



Model Predictive Control

6. Stability and Feasibility

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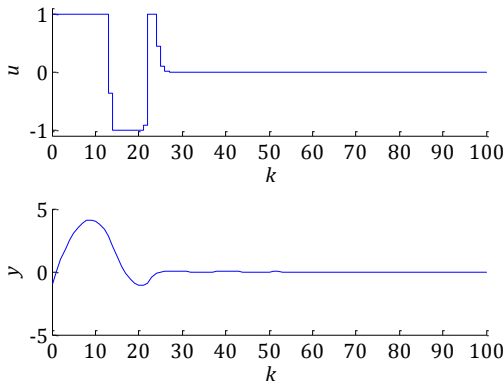
Introduction

Stability of Model Predictive Control

- **MPC without Constraints**
 - **Receding horizon controller** is an **LTI state feedback controller** in the unconstrained case
 - Stability can thus be addressed based on the **eigenvalues** of the closed-loop system
 - Stability is affected by the parameters N , P , Q and R (cf. Illustrative Example on Slide 4-23ff, 4-35)
 - Closed-loop and predicted input and state sequences are identical for $P = P_{LQR}$ and arbitrary N (cf. dual mode control on Slide 4-34f)
 - Stability is guaranteed for $P = P_{LQR}$ but no **formal proof** has been given so far
- **MPC with Constraints**
 - **Receding horizon controller** is a **nonlinear state feedback controller** in the constrained case
 - Stability must thus be addressed based on **Lyapunov's direct method**
 - Closed-loop and predicted input and state sequences are not identical for $P = P_{LQR}$ and arbitrary N
 - Stability is not guaranteed for $P = P_{LQR}$ but can be guaranteed with an additional **terminal constraint**



Illustrative Example



Example from Chapter 4

$$x(0) = (0.5 \quad -0.5)^T$$

$$y(k) = (-1 \quad 1)x(k)$$

$$\text{Constraint } -1 \leq u(k) \leq 1$$

$$\text{Prediction horizon } N = 2$$

$$\text{Terminal weight } P = P_{LQR}$$

$$\text{Input weight } R = 0.01$$

Closed-loop system seems stable

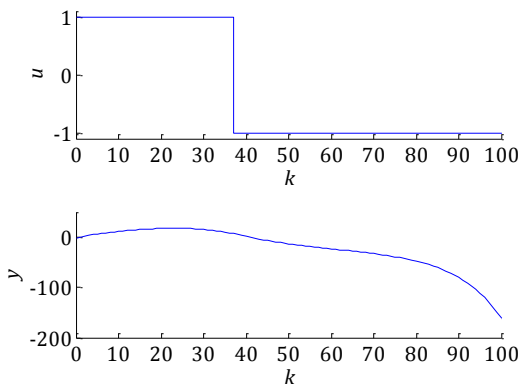
Good performance



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Illustrative Example



Example from Chapter 4

$$x(0) = (0.8 \quad -0.8)^T$$

$$y(k) = (-1 \quad 1)x(k)$$

$$\text{Constraint } -1 \leq u(k) \leq 1$$

$$\text{Prediction horizon } N = 2$$

$$\text{Terminal weight } P = P_{LQR}$$

$$\text{Input weight } R = 0.01$$

Closed-loop system unstable

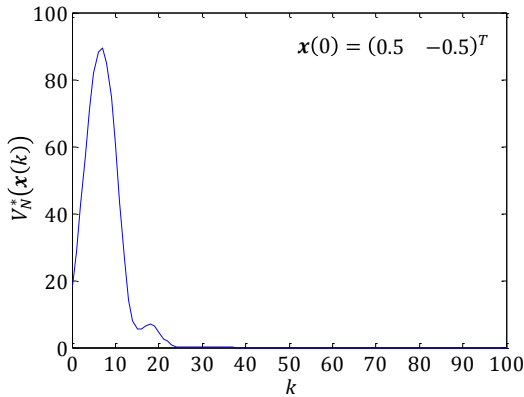
Problem 5.1 is feasible for all k ,
i.e. no indication for instability



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Illustrative Example



Observation

$V_N^*(x(k))$ initially increases
Implies that energy stored in the system initially increases
Implies that closed-loop and predicted sequences differ

Conjecture

Stability guaranteed if $V_N^*(x(k))$ is strictly decreasing over time k
 $V_N^*(x(k))$ is then a Lyapunov fcn.

Stability Condition

Theorem 6.1 The discrete-time linear time-invariant system (4.1) with $x(k) \in \mathbb{R}^n$ and $u(k) \in \mathbb{R}^m$ under the receding horizon control law $u(k) = K_{\text{RHC}}x(k)$ is globally asymptotically stable if

- Q is positive definite
- P is positive definite and chosen such that

$$(A + B\tilde{K})^T P(A + B\tilde{K}) - P \leq -Q - \tilde{K}^T R \tilde{K} \quad (6.1)$$

where \tilde{K} is an arbitrary matrix fulfilling $\rho(A + B\tilde{K}) < 1$.

terminal cost

Proof

- Let's consider the optimal cost function $V_N^*(x(k))$ as a Lyapunov function candidate
- The optimal cost function

$$V_N^*(x(k)) = x^{*T}(k+N)Px^*(k+N) + \sum_{i=0}^{N-1} x^{*T}(k+i)Qx^*(k+i) + u^{*T}(k+i)Ru^*(k+i)$$

is positive definite and radially unbounded since

Stability Condition

- **Proof**

$V_N^*(\mathbf{0}) = 0$ since $\mathbf{x}(k) = \mathbf{0}$ implies $\mathbf{x}^*(k+i) = \mathbf{0} \forall i \in \{1, \dots, N\}$, $\mathbf{u}^*(k+i) = \mathbf{0} \forall i \in \{0, \dots, N-1\}$

$V_N^*(\mathbf{x}(k)) \geq \mathbf{x}^T(k) \mathbf{Q} \mathbf{x}(k) > 0 \forall \mathbf{x}(k) \in \mathbb{R}^n \setminus \{\mathbf{0}\}$ since $\mathbf{Q} > \mathbf{0}$

$V_N^*(\mathbf{x}(k)) \rightarrow \infty$ as $\|\mathbf{x}(k)\| \rightarrow \infty$

– We must still prove that $\Delta V_N^*(\mathbf{x}(k)) = V_N^*(\mathbf{x}(k+1)) - V_N^*(\mathbf{x}(k))$ is **negative definite**

– Consider that at time k we utilize the **optimal input sequence**

$$\mathbf{U}^*(k) = (\mathbf{u}^{*T}(k) \quad \mathbf{u}^{*T}(k+1) \quad \mathbf{u}^{*T}(k+2) \quad \dots \quad \mathbf{u}^{*T}(k+N-2) \quad \mathbf{u}^{*T}(k+N-1))^T$$

– Consider further that at time $k+1$ we utilize a **“shifted” suboptimal input sequence**

$$\begin{aligned} \mathbf{U}^*(k) &= (\underbrace{\mathbf{u}^{*T}(k)}_{\text{implemented}} \quad \mathbf{u}^{*T}(k+1) \quad \mathbf{u}^{*T}(k+2) \quad \dots \quad \mathbf{u}^{*T}(k+N-2) \quad \mathbf{u}^{*T}(k+N-1))^T \\ \tilde{\mathbf{U}}(k+1) &= (\mathbf{u}^{*T}(k+1) \quad \mathbf{u}^{*T}(k+2) \quad \dots \quad \mathbf{u}^{*T}(k+N-2) \quad \mathbf{u}^{*T}(k+N-1) \quad \underbrace{(\tilde{\mathbf{K}}\mathbf{x}^*(k+N))^T}_{\text{new "tail"}})^T \end{aligned}$$



Stability Condition

- **Proof**

– Note that the new tail results from the **suboptimal state feedback controller** $\mathbf{u}(k+N) = \tilde{\mathbf{K}}\mathbf{x}^*(k+N)$

– The **suboptimal cost** for the suboptimal input sequence $\tilde{\mathbf{U}}(k+1)$ is given by

$$\begin{aligned} V_N(\mathbf{x}(k+1), \tilde{\mathbf{U}}(k+1)) &= \\ &+ V_N^*(\mathbf{x}(k), \mathbf{U}^*(k)) && \text{old optimal cost} \\ &- \mathbf{x}^{*T}(k) \mathbf{Q} \mathbf{x}^*(k) - \mathbf{u}^{*T}(k) \mathbf{R} \mathbf{u}^*(k) && \text{old first stage cost} \quad (6.2) \\ &- \mathbf{x}^{*T}(k+N) \mathbf{P} \mathbf{x}^*(k+N) && \text{old terminal cost} \quad (6.3) \\ &+ \mathbf{x}^{*T}(k+N) (\mathbf{Q} + \tilde{\mathbf{K}}^T \mathbf{R} \tilde{\mathbf{K}}) \mathbf{x}^*(k+N) && \text{new } N\text{th stage cost} \quad (6.4) \\ &+ \mathbf{x}^T(k+N+1) \mathbf{P} \mathbf{x}(k+N+1) && \text{new terminal cost} \quad (6.5) \end{aligned}$$

– Note that the **optimal cost** and the **suboptimal cost** at time $k+1$ are **related by**

$$V_N^*(\mathbf{x}(k+1), \mathbf{U}^*(k+1)) \leq V_N(\mathbf{x}(k+1), \tilde{\mathbf{U}}(k+1))$$



Stability Condition

- **Proof**

- Thus it is sufficient to prove that $V_N(x(k+1), \tilde{U}(k+1)) - V_N^*(x(k), U^*(k))$ is negative definite
- To this end the terms (6.2) to (6.5) must be investigated
- The term (6.2) is **negative definite**
- Thus it is sufficient to prove that the **sum** of the terms (6.3), (6.4), (6.5) is **negative semidefinite**, i.e.

$$-x^{*T}(k+N)Px^*(k+N) + x^{*T}(k+N)(Q + \tilde{K}^T R \tilde{K})x^*(k+N) + x^T(k+N+1)Px(k+N+1) \leq 0 \quad \forall x(k+N)$$
- Using that $x(k+N+1) = (A + B\tilde{K})x^*(k+N)$ leads to

$$x^{*T}(k+N) \left((A + B\tilde{K})^T P (A + B\tilde{K}) - P \right) x^*(k+N) \leq x^{*T}(k+N) (-Q - \tilde{K}^T R \tilde{K}) x^*(k+N) \quad \forall x(k+N)$$
- This inequality is fulfilled if (6.1) is fulfilled
- This completes the proof



Stability Condition

- **Interpretation**

- The suboptimal state feedback controller $u(k+N) = \tilde{K}x^*(k+N)$ evidently corresponds to the stabilizing control law utilized in mode 2 in dual mode control (cf. Slide 4-30)
- The terminal weighting matrix P fulfilling (6.1) is used when solving Problem 4.1
- The suboptimal feedback matrix \tilde{K} is only introduced for the proof and not used anymore

- **Remarks**

- For an arbitrary \tilde{K} fulfilling $\rho(A + B\tilde{K}) < 1$ we can choose P as the solution \tilde{P} of the DLE (4.8)
- For $\tilde{K} = K_{LQR}$ we can choose $P = P_{LQR}$
- For a globally asymptotically stable discrete-time linear time-invariant system (4.1) we have $\rho(A) < 1$ and can thus choose $\tilde{K} = 0$ and P as the solution \tilde{P} of the DLE (4.8)
- Q positive definite can be replaced by $(Q^{1/2}, A)$ observable in Theorem 6.1

- **Can we formulate a similar stability condition for model predictive control with constraints?**



Feasibility Condition

- **Observations**

- The stability condition in Theorem 6.1 in principle also applies to MPC with constraints
- The **feasibility** must, however, additionally be guaranteed
- Assume that the optimal input sequence $\mathbf{U}^*(k)$ and state sequence $\mathbf{X}^*(k)$ at time k are feasible
- The suboptimal input sequence and state sequence at time $k + 1$ then obey

$$\begin{aligned}\tilde{\mathbf{U}}(k+1) &= \left(\mathbf{u}^{*T}(k+1) \quad \mathbf{u}^{*T}(k+2) \quad \cdots \quad \mathbf{u}^{*T}(k+N-1) \quad \left(\tilde{\mathbf{K}}\mathbf{x}^*(k+N) \right)^T \right)^T \\ \tilde{\mathbf{X}}(k+1) &= \left(\underbrace{\mathbf{x}^{*T}(k+2) \quad \mathbf{x}^{*T}(k+3) \quad \cdots \quad \mathbf{x}^{*T}(k+N)}_{\text{feasible (by assumption)}} \quad \underbrace{\left((\mathbf{A} + \mathbf{B}\tilde{\mathbf{K}})\mathbf{x}^*(k+N) \right)^T}_{\text{possibly infeasible}} \right)^T\end{aligned}$$

- Impose **terminal constraint** $\mathbf{x}^*(k+N) \in \mathbb{X}_N$ to guarantee feasibility
- Note that the terminal constraint is related to mode 2 in dual mode control
- How must we choose the **terminal constraint set** \mathbb{X}_N to guarantee feasibility?



Feasibility Condition

- **Assumption**

- The constraints are time-invariant, i.e. $\mathbb{X}(k+i) = \mathbb{X}$, $\mathbb{U}(k+i) = \mathbb{U} \quad \forall i \in \{0, \dots, N-1\} \quad \forall k \in \mathbb{N}_0$
- E.g. for standard form $\mathbf{M}(k+i) = \mathbf{M}$, $\mathbf{E}(k+i) = \mathbf{E}$, $\mathbf{b}(k+i) = \mathbf{b} \quad \forall i \in \{0, \dots, N-1\} \quad \forall k \in \mathbb{N}_0$

Definition 6.1 A set $\mathbb{S} \subseteq \mathbb{R}^n$ is an **invariant set** for the discrete-time nonlinear time-invariant system

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k)) \quad (6.6)$$

if

$$\mathbf{x}(0) \in \mathbb{S} \Rightarrow \mathbf{f}(\mathbf{x}(k)) \in \mathbb{S} \quad \forall k \in \mathbb{N}_0.$$

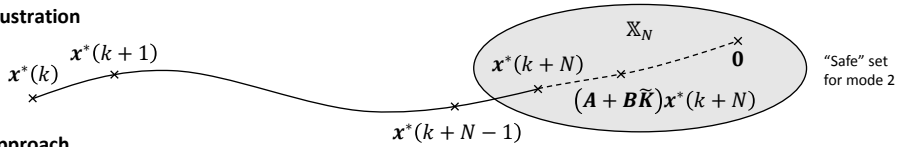
Definition 6.2 A set $\mathbb{S} \subseteq \mathbb{R}^n$ is an **admissible set** for the discrete-time nonlinear time-invariant system (6.6) under the state feedback control law $\mathbf{u}(k) = \mathbf{f}_c(\mathbf{x}(k))$, the state constraint \mathbb{X} and the input constraint \mathbb{U} if

$$\mathbf{x}(k) \in \mathbb{S} \Rightarrow \left(\mathbf{x}(k), \mathbf{f}_c(\mathbf{x}(k)) \right) \in \mathbb{X} \times \mathbb{U}$$



Feasibility Condition

- **Illustration**



- **Approach**

- The **terminal constraint set** \mathbb{X}_N must be constructed such that

$$x^*(k+N) \in \mathbb{X}_N \Rightarrow (x^*(k+N), \tilde{K}x^*(k+N)) \in \mathbb{X} \times \mathbb{U}$$

admissible set

$$x^*(k+N) \in \mathbb{X}_N \Rightarrow (A + B\tilde{K})x^*(k+N) \in \mathbb{X}_N$$

invariant set

- For the **standard form** the terminal constraint set \mathbb{X}_N is represented by $M_N x(k+N) \leq b_N$ and must thus be constructed such that

$$M_N x^*(k+N) \leq b_N \Rightarrow (M + E\tilde{K})x^*(k+N) \leq b$$

admissible set

$$M_N x^*(k+N) \leq b_N \Rightarrow M_N (A + B\tilde{K})x^*(k+N) \leq b_N$$

invariant set



Feasibility Condition

Theorem 6.2 Consider Problem 5.1 used for the receding horizon control law $u^*(k)$ according to (5.2). If the **terminal constraint set** \mathbb{X}_N is **invariant** and **admissible** for the closed-loop system

$$x(k+1) = (A + B\tilde{K})x(k)$$

where \tilde{K} is an arbitrary feedback matrix fulfilling $\rho(A + B\tilde{K}) < 1$ and Problem 5.1 is feasible for $k = 0$, then **Problem 5.1** is **feasible** for all $k > 0$ if the receding horizon control law $u^*(k)$ is used.

- **Proof**

- The proof follows immediately from the discussion on the previous slides

- **Remark**

- The invariant and admissible terminal constraint set \mathbb{X}_N can be constructed with efficient algorithms, see [BBM15, Chapter 11 and Section 13.2.1] for a detailed discussion
- The invariant and admissible terminal constraint set \mathbb{X}_N can be constructed under **MATLAB** with the **Multi-Parametric Toolbox** [KGB+04]



Terminal Constraint Set for Box Constraints

- **Box Constraints**

$$\underline{u} \leq u(k+i) \leq \bar{u}$$

$$\underline{x} \leq x(k+i) \leq \bar{x}$$

- **Approach**

- Recall that the **constraints** must be fulfilled over the entire **prediction horizon** for **mode 2**, i.e.

$$\underline{u} \leq u(k+i) \leq \bar{u} \quad \forall i \in \{N, N+1, \dots\}$$

$$\underline{x} \leq x(k+i) \leq \bar{x} \quad \forall i \in \{N, N+1, \dots\}$$

- Using that $u(k+i) = \tilde{K}x(k+i)$ and $x(k+i) = (A + B\tilde{K})^{i-N}x(k+N)$ leads to

$$\underline{u} \leq \tilde{K}(A + B\tilde{K})^{i-N}x(k+N) \leq \bar{u} \quad \forall i \in \{N, N+1, \dots\} \quad (6.7)$$

$$\underline{x} \leq (A + B\tilde{K})^{i-N}x(k+N) \leq \bar{x} \quad \forall i \in \{N, N+1, \dots\} \quad (6.8)$$

- We must essentially check (6.7), (6.8) over an **infinite horizon** which is clearly **intractable**



Terminal Constraint Set for Box Constraints

- **Approach**

- We can show that (6.7), (6.8) must only be checked over a **constraint checking horizon** $N \leq N_{cc} < \infty$

- This means that (6.7), (6.8) are ensured for all $i \geq N_{cc}$

- The proof relies on $(A + B\tilde{K})^{i-N} \rightarrow \mathbf{0}$ for $i \rightarrow \infty$ since $\rho(A + B\tilde{K}) < 1$

- The **terminal constraint set** \mathbb{X}_N can be **constructed iteratively**, i.e.

$$\mathbb{X}_N^{(0)} = \{x(k+N) | \underline{u} \leq \tilde{K}(A + B\tilde{K})^0 x(k+N) \leq \bar{u}, \underline{x} \leq (A + B\tilde{K})^0 x(k+N) \leq \bar{x}\}$$

$$\mathbb{X}_N^{(1)} = \mathbb{X}_N^{(0)} \cap \{x(k+N) | \underline{u} \leq \tilde{K}(A + B\tilde{K})^1 x(k+N) \leq \bar{u}, \underline{x} \leq (A + B\tilde{K})^1 x(k+N) \leq \bar{x}\}$$

⋮

$$\mathbb{X}_N^{(N_{cc})} = \mathbb{X}_N^{(N_{cc}-1)} \cap \{x(k+N) | \underline{u} \leq \tilde{K}(A + B\tilde{K})^{N_{cc}-N} x(k+N) \leq \bar{u}, \underline{x} \leq (A + B\tilde{K})^{N_{cc}-N} x(k+N) \leq \bar{x}\}$$

The iteration can be stopped if $\mathbb{X}_N^{(N_{cc})} = \mathbb{X}_N^{(N_{cc}+1)}$



Terminal Constraint Set for Box Constraints

- Approach

- Problem 5.1 then becomes

$$\begin{aligned} & \min_{U(k)} V_N(x(k), U(k)) \\ & \text{subject to} \begin{cases} x(k+i+1) = Ax(k+i) + Bu(k+i), & i = 0, 1, \dots, N-1 \\ \underline{x} \leq x(k+i) \leq \bar{x}, & i = 1, 2, \dots, N \\ \underline{u} \leq u(k+i) \leq \bar{u}, & i = 0, 1, \dots, N-1 \\ \underline{x} \leq (A + B\tilde{K})^{i-N} x(k+N) \leq \bar{x}, & i = N, N+1, \dots, N_{cc} \\ \underline{u} \leq \tilde{K}(A + B\tilde{K})^{i-N} x(k+N) \leq \bar{u}, & i = N, N+1, \dots, N_{cc} \end{cases} \end{aligned}$$

- Remarks

- Problem 5.1 can still be written as a quadratic program with additional constraints
- The terminal constraint set depends only on $A, B, \tilde{K}, \underline{x}, \bar{x}, \underline{u}, \bar{u}$ and N_{cc} but not on P, Q, R and N
- The constraint checking horizon N_{cc} can be computed by checking $\mathbb{X}_N^{(N_{cc})} = \mathbb{X}_N^{(N_{cc}+1)}$ during iteration



Terminal Constraint Set for Box Constraints

- Algorithm for the Computation of N_{cc} (for $\mathbb{X} = \mathbb{R}^n$ and $m = 1$)

1. Set $N_{cc} := 0$

2. Determine

$$\begin{aligned} u_{\max} &:= \max_{x(k+N)} \tilde{K}(A + B\tilde{K})^{N_{cc}+1} x(k+N) \quad \leftarrow u(k+N_{cc}+1) \\ & \text{subject to } \underline{u} \leq \tilde{K}(A + B\tilde{K})^{i-N} x(k+N) \leq \bar{u}, i = N, N+1, \dots, N_{cc} \quad \leftarrow u(k+i) \\ u_{\min} &:= \min_{x(k+N)} \tilde{K}(A + B\tilde{K})^{N_{cc}+1} x(k+N) \\ & \text{subject to } \underline{u} \leq \tilde{K}(A + B\tilde{K})^{i-N} x(k+N) \leq \bar{u}, i = N, N+1, \dots, N_{cc} \end{aligned} \quad \left. \vphantom{\begin{aligned} u_{\max} &:= \max_{x(k+N)} \tilde{K}(A + B\tilde{K})^{N_{cc}+1} x(k+N) \\ & \text{subject to } \underline{u} \leq \tilde{K}(A + B\tilde{K})^{i-N} x(k+N) \leq \bar{u}, i = N, N+1, \dots, N_{cc} \\ u_{\min} &:= \min_{x(k+N)} \tilde{K}(A + B\tilde{K})^{N_{cc}+1} x(k+N) \\ & \text{subject to } \underline{u} \leq \tilde{K}(A + B\tilde{K})^{i-N} x(k+N) \leq \bar{u}, i = N, N+1, \dots, N_{cc} \end{aligned}} \right\} \text{linear programs}$$

3. If $u_{\max} \leq \bar{u}$ and $u_{\min} \geq \underline{u}$ then

stop

else

set $N_{cc} := N_{cc} + 1$ and goto 2.



Terminal Constraint Set for Box Constraints

- Illustrative Example

- Reconsider the **Illustrative Example** from **Chapter 4** (cf. Slide 4-11) with the input constraint $-1 \leq u(k) \leq 1$, the input weight $R = 1$ and $\tilde{K} = K_{LQR}$

- The **terminal constraint set** \mathbb{X}_N follows from

$$\mathbb{X}_N^{(0)} = \{x(k+N) \mid -1 \leq (-1.19 \quad -7.88)x(k+N) \leq 1\} \quad \text{intersection of 2 half-spaces}$$

$$\mathbb{X}_N^{(1)} = \mathbb{X}_N^{(0)} \cap \{x(k+N) \mid -1 \leq (-0.57 \quad -4.98)x(k+N) \leq 1\} \quad \text{intersection of 4 half-spaces}$$

$$\mathbb{X}_N^{(2)} = \mathbb{X}_N^{(1)} \cap \{x(k+N) \mid -1 \leq (-0.16 \quad -2.78)x(k+N) \leq 1\} \quad \text{intersection of 6 half-spaces}$$

$$\mathbb{X}_N^{(3)} = \mathbb{X}_N^{(2)} \cap \{x(k+N) \mid -1 \leq (0.08 \quad -1.24)x(k+N) \leq 1\} \quad \text{intersection of 8 half-spaces}$$

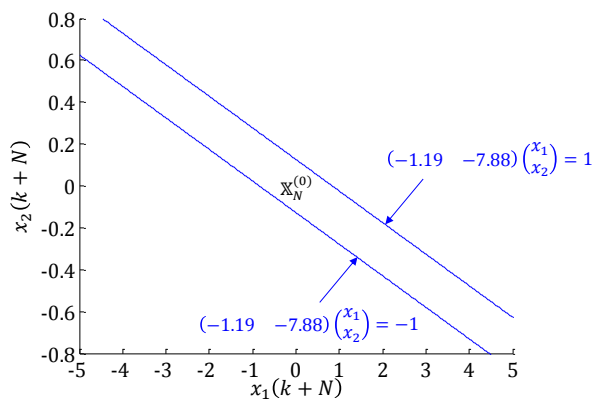
$$\mathbb{X}_N^{(4)} = \mathbb{X}_N^{(3)} \cap \{x(k+N) \mid -1 \leq (0.21 \quad -0.25)x(k+N) \leq 1\} \quad \text{intersection of 10 half-spaces}$$

- We can show that $\mathbb{X}_N^{(i)} = \mathbb{X}_N^{(4)}$ for all $i > 4$ and thus $N_{cc} = 4$



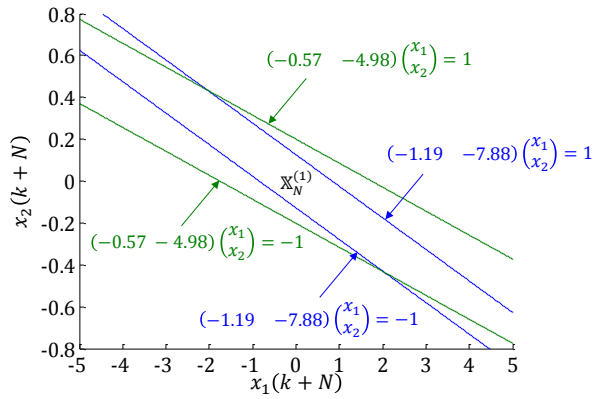
Terminal Constraint Set for Box Constraints

- Illustrative Example



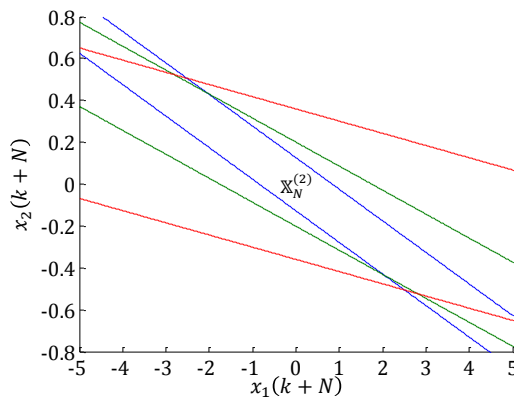
Terminal Constraint Set for Box Constraints

- Illustrative Example



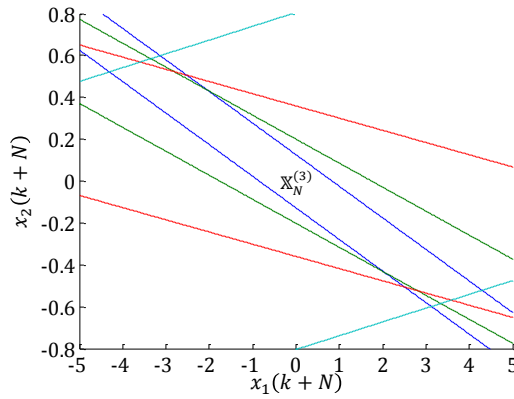
Terminal Constraint Set for Box Constraints

- Illustrative Example



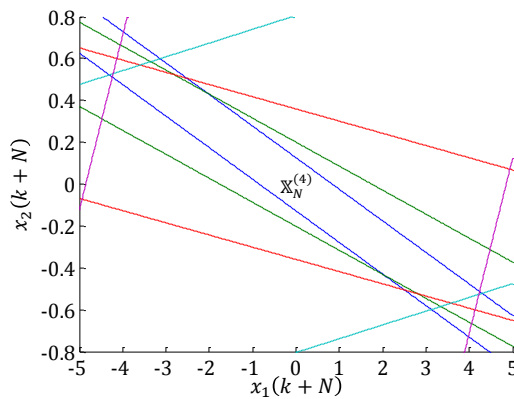
Terminal Constraint Set for Box Constraints

- Illustrative Example



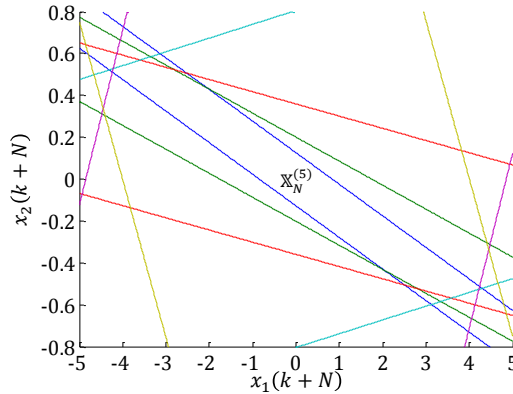
Terminal Constraint Set for Box Constraints

- Illustrative Example



Terminal Constraint Set for Box Constraints

- Illustrative Example



Stability Condition

Theorem 6.3 The discrete-time linear time-invariant system (4.1) with $x(k) \in \mathbb{X}$ and $u(k) \in \mathbb{U}$ under the receding horizon control law $u^*(k)$ according to (5.2) is asymptotically stable if

- Q is positive definite
- P is positive definite and chosen such that

$$(A + B\tilde{K})^T P (A + B\tilde{K}) - P \leq -Q - \tilde{K}^T R \tilde{K} \quad (6.1)$$

where \tilde{K} is an arbitrary matrix fulfilling $\rho(A + B\tilde{K}) < 1$

- $x(k+N) \in \mathbb{X}_N$

where \mathbb{X}_N is invariant and admissible for $x(k+1) = (A + B\tilde{K})x(k)$.

The domain of attraction is $\mathbb{D} = \{x(0) \in \mathbb{X} | \exists U(0): x(i) \in \mathbb{X}, u(i) \in \mathbb{U} \forall i \in \{0, \dots, N-1\}, x(N) \in \mathbb{X}_N\}$.

- Proof

- The proof follows immediately from the discussion on the previous slides

Stability Condition

- **Remark on the Domain of Attraction**
 - The **domain of attraction** \mathbb{D} increases with the **prediction horizon** N and **terminal constraint set** \mathbb{X}_N
 - For a given prediction horizon N the domain of attraction \mathbb{D} should ideally be as large as possible
 - This is achieved for the **maximal invariant and admissible terminal constraint set** \mathbb{X}_N
- **Remark on the Selection of the Terminal Constraint**
 - The **terminal constraint** $\mathbf{x}(k + N) = \mathbf{0}$ satisfies the conditions in Theorem 6.3 trivially since then the “tail” is always feasible (cf. Slide 6-11)
 - This terminal constraint has been proposed in [KG88] and is commonly considered as the **first stability condition** presented for MPC with constraints
 - This terminal constraint is unfortunately **very restrictive** and usually **impairs performance**
 - This terminal constraint is still useful if the construction of a terminal constraint set is difficult, e.g. for nonlinear systems



Stability Condition

- **Remark on the Need for a Terminal Constraint**
 - The terminal constraint is not needed if $N \geq N_{\text{stab}}$ for a given $\mathbf{x}(0)$ since then \mathbb{X}_N is inactive
 - Computing the **stabilizing prediction horizon** N_{stab} is, however, involved and subject to research
 - Note that the stabilizing prediction horizon N_{stab} depends on the initial state $\mathbf{x}(0)$
 - Note furthermore that for $N \geq N_{\text{stab}}$ also the closed-loop cost does not change anymore
- **Remark on the Influence of the Terminal Constraint**
 - The terminal constraint influences the **performance**
 - We generally have that
 - large computation time \Leftrightarrow large $N \Leftrightarrow$ large $\mathbb{X}_N \Leftrightarrow$ good performance
 - small computation time \Leftrightarrow small $N \Leftrightarrow$ small $\mathbb{X}_N \Leftrightarrow$ poor performance
 - Constructing the **maximal invariant and admissible terminal constraint set** is thus crucial
- **More details on stability of MPC can be found in the seminal paper [MRR+00]**



Stability Condition

- Illustrative Example

- Reconsider the Illustrative Example from Chapter 4 (cf. Slide 4-11) with $x(0) = (-7 \ 0.5)^T$, $-1 \leq u(k) \leq 1$, $R = 1$, $\tilde{K} = K_{LQR}$ and $P = P_{LQR}$
- Compute the closed-loop cost $V_\infty(x(0))$ and the optimal predicted cost $V_N^*(x(0))$ for different N

N	5	6	7	10	> 10
$V_\infty(x(0))$	295.2	287.7	286.8	286.6	286.6
$V_N(x(0))$	286.7	286.7	286.6	286.6	286.6

- Evidently the closed-loop cost $V_\infty(x(0))$ and optimal predicted cost $V_N^*(x(0))$ are equal for $N \geq 10$
- This implies that the terminal constraint $x(k + N) \in \mathbb{X}_N$ is inactive for $N \geq 10$
- This implies in turn that $N_{\text{stab}} = 10$
- The receding horizon controller for $N \geq N_{\text{stab}}$ is called constrained linear quadratic regulator (CLQR)



Miscellaneous

- [KG88] S. S. Keerthi and E. G. Gilbert. Optimal infinite-horizon feedback laws for a general class of constrained discrete-time systems: Stability and moving-horizon approximations. *Journal of Optimization Theory and Applications*, 57(2):265–293, 1988.
- [KGB+04] Michal Kvasnica, Pascal Grieder, Mato Baotić, and Manfred Morari. Multi-Parametric Toolbox (MPT). In *Proceedings of the 7th International Workshop on Hybrid Systems: Computation and Control*, pages 448–462, Philadelphia, PA, USA, 2004. – control.ee.ethz.ch/~mpt/3/
- [MRR+00] David Q. Mayne, James B. Rawlings, Christopher V. Rao, and Pierre O. M. Scokaert. Constrained model predictive control: Stability and optimality. *Automatica*, 36(6):789–814, 2000.

