

# Introduction

- LQR, is a robust controller, in the following sense
  - ▶ infinite gain amplification in any input,
  - ▶ 1/2 gain reduction in any input,
  - ▶ phase margin of  $\pi/3$
- In MPC, controller robustness means to require
  - ▶ feasibility of the controller for all time, in the presence of persistent perturbations (disturbances).
  - ▶ convergence to a set  $\mathcal{X}_f$  that contains the desired equilibrium point, in the presence of persistent perturbations (disturbances).
- in the next lectures we will show how to address the effect of disturbances on a constrained systems and synthesize robust model predictive control

# System Model

- Consider the uncertain discrete-time dynamical system:

$$x(t+1) = A(w^p(t))x(t) + B(w^p(t))u(t) + Ew^a(t)$$

where

$$x(t) \in \mathcal{X}, \quad u(t) \in \mathcal{U}, \quad \forall t \geq 0.$$

The sets  $\mathcal{X} \subseteq \mathbb{R}^n$  and  $\mathcal{U} \subseteq \mathbb{R}^m$  are polytopes.

- Vectors  $w^a(t) \in \mathbb{R}^{n_a}$  and  $w^p(t) \in \mathbb{R}^{n_p}$  are unknown additive disturbances and parametric uncertainties, respectively.
- The disturbance vector is  $w(t) = [w^a(t); w^p(t)] \in \mathbb{R}^{n_w}$  with  $n_w = n_a + n_p$ .
- Only bounds on  $w^a(t)$  and  $w^p(t)$  are known, namely that  $w \in \mathcal{W} = \mathcal{V} \times \mathcal{W}$  with  $w^a(t) \in \mathcal{V}$

$$\mathcal{V} = \text{conv}(\{w^{a,1}, \dots, w^{a,n_v}\})$$

and  $w^p(t) \in \mathcal{W}$ ,

$$\mathcal{W} = \text{conv}(\{w^{p,1}, \dots, w^{p,n_w}\})$$

# System Model

- Consider the uncertain discrete-time dynamical system:

$$x(t+1) = A(w^p(t))x(t) + B(w^p(t))u(t) + Ew^a(t)$$

- $A(\cdot)$ ,  $B(\cdot)$  are **affine functions** of  $w^p$

$$A(w^p) = A^0 + \sum_{i=1}^{n_p} A^i w_c^{p,i}, \quad B(w^p) = B^0 + \sum_{i=1}^{n_p} B^i w_c^{p,i}$$

where  $A^i \in \mathbb{R}^{n \times n}$  and  $B^i \in \mathbb{R}^{n \times m}$  are given matrices

- For  $i = 0 \dots, n_p$  and  $w_c^{p,i}$  is the  $i$ -th component of the vector  $w^p$ , i.e.,  $w^p = [w_c^{p,1}, \dots, w_c^{p,n_p}]$ .

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# Constrained Robust Optimal Control. Batch Approach

Define the worst case cost function

$$J_0(x(0), U_0) \triangleq \max_{w_0, \dots, w_{N-1}} \left[ p(x_N) + \sum_{k=0}^{N-1} q(x_k, u_k) \right]$$
$$\text{subj. to } \begin{cases} x_{k+1} = A(w_k^p)x_k + B(w_k^p)u_k + Ew_k^a \\ w_k^a \in \mathcal{V}, w_k^p \in \mathcal{W}, \\ k = 0, \dots, N-1 \end{cases}$$

where  $N$  is the time horizon and  $U_0 \triangleq [u'_0, \dots, u'_{N-1}]' \in \mathbb{R}^s$ ,  $s \triangleq mN$  the vector of the input sequence.

The robust optimal control problem is

$$J_0^*(x_0) = \min_{U_0} J_0(x_0, U_0)$$
$$\text{subj. to } \left\{ \begin{array}{l} x_k \in \mathcal{X}, u_k \in \mathcal{U} \\ x_{k+1} = A(w_k^p)x_k + B(w_k^p)u_k + Ew_k^a \\ x_N \in \mathcal{X}_f \\ k = 0, \dots, N-1 \end{array} \right\} \quad \begin{array}{l} \forall w_k^a \in \mathcal{V}, w_k^p \in \mathcal{W} \\ \forall k = 0, \dots, N-1 \end{array}$$

# Constrained Robust Optimal Control. Batch Approach

- $x_k$  denotes the state vector at time  $k$  obtained by starting from the state  $x_0 = x(0)$  and applying to the system model

$$x_{k+1} = A(w_k^p)x_k + B(w_k^p)u_k + Ew_k^a$$

the input sequence  $u_0, \dots, u_{k-1}$  and the disturbance sequences  $\mathbf{w}^a \triangleq \{w_0^a, \dots, w_{N-1}^a\}$ ,  $\mathbf{w}^p \triangleq \{w_0^p, \dots, w_{N-1}^p\}$ .

- We denote with  $\mathcal{X}_i^{OL} \subseteq \mathcal{X}$  the set of states  $x_i$  for which the robust optimal control problem is feasible, i.e.,

$$\mathcal{X}_i^{OL} = \{x_i \in \mathcal{X} \text{ such that } \exists (u_i, \dots, u_{N-1}) \text{ such that } \\ x_k \in \mathcal{X}, u_k \in \mathcal{U}, k = i, \dots, N-1, x_N \in \mathcal{X}_f \forall w_k^a \in \mathcal{V}, w_k^p \in \mathcal{W} \\ k = i, \dots, N-1 \text{ where } x_{k+1} = A(w_k^p)x_k + B(w_k^p)u_k + Ew_k^a\}.$$

- The reason for including constraints in the minimization problem and not in the maximization problem is that  $w_j^a$  and  $w_j^p$  are free to act regardless of the state constraints. On the other hand, the input  $u_j$  has the duty of keeping the state within the constraints for all possible disturbance realization.



# Constrained Robust Optimal Control. Batch Approach

- The optimal control problem looks for the worst value  $J(x_0, U)$  of the performance index and the corresponding worst sequences  $\mathbf{w}^{p*}$ ,  $\mathbf{w}^{a*}$  as a function of  $x_0$  and  $U_0$ .
- It minimizes such a worst performance subject to the constraint that the input sequence must be feasible *for all* possible disturbance realizations.
- Note that worst sequences  $\mathbf{w}^{a*}$ ,  $\mathbf{w}^{p*}$  for the performance are not necessarily worst sequences in terms of constraints satisfaction.
- The min-max formulation is based on an *open-loop* prediction and thus referred to as Constrained Robust Optimal Control with open-loop predictions (CROC-OL).
- The optimal control problem can be viewed as a deterministic zero-sum dynamic game between two players: the controller  $U$  and the disturbance  $W$ .

# Constrained Robust Optimal Control. Batch Approach or Open-Loop Predictions

- The player  $U$  plays first. Given the initial state  $x(0)$ ,  $U$  chooses his action over the whole horizon  $\{u_0, \dots, u_{N-1}\}$ , reveals his plan to the opponent  $W$ , who decides on his actions next  $\{w_0^a, w_0^p, \dots, w_{N-1}^a, w_{N-1}^p\}$ .
- For this reason the player  $U$  has the duty of counteracting *any* feasible disturbance realization with just *one* single sequence  $\{u_0, \dots, u_{N-1}\}$ .
- This prediction model does not consider that at the next time step, the payer can measure the state  $x(1)$  and “adjust” his input  $u(1)$  based on the current measured state.
- By not considering this fact, the effect of the uncertainty may grow over the prediction horizon and may easily lead to infeasibility of the min problem

# Constrained Robust Optimal Control. Recursive Approach or Closed-Loop Predictions

The constrained robust optimal control problem based on closed-loop predictions (CROC-CL) is defined as:

$$J_j^*(x_j) \triangleq \min_{u_j} J_j(x_j, u_j)$$
$$\text{s.t. } \left\{ \begin{array}{l} x_j \in \mathcal{X}, u_j \in \mathcal{U} \\ A(w_j^p)x_j + B(w_j^p)u_j + Ew_j^a \in \mathcal{X}_{j+1} \end{array} \right\} \quad \forall w_j^a \in \mathcal{V}, w_j^p \in \mathcal{W}$$

$$J_j(x_j, u_j) \triangleq \max_{w_j^a \in \mathcal{V}, w_j^p \in \mathcal{W}} \{q(x_j, u_j) + J_{j+1}^*(A(w_j^p)x_j + B(w_j^p)u_j + Ew_j^a)\},$$

for  $j = 0, \dots, N-1$  and with boundary conditions

$$J_N^*(x_N) = p(x_N)$$
$$\mathcal{X}_N = \mathcal{X}_f,$$

# Constrained Robust Optimal Control. Closed-Loop Predictions

$\mathcal{X}_j$  denotes the set of states  $x$  for which the CROC-CL is feasible

$$\begin{aligned} \mathcal{X}_j = \quad & \{x \in \mathcal{X} \text{ such that } \exists u \in \mathcal{U} \\ & \text{s.t. } A(w^p)x + B(w^p)u + Ew^a \in \mathcal{X}_{j+1} \quad \forall w^a \in \mathcal{V}, w^p \in \mathcal{W}\}. \end{aligned}$$

- The reason for including constraints in the minimization problem and not in the maximization problem is that  $w_j^a$  and  $w_j^p$  are free to act regardless of the state constraints. On the other hand, the input  $u_j$  has the duty of keeping the state within the constraints for all possible disturbance realization.

# Constrained Robust Optimal Control. Closed-Loop Predictions

- The optimal control problem can be viewed as a deterministic zero-sum dynamic game between two players: the controller  $U$  and the disturbance  $W$ .
- The game is played as follows. At the generic time  $j$  player  $U$  observes  $x_j$  and responds with  $u_j(x_j)$ . Player  $W$  observes  $(x_j, u_j(x_j))$  and responds with  $w_j^a$  and  $w_j^p$ .
- Note that player  $U$  does *not* need to reveal his action  $u_j$  to player  $W$  (the disturbance). This happens for instance in games where  $U$  and  $W$  play at the same time, e.g. rock-paper-scissors.
- The player  $W$  will always play the worst case action only if it has knowledge of both  $x_j$  and  $u_j(x_j)$ . In fact,  $w_j^a$  and  $w_j^p$  are a function of  $x_j$  and  $u_j$ .
- If  $U$  does *not* reveal his action to player  $W$ , then we can only claim that the player  $W$  *might* play the worst case action.
- Robust constraint satisfaction and worst case minimization will always be guaranteed.

# Constrained Robust Optimal Control. Closed-Loop Predictions

Consider the system

$$x_{k+1} = x_k + u_k + w_k$$

where  $x$ ,  $u$  and  $w$  are state, input and disturbance, respectively.

- Let  $u_k \in \{-1, 0, 1\}$  and  $w_k \in \{-1, 0, 1\}$  be feasible input and disturbance.
- Here  $\{-1, 0, 1\}$  denotes the set with three elements: -1, 0 and 1.
- Let  $x(0) = 0$  be the initial state. The objective for player  $U$  is to play two moves in order to keep the state  $x_2$  at time 2 in the set  $[-1, 1]$ .
- If  $U$  is able to do so for any possible disturbance, then he will win the game.
- The open-loop formulation is infeasible. In fact, in open-loop  $U$  can choose from nine possible sequences: (0,0), (1,1), (-1,-1), (-1,1) (1,-1), (-1,0), (1,0), (0,1) and (0,-1). For any of those sequence there will always exist a disturbance sequence  $w_0, w_1$  which will bring  $x_2$  outside the feasible set  $[-1, 1]$ .
- The closed-loop formulation is feasible and has a simple solution:  $u_k = -x_k$ . In this case the system becomes  $x_{k+1} = w_k$  and  $x_2 = w_1$  lies in the feasible set  $[-1, 1]$  for all admissible disturbances  $w_1$ .

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# Basic Results

## Proposition

*Let  $g : \mathbb{R}^{n_z} \times \mathbb{R}^n \times \mathbb{R}^{n_w} \rightarrow \mathbb{R}^{n_g}$  be a function of  $(z, x, w)$  convex in  $w$  for each  $(z, x)$ . Assume that the variable  $w$  belongs to the polytope  $\mathcal{W}$  with vertices  $\{\bar{w}_i\}_{i=1}^{n_{\mathcal{W}}}$ . Then, the constraint*

$$g(z, x, w) \leq 0 \quad \forall w \in \mathcal{W} \quad (1)$$

*is satisfied if and only if*

$$g(z, x, \bar{w}_i) \leq 0, \quad i = 1, \dots, n_{\mathcal{W}}. \quad (2)$$



# Basic Results

## Proposition

Assume  $g(z, x, w) = g^1(z, x) + g^2(w)$ . Then, the constraint (1) can be replaced by  $g^1(z, x) \leq -\bar{g}$ , where  $\bar{g} \triangleq [\bar{g}_1, \dots, \bar{g}_{n_g}]'$  is a vector whose  $i$ -th component is

$$\bar{g}_i = \max_{w \in \mathcal{W}} g_i^2(w), \quad (3)$$

and  $g_i^2(w)$  denotes the  $i$ -th component of  $g^2(w)$ .

# Basic Results

Consider the second order autonomous system

$$x(t+1) = A(w^p(t))x(t) + w^a(t) = \begin{bmatrix} 0.5 + w^p(t) & 0 \\ 1 & -0.5 \end{bmatrix} x(t) + w^a(t) \quad (4)$$

subject to the state constraints

$$\begin{aligned} x(t) &\in \mathcal{X} = \left\{ x \text{ s.t. } \begin{bmatrix} -10 \\ -10 \end{bmatrix} \leq x \leq \begin{bmatrix} 10 \\ 10 \end{bmatrix} \right\}, \forall t \geq 0 \\ w^a(t) &\in \mathcal{W}^a = \left\{ w^a \text{ s.t. } \begin{bmatrix} -1 \\ -1 \end{bmatrix} \leq w^a \leq \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}, \forall t \geq 0 \\ w^p(t) &\in \mathcal{W}^p = \{ w^p \text{ s.t. } 0 \leq w^p \leq 0.5 \}, \forall t \geq 0. \end{aligned} \quad (5)$$

Let  $w = [w^a; w^p]$  and  $\mathcal{W} = \mathcal{W}^a \times \mathcal{W}^p$ .

# Basic Results

The set  $\mathcal{X}$  is a polytope and it can be represented as an  $\mathcal{H}$ -polytope

$$\mathcal{X} = \{x \text{ s.t. } Hx \leq h\}, \quad (6)$$

The set  $\text{Pre}(\mathcal{X}, \mathcal{W})$  can be rewritten as

$$\text{Pre}(\mathcal{X}, \mathcal{W}) = \{x \text{ s.t. } Hf_a(x, w) \leq h, \forall w \in \mathcal{W}\} \quad (7)$$

$$= \{x \text{ s.t. } HA(w^p)x \leq h - Hw^a, \forall w^a \in \mathcal{W}^a, w^p \in \mathcal{W}^p\}. \quad (8)$$

By using the propositions on previous slides we obtain

$$x \in \text{Pre}(\mathcal{X}, \mathcal{W}) = \{x \in \mathbb{R}^n \text{ s.t. } \begin{bmatrix} HA(0) \\ HA(0.5) \end{bmatrix} x \leq \begin{bmatrix} \tilde{h} \\ \tilde{h} \end{bmatrix}\} \quad (9)$$

with

$$\tilde{h}_i = \min_{w^a \in \mathcal{W}^a} (h_i - H_i w^a). \quad (10)$$

# Feasible Set Computation. Batch Approach

Consider  $\mathcal{X}_i^{OL} \subseteq \mathcal{X}$  the set of states  $x_i$  for which the robust optimal control problem is feasible, i.e.,

$$\mathcal{X}_i^{OL} = \{x_i \in \mathcal{X} \text{ such that } \exists(u_i, \dots, u_{N-1}) \text{ such that} \\ x_k \in \mathcal{X}, u_k \in \mathcal{U}, k = i, \dots, N-1, x_N \in \mathcal{X}_f, \forall w_k^a \in \mathcal{V}, w_k^p \in \mathcal{W} \\ k = i, \dots, N-1 \text{ where } x_{k+1} = A(w_k^p)x_k + B(w_k^p)u_k + Ew_k^a\}.$$

- For any initial state  $x_i \in \mathcal{X}_i^{OL}$  there exists a feasible sequence of inputs  $U_i \triangleq [u'_i, \dots, u'_{N-1}]$  which keeps the state evolution in the feasible set  $\mathcal{X}$  at future time instants  $k = i+1, \dots, N-1$  and forces  $x_N$  into  $\mathcal{X}_f$  at time  $N$  for all feasible disturbance sequence  $w_k^a \in \mathcal{V}, w_k^p \in \mathcal{W}, k = i, \dots, N-1$ .
- Clearly  $\mathcal{X}_N^{OL} = \mathcal{X}_f$ .
- How to compute  $\mathcal{X}_i^{OL}$  for  $i = 0, \dots, N-1$ ?

# Feasible Set Computation. Batch Approach

- Let the state and input constraint sets  $\mathcal{X}$ ,  $\mathcal{X}_f$  and  $\mathcal{U}$  be the  $\mathcal{H}$ -polyhedra  $A_x x \leq b_x$ ,  $A_f x \leq b_f$ ,  $A_u u \leq b_u$ .
- Recall that the disturbance sets are defined as  $\mathcal{V} = \text{conv}\{w^{a,1}, \dots, w^{a,n_v}\}$  and  $\mathcal{W} = \text{conv}\{w^{p,1}, \dots, w^{p,n_w}\}$ .
- Define  $U_i \triangleq [u'_i, \dots, u'_{N-1}]$  and the polyhedron  $\mathcal{P}_i$  of robustly feasible states and input sequences at time  $i$ , defined as

$$\mathcal{P}_i = \{(U_i, x_i) \in \mathbb{R}^{m(N-i)+n} \text{ s.t. } G_i U_i - E_i x_i \leq W_i\}.$$

- $G_i$ ,  $E_i$  and  $W_i$  are obtained by collecting all the following inequalities:
  - Input Constraints

$$A_u u_k \leq b_u, \quad k = i, \dots, N-1$$

- State Constraints

$$A_x x_k \leq b_x, \quad k = i, \dots, N-1 \text{ for all } w_l^a \in \mathcal{V}, w_l^p \in \mathcal{W}, l = i, \dots, k-1. \quad (11)$$

- Terminal State Constraints

$$A_f x_N \leq b_f, \quad \text{for all } w_l^a \in \mathcal{V}, w_l^p \in \mathcal{W}, l = i, \dots, N-1. \quad (12)$$

- Constraints are enforced for all feasible disturbance sequences.

# Feasible Set Computation. Batch Approach

- To enforce constraints for all feasible disturbance sequences. rewrite them as a function of  $x_i$  and the input sequence  $U_i$ .
- Since we assumed that  $A(\cdot)$ ,  $B(\cdot)$  are affine functions of  $w^p$  and since the composition of a convex constraint with an affine map generates a convex constraint we can use the Propositions presented in “basic results” and impose the constraints at all the vertices of the sets  $\underbrace{\mathcal{V} \times \mathcal{V} \times \dots \times \mathcal{V}}_{i, \dots, N-1}$  and  $\underbrace{\mathcal{W} \times \mathcal{W} \times \dots \times \mathcal{W}}_{i, \dots, N-1}$ .
- Note that the resulting constraints are now linear in  $x_i$  and  $U_i$ .
- Once the matrices  $G_i$ ,  $E_i$  and  $W_i$  have been computed, the set  $\mathcal{X}_i^{OL}$  is a polyhedron and can be computed by projecting the polyhedron  $\mathcal{P}_i$  on the  $x_i$  space.

# Feasible Set Computation. Recursive Approach

In the *recursive approach* we have

$$\begin{aligned}\mathcal{X}_i &= \{x \in \mathcal{X} \text{ s.t. } \exists u \in \mathcal{U} \text{ such that } A(w_i^p)x + B(w_i^p)u + Ew_i^a \in \mathcal{X}_{i+1} \\ &\quad \forall w_i^a \in \mathcal{V}, w_i^p \in \mathcal{W}\}, \quad i = 0, \dots, N-1 \\ \mathcal{X}_N &= \mathcal{X}_f.\end{aligned}\tag{13}$$

- The definition of  $\mathcal{X}_i$  is recursive and it requires that for any feasible initial state  $x_i \in \mathcal{X}_i$  there exists a feasible input  $u_i$  which keeps the next state  $A(w_i^p)x + B(w_i^p)u + Ew_i^a$  in the feasible set  $\mathcal{X}_{i+1}$  for all feasible disturbances  $w_i^a \in \mathcal{V}$ ,  $w_i^p \in \mathcal{W}$ .
- Recall that  $\mathcal{X}_0$  is different from  $\mathcal{X}_0^{OL}$ .
- Let  $\mathcal{X}_i$  be the  $\mathcal{H}$ -polyhedron  $A_{\mathcal{X}_i}x \leq b_{\mathcal{X}_i}$ .
- The set  $\mathcal{X}_{i-1}$  is the projection of the following polyhedron on the  $x_i$  space

$$\begin{bmatrix} A_u \\ 0 \\ A_{\mathcal{X}_i}B(w_i^p) \end{bmatrix} u_i + \begin{bmatrix} 0 \\ A_x \\ A_{\mathcal{X}_i}A(w_i^p) \end{bmatrix} x_i \leq \begin{bmatrix} b_u \\ b_x \\ b_{\mathcal{X}_i} - Ew_i^a \end{bmatrix}\tag{14}$$

$$\text{for all } w_i^a \in \{w^{a,i}\}_{i=1}^{n_{\mathcal{V}}}, w_i^p \in \{w^{p,i}\}_{i=1}^{n_{\mathcal{W}}}$$

## Feasible Set Computation. Example

Consider the system

$$x_{k+1} = x_k + u_k + w_k \quad (15)$$

Let  $u_k \in [-1, 1]$  and  $w_k \in [-1, 1]$  be the feasible input and disturbance. The objective for player  $U$  is to play two moves in order to keep the state at time three  $x_3$  in the set  $\mathcal{X}_f = [-1, 1]$ .

### Batch approach

We rewrite the terminal constraint as

$$\begin{aligned} x_3 = x_0 + u_0 + u_1 + u_2 + w_0 + w_1 + w_2 &\in [-1, 1] \\ \text{for all } w_0 \in [-1, 1], w_1 \in [-1, 1], w_2 \in [-1, 1] \end{aligned} \quad (16)$$

which becomes

$$\begin{aligned} -1 &\leq x_0 + u_0 + u_1 + u_2 + 3 \leq 1 \\ -1 &\leq x_0 + u_0 + u_1 + u_2 + 1 \leq 1 \\ -1 &\leq x_0 + u_0 + u_1 + u_2 - 1 \leq 1 \\ -1 &\leq x_0 + u_0 + u_1 + u_2 - 3 \leq 1 \end{aligned} \quad (17)$$

which by removing redundant constraints becomes the (infeasible) constraint

$$2 \leq x_0 + u_0 + u_1 + u_2 \leq -2$$



## Feasible Set Computation. Example

The set  $\mathcal{X}_0^{OL}$  is the projection on the  $x_0$  space of the polyhedron  $\mathcal{P}_0$

$$\mathcal{P}_0 = \{(u_0, u_1, u_2, x_0) \in \mathbb{R}^4 \text{ s.t. } \begin{bmatrix} 1 & 0 & 0 \\ -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -1 \\ 1 & 1 & 1 \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} u_0 \\ u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ -1 \end{bmatrix} x_0 \leq \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ -2 \\ -2 \end{bmatrix}\} \quad (18)$$

which is empty since the terminal state constraint is infeasible.

# Feasible Set Computation. Example

## Recursive approach

By using the recursive we have  $\mathcal{X}_3 = \mathcal{X}_f = [-1, 1]$ .

Rewrite the terminal constraint as

$$x_3 = x_2 + u_2 + w_2 \in [-1, 1] \quad \text{for all } w_2 \in [-1, 1] \quad (19)$$

which becomes

$$\begin{aligned} -1 &\leq x_2 + u_2 + 1 \leq 1 \\ -1 &\leq x_2 + u_2 - 1 \leq 1 \end{aligned} \quad (20)$$

which by removing redundant constraints becomes

$$0 \leq x_2 + u_2 \leq 0$$

The set  $\mathcal{X}_2$  is the projection on the  $x_2$  space of the polyhedron

$$\begin{bmatrix} 1 & 0 \\ -1 & 0 \\ 1 & 1 \\ -1 & -1 \end{bmatrix} [u_2, x_2] \leq \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad (21)$$

which yields  $\mathcal{X}_2 = [-1, 1]$ . Since  $\mathcal{X}_2 = \mathcal{X}_3$  one can conclude that  $\mathcal{X}_2$  is the maximal controllable robust invariant set and  $\mathcal{X}_0 = \mathcal{X}_1 = \mathcal{X}_2 = [-1, 1]$ .

# Feasible Set Computation. Example

## Batch approach with closed-loop predictions

- The horizon is three and therefore we consider the disturbance set over the horizon  $3-1=2$ ,  $\mathcal{W} \times \mathcal{W} = [-1, 1] \times [-1, 1]$ .
- Such a set has four vertices:  $\{\tilde{w}_0^1 = 1, \tilde{w}_1^1 = 1\}$ ,  $\{\tilde{w}_0^2 = -1, \tilde{w}_1^2 = 1\}$ ,  $\{\tilde{w}_0^1 = 1, \tilde{w}_1^3 = -1\}$ ,  $\{\tilde{w}_0^2 = -1, \tilde{w}_1^4 = -1\}$ .
- We introduce an input sequence  $u_0, \tilde{u}_1^i, \tilde{u}_2^j$ , where the index  $i \in \{1, 2\}$  is associated with the vertices  $\tilde{w}_0^1$  and  $\tilde{w}_0^2$  and the index  $j \in \{1, 2, 3, 4\}$  is associated with the vertices  $\tilde{w}_1^1, \tilde{w}_1^2, \tilde{w}_1^3, \tilde{w}_1^4$ .
- The terminal constraint is thus rewritten as

$$x_3 = x_0 + u_0 + \tilde{u}_1^i + \tilde{u}_2^j + \tilde{w}_0^i + \tilde{w}_1^j + w_2 \in [-1, 1], \quad i = 1, 2, \quad j = 1, \dots, 4, \quad (22)$$

$$\forall w_2 \in [-1, 1]$$

## Feasible Set Computation. Example

which becomes

$$\begin{aligned} -1 &\leq x_0 + u_0 + \tilde{u}_1^1 + \tilde{u}_2^1 + 0 + w_2 \leq 1, & \forall w_2 \in [-1, 1] \\ -1 &\leq x_0 + u_0 + \tilde{u}_1^2 + \tilde{u}_2^2 + 0 + w_2 \leq 1, & \forall w_2 \in [-1, 1] \\ -1 &\leq x_0 + u_0 + \tilde{u}_1^1 + \tilde{u}_2^3 + 2 + w_2 \leq 1, & \forall w_2 \in [-1, 1] \\ -1 &\leq x_0 + u_0 + \tilde{u}_1^2 + \tilde{u}_2^4 - 2 + w_2 \leq 1, & \forall w_2 \in [-1, 1] \\ -1 &\leq u_0 \leq 1 \\ -1 &\leq \tilde{u}_1^1 \leq 1 \\ -1 &\leq \tilde{u}_1^2 \leq 1 \\ -1 &\leq \tilde{u}_2^1 \leq 1 \\ -1 &\leq \tilde{u}_2^2 \leq 1 \\ -1 &\leq \tilde{u}_2^3 \leq 1 \\ -1 &\leq \tilde{u}_2^4 \leq 1 \end{aligned} \tag{23}$$

The set  $\mathcal{X}_0$  can be obtained by using Proposition 2 for the polyhedron (23) and projecting the resulting polyhedron in the  $(x_0, u_0, \tilde{u}_1^1, \tilde{u}_1^2, \tilde{u}_2^1, \tilde{u}_2^2, \tilde{u}_2^3, \tilde{u}_2^4)$ -space on the  $x_0$  space. This yields  $\mathcal{X}_0 = [-1, 1]$ .

# Outline

- 1 Introduction
- 2 Robust Constrained Optimal Control
- 3 Feasible Set Computation
- 4 Min-Max Constrained Robust Optimal Control**
  - Basic Result
  - Recursive Approach

# Basic Result

## Lemma

Let  $f : \mathbb{R}^s \times \mathbb{R}^n \times \mathbb{R}^{n_w} \rightarrow \mathbb{R}$  and  $g : \mathbb{R}^s \times \mathbb{R}^n \times \mathbb{R}^{n_w} \rightarrow \mathbb{R}^{n_g}$  be functions of  $(z, x, w)$  convex in  $w$  for each  $(z, x)$ . Assume that the variable  $w$  belongs to the polyhedron  $\mathcal{W}$  with vertices  $\{\bar{w}_i\}_{i=1}^{N_{\mathcal{W}}}$ . Then the min-max multiparametric problem

$$J^*(x) = \min_z \quad \max_{w \in \mathcal{W}} f(z, x, w) \\ \text{subj. to} \quad g(z, x, w) \leq 0 \quad \forall w \in \mathcal{W} \quad (24)$$

is equivalent to the multiparametric optimization problem

$$J^*(x) = \min_{\mu, z} \quad \mu \\ \text{subj. to} \quad \mu \geq f(z, x, \bar{w}_i), \quad i = 1, \dots, N_{\mathcal{W}} \\ g(z, x, \bar{w}_i) \leq 0, \quad i = 1, \dots, N_{\mathcal{W}}. \quad (25)$$

# Basic Result

## Corollary

*If  $f$  is convex and piecewise affine in  $(z, x)$ , i.e.  $f(z, x, w) = \max_{i=1, \dots, n_f} \{L_i(w)z + H_i(w)x + K_i(w)\}$  and  $g$  is linear in  $(z, x)$  for all  $w \in \mathcal{W}$ ,  $g(z, x, w) = K_g(w) + L_g(w)x + H_g(w)z$  (with  $K_g(\cdot)$ ,  $L_g(\cdot)$ ,  $H_g(\cdot)$ ,  $L_i(\cdot)$ ,  $H_i(\cdot)$ ,  $K_i(\cdot)$ ,  $i = 1, \dots, n_f$ , convex functions), then the min-max multiparametric problem (24) is equivalent to the mp-LP problem*

$$\begin{aligned} J^*(x) = \quad & \min_{\mu, z} \quad \mu \\ \text{subj. to} \quad & \mu \geq K_j(\bar{w}_i) + L_j(\bar{w}_i)z + H_j(\bar{w}_i)x, \\ & i = 1, \dots, N_{\mathcal{W}}, j = 1, \dots, n_f \\ & L_g(\bar{w}_i)x + H_g(\bar{w}_i)z \leq -K_g(\bar{w}_i), \quad i = 1, \dots, N_{\mathcal{W}} \end{aligned} \tag{26}$$

# Min-Max Constrained Robust Optimal Control-Recursive Approach

## Theorem

*There exists a state-feedback control law  $u^*(k) = f_k(x(k))$ ,  $f_k : \mathcal{X}_k \subseteq \mathbb{R}^n \rightarrow \mathcal{U} \subseteq \mathbb{R}^m$ , solution of the CROC-CL with cost based on one or infinity norm which is time-varying, continuous and piecewise affine on polyhedra*

$$f_k(x) = F_k^i x + g_k^i \quad \text{if } x \in CR_k^i, \quad i = 1, \dots, N_k^r \quad (27)$$

*where the polyhedral sets  $CR_k^i = \{x \in \mathbb{R}^n \text{ s.t. } H_k^i x \leq K_k^i\}$ ,  $i = 1, \dots, N_k^r$  are a partition of the feasible polyhedron  $\mathcal{X}_k$ . Moreover  $f_i$ ,  $i = 0, \dots, N - 1$  can be found by solving  $N$  mp-LPs.*



# Min-Max Constrained Robust Optimal Control-Recursive Approach

Consider the first step  $j = N - 1$  of dynamic programming

$$J_{N-1}^*(x_{N-1}) \triangleq \min_{u_{N-1}} J_{N-1}(x_{N-1}, u_{N-1}) \quad (28)$$

$$\text{subj. to } \begin{cases} Fx_{N-1} + Gu_{N-1} \leq f \\ A(w_{N-1}^p)x_{N-1} + B(w_{N-1}^p)u_{N-1} + Ew_{N-1}^a \in \mathcal{X}_f \\ \forall w_{N-1}^a \in \mathcal{V}, w_{N-1}^p \in \mathcal{W} \end{cases} \quad (29)$$

$$J_{N-1}(x_{N-1}, u_{N-1}) \triangleq \max_{w_{N-1}^a \in \mathcal{V}, w_{N-1}^p \in \mathcal{W}} \left\{ \begin{aligned} &\|Qx_{N-1}\|_p + \|Ru_{N-1}\|_p + \\ &+ \|P(A(w_{N-1}^p)x_{N-1} + \\ &+ B(w_{N-1}^p)u_{N-1} + Ew_{N-1}^a)\|_p \end{aligned} \right\}. \quad (30)$$

# Min-Max Constrained Robust Optimal Control-Recursive Approach

- The cost function in the maximization problem (30) is piecewise affine and convex with respect to the optimization vector  $w_{N-1}^a, w_{N-1}^p$  and the parameters  $u_{N-1}, x_{N-1}$ .
- The constraints in the minimization problem linear in  $(u_{N-1}, x_{N-1})$  for all vectors  $w_{N-1}^a, w_{N-1}^p$ .
- Therefore, by “basic Results”  $J_{N-1}^*(x_{N-1})$ ,  $u_{N-1}^*(x_{N-1})$  and  $\mathcal{X}_{N-1}$  are computable via the mp-LP:

$$J_{N-1}^*(x_{N-1}) \triangleq \min_{\mu, u_{N-1}} \mu \quad (31a)$$

$$\text{subj. to } \mu \geq \|Qx_{N-1}\|_p + \|Ru_{N-1}\|_p + \|P(A(\bar{w}_h^p)x_{N-1} + B(\bar{w}_h^p)u_{N-1} + E\bar{w}_i^a)\|_p \quad (31b)$$

$$Fx_{N-1} + Gu_{N-1} \leq f \quad (31c)$$

$$A(\bar{w}_h^p)x_{N-1} + B(\bar{w}_h^p)u_{N-1} + E\bar{w}_i^a \in \mathcal{X}_N \quad (31d)$$

$$\forall i = 1, \dots, n_{\mathcal{V}}, \forall h = 1, \dots, n_{\mathcal{W}}.$$

The convexity and linearity arguments still hold for  $j = N - 2, \dots, 0$  and the procedure can be iterated backwards in time  $j$ .

# We Will not Cover

- Robust Invariant Set
- Robust invariant Set Evolution
- Robust MPC Theorem
- Robust Estimation