Nonlinear Model Predictive Control

Lars Grüne

Mathematical Institute, University of Bayreuth, Germany

Elgersburg School, March 2–6, 2015

Contents

Part A: Stabilizing Model Predictive Control

Contents

Part A: Stabilizing Model Predictive Control

(1) Introduction

What is Model Predictive Control (MPC)?

Setup

We consider nonlinear discrete time control systems

$$x_{\mathbf{u}}(n+1) = f(x_{\mathbf{u}}(n), \mathbf{u}(n)), \;\; x_{\mathbf{u}}(0) = x_0$$

or, briefly

$$x^+ = f(x, u)$$

with $x \in X$, $u \in U$

Setup

We consider nonlinear discrete time control systems

$$x_{\mathbf{u}}(n+1) = f(x_{\mathbf{u}}(n), \mathbf{u}(n)), \;\; x_{\mathbf{u}}(0) = x_0$$

or, briefly

$$x^+ = f(x, u)$$

with $x \in X$, $u \in U$

- we consider discrete time systems for simplicity of exposition

Setup

We consider nonlinear discrete time control systems

$$x_{\mathbf{u}}(n+1) = f(x_{\mathbf{u}}(n), \mathbf{u}(n)), \;\; x_{\mathbf{u}}(0) = x_0$$

or, briefly

$$x^+ = f(x, u)$$

with $x \in X$, $u \in U$

- we consider discrete time systems for simplicity of exposition
- continuous time systems can be treated by using the discrete time representation of the corresponding sampled data system or a numerical approximation

Setup

We consider nonlinear discrete time control systems

$$x_{\mathbf{u}}(n+1) = f(x_{\mathbf{u}}(n), \mathbf{u}(n)), \;\; x_{\mathbf{u}}(0) = x_0$$

or, briefly

$$x^+ = f(x, u)$$

with $x \in X$, $u \in U$

- we consider discrete time systems for simplicity of exposition
- continuous time systems can be treated by using the discrete time representation of the corresponding sampled data system or a numerical approximation
- X and U depend on the model. These may be Euclidean spaces $\mathbb{R}^n$ and $\mathbb{R}^m$ or more general (e.g., infinite dimensional) spaces.

Setup

We consider nonlinear discrete time control systems

$$x_{\mathbf{u}}(n+1) = f(x_{\mathbf{u}}(n), \mathbf{u}(n)), \;\; x_{\mathbf{u}}(0) = x_0$$

or, briefly

$$x^+ = f(x, u)$$

with $x \in X$, $u \in U$

- we consider discrete time systems for simplicity of exposition
- continuous time systems can be treated by using the discrete time representation of the corresponding sampled data system or a numerical approximation
- X and U depend on the model. These may be Euclidean spaces $\mathbb{R}^n$ and $\mathbb{R}^m$ or more general (e.g., infinite dimensional) spaces. For simplicity of exposition we assume that we have a norm $\|\cdot\|$ on both spaces

Prototype Problem

Assume there exists an equilibrium $x_* \in X$ for $u = 0$, i.e.

$$f(x_*, 0) = x_*$$

Prototype Problem

Assume there exists an equilibrium $x_* \in X$ for $u = 0$, i.e.

$$f(x_*, 0) = x_*$$

Task: stabilize the system $\quad x^+ = f(x, u)$
at x_* via static state feedback,

Prototype Problem

Assume there exists an equilibrium $x_* \in X$ for $u = 0$, i.e.

$$f(x_*, 0) = x_*$$

Task: stabilize the system $\quad x^+ = f(x, u)$
at x_* via static state feedback, i.e., find $\mu : X \to U$, such that x_* is asymptotically stable for the feedback controlled system

$$x_\mu(n+1) = f(x_\mu(n), \mu(x_\mu(n))), \;\; x_\mu(0) = x_0$$

Prototype Problem

Assume there exists an equilibrium $x_* \in X$ for $u = 0$, i.e.

$$f(x_*, 0) = x_*$$

Task: stabilize the system $\quad x^+ = f(x, u)$
at x_* via static state feedback, i.e., find $\mu : X \to U$, such that x_* is asymptotically stable for the feedback controlled system

$$x_\mu(n+1) = f(x_\mu(n), \mu(x_\mu(n))), \;\; x_\mu(0) = x_0$$

Additionally, we impose state constraints $x_\mu(n) \in \mathbb{X}$
and control constraints $\mu(x(n)) \in \mathbb{U}$

for all $n \in \mathbb{N}$ and given sets $\mathbb{X} \subseteq X$, $\mathbb{U} \subseteq U$

Prototype Problem

Asymptotic stability means

Prototype Problem

Asymptotic stability means

Attraction: $x_\mu(n) \to x_*$ as $n \to \infty$

plus

Stability: Solutions starting close to x_* remain close to x_*

(we will later formalize this property using $\mathcal{KL}$ functions)

Prototype Problem

Asymptotic stability means

Attraction: $x_\mu(n) \to x_*$ as $n \to \infty$

plus

Stability: Solutions starting close to x_* remain close to x_*

(we will later formalize this property using $\mathcal{KL}$ functions)

Informal interpretation: control the system to x_* and keep it there while obeying the state and control constraints

Prototype Problem

Asymptotic stability means

Attraction: $x_\mu(n) \to x_*$ as $n \to \infty$

plus

Stability: Solutions starting close to x_* remain close to x_*

(we will later formalize this property using $\mathcal{KL}$ functions)

Informal interpretation: control the system to x_* and keep it there while obeying the state and control constraints

Idea of MPC: use an optimal control problem which minimizes the distance to x_* in order to synthesize a feedback law μ

The idea of MPC

For defining the MPC scheme, we choose a stage cost $\ell(x,u)$ penalizing the distance from x_* and the control effort, e.g., $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ for $\lambda \geq 0$

The idea of MPC

For defining the MPC scheme, we choose a stage cost $\ell(x,u)$ penalizing the distance from x_* and the control effort, e.g., $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ for $\lambda \geq 0$

The basic idea of MPC is:

- minimize the summed stage cost along trajectories generated from our model over a prediction horizon N
- use the first element of the resulting optimal control sequence as feedback value
- repeat this procedure iteratively for all sampling instants $n = 0, 1, 2, \ldots$

The idea of MPC

For defining the MPC scheme, we choose a stage cost $\ell(x,u)$ penalizing the distance from x_* and the control effort, e.g., $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ for $\lambda \geq 0$

The basic idea of MPC is:

- minimize the summed stage cost along trajectories generated from our model over a prediction horizon N
- use the first element of the resulting optimal control sequence as feedback value
- repeat this procedure iteratively for all sampling instants $n = 0, 1, 2, \ldots$

Notation in what follows:

- general feedback laws will be denoted by μ
- the MPC feedback law will be denoted by μ_N

The basic MPC scheme

Formal description of the basic MPC scheme:

At each time instant n solve for the current state $x_{\mu_N}(n)$

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n),\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

($\mathbf{u}$ admissible $\quad\Leftrightarrow\quad \mathbf{u} \in \mathbb{U}^N$ and $x_{\mathbf{u}}(k) \in \mathbb{X}$)

The basic MPC scheme

Formal description of the basic MPC scheme:

At each time instant n solve for the current state $x_{\mu_N}(n)$

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n), \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

($\mathbf{u}$ admissible $\Leftrightarrow$ $\mathbf{u} \in \mathbb{U}^N$ and $x_{\mathbf{u}}(k) \in \mathbb{X}$)

$\leadsto$ optimal trajectory $\quad x^\star(0), \ldots, x^\star(N)$

The basic MPC scheme

Formal description of the basic MPC scheme:

At each time instant n solve for the current state $x_{\mu_N}(n)$

$$\underset{\mathbf{u} \text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n), \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

($\mathbf{u}$ admissible $\Leftrightarrow$ $\mathbf{u} \in \mathbb{U}^N$ and $x_{\mathbf{u}}(k) \in \mathbb{X}$)

$\rightsquigarrow$ optimal trajectory $x^\star(0), \ldots, x^\star(N)$

with optimal control $\mathbf{u}^\star(0), \ldots, \mathbf{u}^\star(N-1)$

The basic MPC scheme

Formal description of the basic MPC scheme:

At each time instant n solve for the current state $x_{\mu_N}(n)$

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n),\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

($\mathbf{u}$ admissible $\Leftrightarrow$ $\mathbf{u} \in \mathbb{U}^N$ and $x_{\mathbf{u}}(k) \in \mathbb{X}$)

$\rightsquigarrow$ optimal trajectory $x^\star(0), \ldots, x^\star(N)$

with optimal control $\mathbf{u}^\star(0), \ldots, \mathbf{u}^\star(N-1)$

Define the MPC feedback law $\mu(x_{\mu_N}(n)) := \mathbf{u}^*(0)$

The basic MPC scheme

Formal description of the basic MPC scheme:

At each time instant n solve for the current state $x_{\mu_N}(n)$

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n),\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

($\mathbf{u}$ admissible $\Leftrightarrow$ $\mathbf{u} \in \mathbb{U}^N$ and $x_{\mathbf{u}}(k) \in \mathbb{X}$)

$\rightsquigarrow$ optimal trajectory $x^\star(0),\ldots,x^\star(N)$

with optimal control $\mathbf{u}^\star(0),\ldots,\mathbf{u}^\star(N-1)$

Define the MPC feedback law $\mu(x_{\mu_N}(n)) := \mathbf{u}^*(0)$

$\rightsquigarrow x_{\mu_N}(n+1) = f(x_{\mu_N}(n),\mu_N(x_{\mu_N}(n)))$

The basic MPC scheme

Formal description of the basic MPC scheme:

At each time instant n solve for the current state $x_{\mu_N}(n)$

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n),\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

($\mathbf{u}$ admissible $\Leftrightarrow$ $\mathbf{u} \in \mathbb{U}^N$ and $x_{\mathbf{u}}(k) \in \mathbb{X}$)

$\rightsquigarrow$ optimal trajectory $x^\star(0),\ldots,x^\star(N)$

with optimal control $\mathbf{u}^\star(0),\ldots,\mathbf{u}^\star(N-1)$

Define the MPC feedback law $\mu(x_{\mu_N}(n)) := \mathbf{u}^*(0)$

$\rightsquigarrow$ $x_{\mu_N}(n+1) = f(x_{\mu_N}(n),\mu_N(x_{\mu_N}(n))) = f(x_{\mu_N}(n),\mathbf{u}^\star(0))$

The basic MPC scheme

Formal description of the basic MPC scheme:

At each time instant n solve for the current state $x_{\mu_N}(n)$

$$\operatorname*{minimize}_{\mathbf{u}\text{ admissible}} \; J_N(x_{\mu_N}(n),\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \;\; x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

($\mathbf{u}$ admissible $\Leftrightarrow$ $\mathbf{u} \in \mathbb{U}^N$ and $x_{\mathbf{u}}(k) \in \mathbb{X}$)

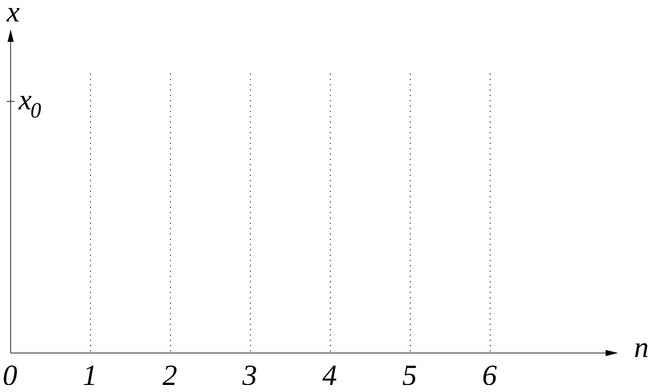
⇝ optimal trajectory $x^\star(0), \ldots, x^\star(N)$

with optimal control $\mathbf{u}^\star(0), \ldots, \mathbf{u}^\star(N-1)$

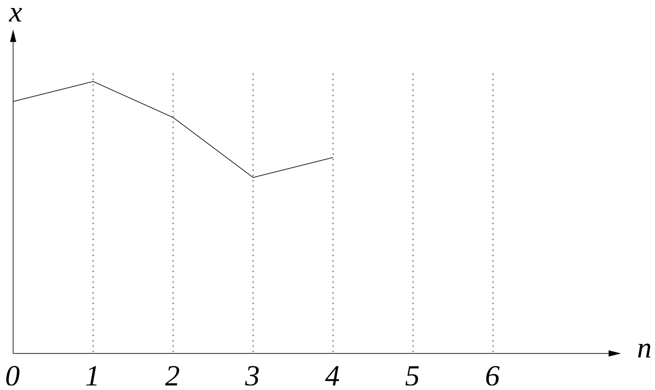
Define the MPC feedback law $\mu(x_{\mu_N}(n)) := \mathbf{u}^*(0)$

⇝ $x_{\mu_N}(n+1) = f(x_{\mu_N}(n), \mu_N(x_{\mu_N}(n))) = f(x_{\mu_N}(n), \mathbf{u}^\star(0)) = x^\star(1)$

MPC from the trajectory point of view

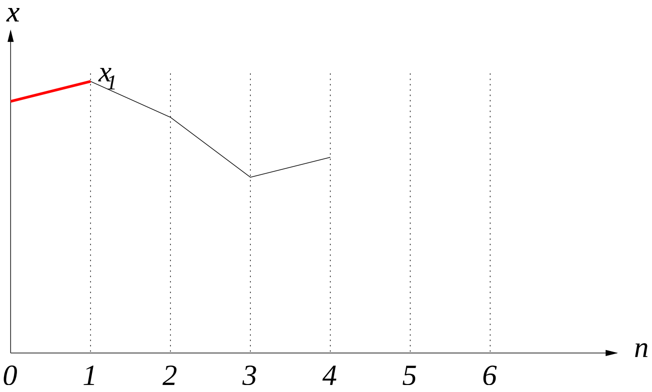


MPC from the trajectory point of view



black = predictions (open loop optimization)

MPC from the trajectory point of view

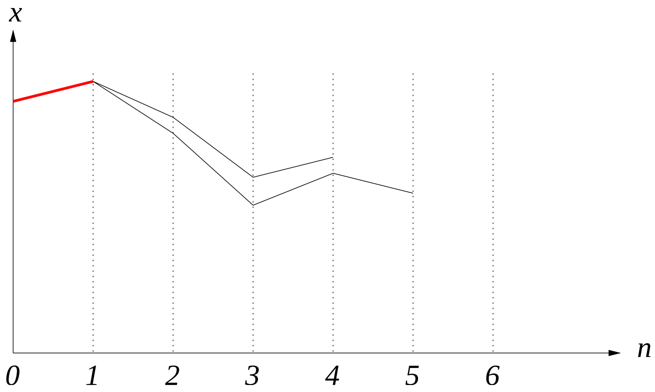


black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

UNIVERSITÄT BAYREUTH

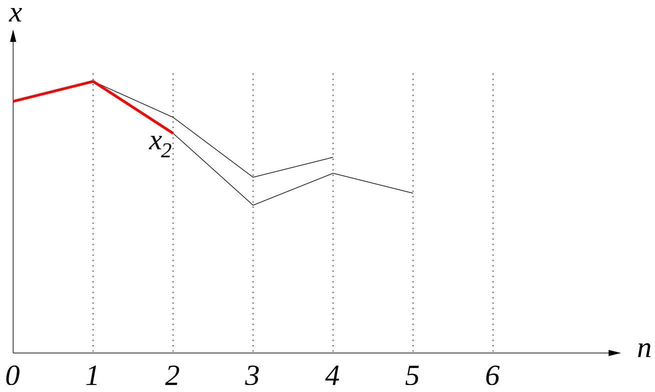
MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

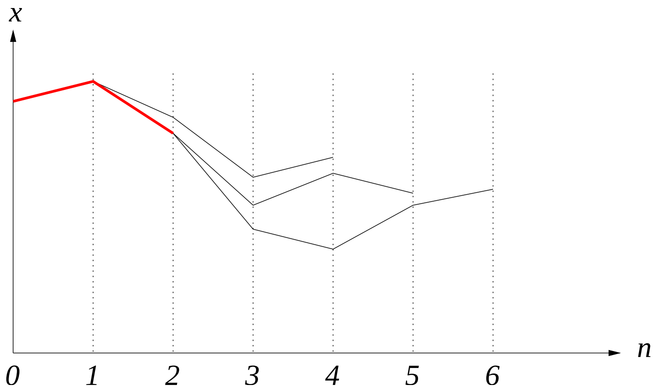
MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

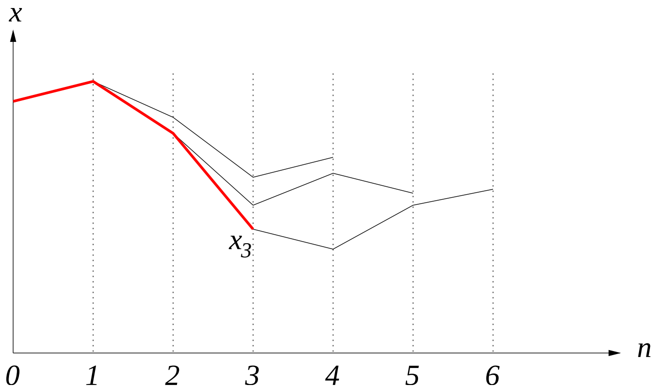
MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

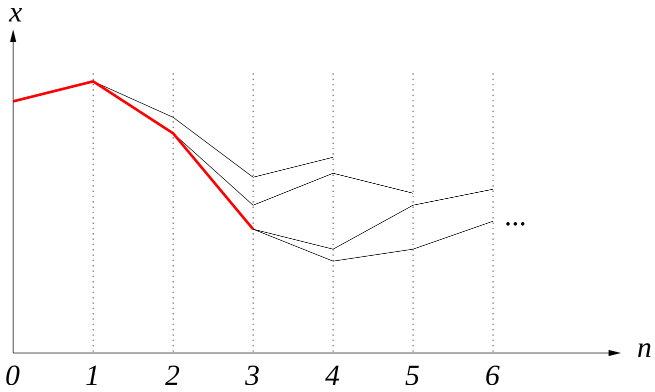
MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

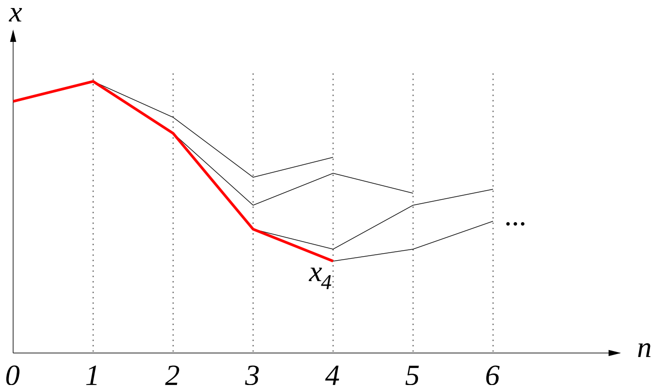
MPC from the trajectory point of view



black = predictions (open loop optimization)
red = MPC closed loop, $x_n = x_{\mu_N}(n)$

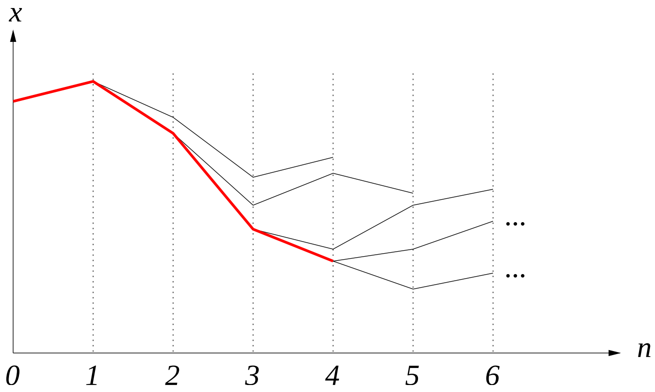
UNIVERSITÄT BAYREUTH

MPC from the trajectory point of view



black = predictions (open loop optimization)
red = MPC closed loop, $x_n = x_{\mu_N}(n)$

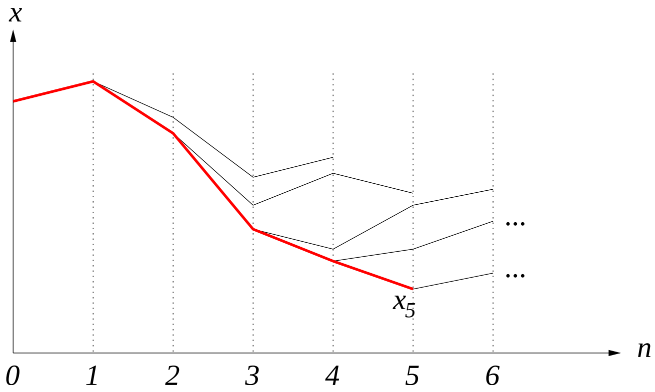
MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

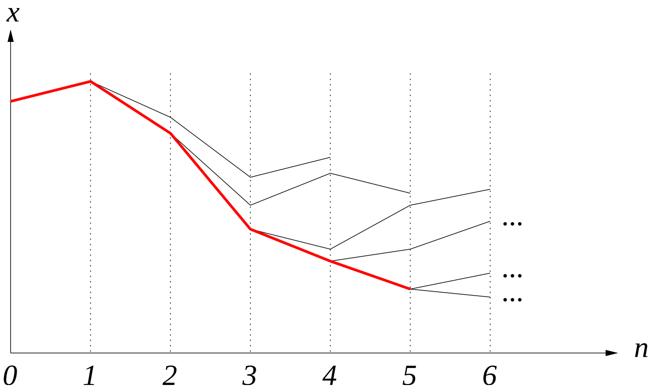
MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

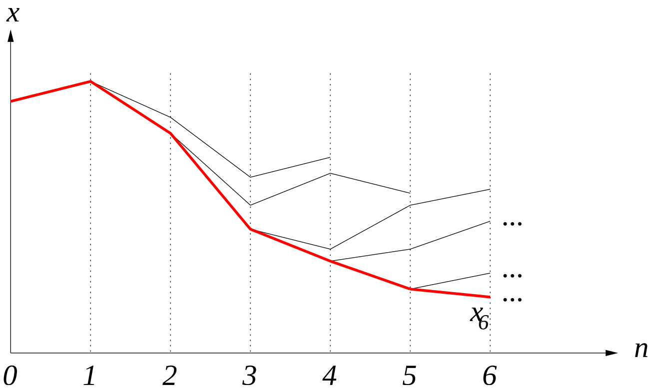
MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

MPC from the trajectory point of view



black = predictions (open loop optimization)

red = MPC closed loop, $x_n = x_{\mu_N}(n)$

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963]

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

UNIVERSITÄT BAYREUTH

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

used in industrial applications since the mid 1970s, mainly for constrained linear systems [Qin & Badgwell, 1997, 2001]

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

used in industrial applications since the mid 1970s, mainly for constrained linear systems [Qin & Badgwell, 1997, 2001]

more than 9000 industrial MPC applications in Germany counted in [Dittmar & Pfeifer, 2005]

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

used in industrial applications since the mid 1970s, mainly for constrained linear systems [Qin & Badgwell, 1997, 2001]

more than 9000 industrial MPC applications in Germany counted in [Dittmar & Pfeifer, 2005]

development of theory since ∼1980 (linear), ∼1990 (nonlinear)

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

used in industrial applications since the mid 1970s, mainly for constrained linear systems [Qin & Badgwell, 1997, 2001]

more than 9000 industrial MPC applications in Germany counted in [Dittmar & Pfeifer, 2005]

development of theory since ∼1980 (linear), ∼1990 (nonlinear)

Central questions:

- When does MPC stabilize the system?

UNIVERSITÄT BAYREUTH

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

used in industrial applications since the mid 1970s, mainly for constrained linear systems [Qin & Badgwell, 1997, 2001]

more than 9000 industrial MPC applications in Germany counted in [Dittmar & Pfeifer, 2005]

development of theory since ∼1980 (linear), ∼1990 (nonlinear)

Central questions:

- When does MPC stabilize the system?
- How good is the performance of the MPC feedback law?

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

used in industrial applications since the mid 1970s, mainly for constrained linear systems [Qin & Badgwell, 1997, 2001]

more than 9000 industrial MPC applications in Germany counted in [Dittmar & Pfeifer, 2005]

development of theory since ∼1980 (linear), ∼1990 (nonlinear)

Central questions:

- When does MPC stabilize the system?
- How good is the performance of the MPC feedback law?
- How long does the optimization horizon N need to be?

Model predictive control (aka Receding horizon control)

Idea first formulated in [A.I. Propoi, *Use of linear programming methods for synthesizing sampled-data automatic systems*, Automation and Remote Control 1963], often rediscovered

used in industrial applications since the mid 1970s, mainly for constrained linear systems [Qin & Badgwell, 1997, 2001]

more than 9000 industrial MPC applications in Germany counted in [Dittmar & Pfeifer, 2005]

development of theory since ∼1980 (linear), ∼1990 (nonlinear)

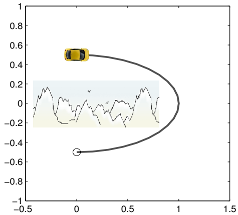
Central questions:

- When does MPC stabilize the system?
- How good is the performance of the MPC feedback law?
- How long does the optimization horizon N need to be?

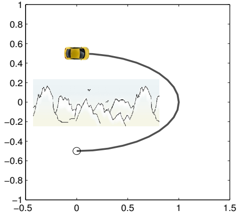
and, of course, the development of good algorithms (not topic of this course)

UNIVERSITÄT BAYREUTH

An example



An example



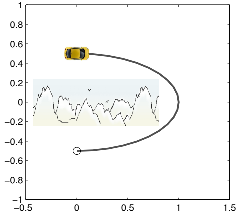
$$
\begin{aligned}
x_1^+ &= \sin(\varphi + u) \\
x_2^+ &= \cos(\varphi + u)/2
\end{aligned}
$$

with $\varphi = \begin{cases} \arccos 2x_2, & x_1 \geq 0 \\ 2\pi - \arccos 2x_2, & x_1 < 0, \end{cases}$

$\mathbb{X} = \{x \in \mathbb{R}^2 \, : \, \|(x_1, 2x_2)^T\| = 1\}$, $\mathbb{U} = [0, u_{\max}]$

$x_* = (0, -1/2)^T$, $x_0 = (0, 1/2)^T$

An example



$$\begin{aligned} x_1^+ &= \sin(\varphi + u) \\ x_2^+ &= \cos(\varphi + u)/2 \end{aligned}$$

with $\varphi = \begin{cases} \arccos 2x_2, & x_1 \geq 0 \\ 2\pi - \arccos 2x_2, & x_1 < 0, \end{cases}$

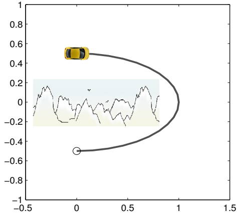
$\mathbb{X} = \{x \in \mathbb{R}^2 \,:\, \|(x_1, 2x_2)^T\| = 1\}$, $\mathbb{U} = [0, u_{\max}]$

$x_* = (0, -1/2)^T$, $x_0 = (0, 1/2)^T$

MPC with $\ell(x,u) = \|x - x_*\|^2 + |u|^2$ and $u_{\max} = 0.2$ yields
asymptotic stability for $N = 11$

UNIVERSITÄT BAYREUTH

An example



$$\begin{aligned} x_1^+ &= \sin(\varphi + u) \\ x_2^+ &= \cos(\varphi + u)/2 \end{aligned}$$

with $\varphi = \begin{cases} \arccos 2x_2, & x_1 \geq 0 \\ 2\pi - \arccos 2x_2, & x_1 < 0, \end{cases}$

$\mathbb{X} = \{x \in \mathbb{R}^2 \,:\, \|(x_1, 2x_2)^T\| = 1\}$, $\mathbb{U} = [0, u_{\max}]$

$x_* = (0, -1/2)^T$, $x_0 = (0, 1/2)^T$

MPC with $\ell(x,u) = \|x - x_*\|^2 + |u|^2$ and $u_{\max} = 0.2$ yields asymptotic stability for $N = 11$ but not for $N \leq 10$

UNIVERSITÄT BAYREUTH

Summary of Section (1)

- MPC is an online optimal control based method for computing stabilizing feedback laws

Summary of Section (1)

- MPC is an online optimal control based method for computing stabilizing feedback laws
- MPC computes the feedback law by iteratively solving finite horizon optimal control problems using the current state $x_0 = x_{\mu_N}(n)$ as initial value

Summary of Section (1)

- MPC is an online optimal control based method for computing stabilizing feedback laws
- MPC computes the feedback law by iteratively solving finite horizon optimal control problems using the current state $x_0 = x_{\mu_N}(n)$ as initial value
- the feedback value $\mu_N(x_0)$ is the first element of the resulting optimal control sequence

Summary of Section (1)

- MPC is an online optimal control based method for computing stabilizing feedback laws
- MPC computes the feedback law by iteratively solving finite horizon optimal control problems using the current state $x_0 = x_{\mu_N}(n)$ as initial value
- the feedback value $\mu_N(x_0)$ is the first element of the resulting optimal control sequence
- the example shows that MPC does not always yield an asymptotically stabilizing feedback law

(2a) Background material:

Lyapunov functions

Purpose of this section

We introduce Lyapunov functions as a tool to rigorously verify asymptotic stability

Purpose of this section

We introduce Lyapunov functions as a tool to rigorously verify asymptotic stability

In the subsequent sections, this will be used in order to establish asymptotic stability of the MPC closed loop

Purpose of this section

We introduce Lyapunov functions as a tool to rigorously verify asymptotic stability

In the subsequent sections, this will be used in order to establish asymptotic stability of the MPC closed loop

In this section, we consider discrete time systems without input, i.e.,

$$x^+ = g(x)$$

with $x \in X$ or, in long form

$$x(n+1) = g(x(n)), \;\; x(0) = x_0$$

Purpose of this section

We introduce Lyapunov functions as a tool to rigorously verify asymptotic stability

In the subsequent sections, this will be used in order to establish asymptotic stability of the MPC closed loop

In this section, we consider discrete time systems without input, i.e.,

$$x^+ = g(x)$$

with $x \in X$ or, in long form

$$x(n+1) = g(x(n)), \;\; x(0) = x_0$$

(later we will apply the results to $g(x) = f(x, \mu_N(x))$)

Purpose of this section

We introduce Lyapunov functions as a tool to rigorously verify asymptotic stability

In the subsequent sections, this will be used in order to establish asymptotic stability of the MPC closed loop

In this section, we consider discrete time systems without input, i.e.,

$$x^+ = g(x)$$

with $x \in X$ or, in long form

$$x(n+1) = g(x(n)), \;\; x(0) = x_0$$

(later we will apply the results to $g(x) = f(x, \mu_N(x))$)

Note: we do not require g to be continuous

Comparison functions

For $\mathbb{R}_0^+ = [0, \infty)$ we use the following classes of comparison functions

$$\mathcal{K} := \left\{ \alpha : \mathbb{R}_0^+ \to \mathbb{R}_0^+ \;\middle|\; \begin{array}{l} \alpha \text{ is continuous and strictly} \\ \text{increasing with } \alpha(0) = 0 \end{array} \right\}$$

$$\mathcal{K}_\infty := \left\{ \alpha : \mathbb{R}_0^+ \to \mathbb{R}_0^+ \;\middle|\; \alpha \in \mathcal{K} \text{ and } \alpha \text{ is unbounded} \right\}$$

$$\mathcal{KL} := \left\{ \beta : \mathbb{R}_0^+ \times \mathbb{R}_0^+ \to \mathbb{R}_0^+ \;\middle|\; \begin{array}{l} \beta \text{ is continuous,} \\ \beta(\cdot, t) \in \mathcal{K} \text{ for all } t \in \mathbb{R}_0^+ \\ \text{and } \beta(r, \cdot) \text{ is strictly de-} \\ \text{creasing to } 0 \text{ for all } r \in \mathbb{R}_0^+ \end{array} \right\}$$

Asymptotic stability revisited

A point x_* is called an equilibrium of $x^+ = g(x)$ if $g(x_*) = x_*$

Asymptotic stability revisited

A point x_* is called an equilibrium of $x^+ = g(x)$ if $g(x_*) = x_*$

A set $Y \subseteq X$ is called forward invariant for $x^+ = g(x)$ if $g(x) \in Y$ holds for each $x \in Y$

Asymptotic stability revisited

A point x_* is called an equilibrium of $x^+ = g(x)$ if $g(x_*) = x_*$

A set $Y \subseteq X$ is called forward invariant for $x^+ = g(x)$ if $g(x) \in Y$ holds for each $x \in Y$

We say that x_* is asymptotically stable for $x^+ = g(x)$ on a forward invariant set Y if there exists $\beta \in \mathcal{KL}$ such that

$$\|x(n) - x_*\| \leq \beta(\|x(0) - x_*\|, n)$$

holds for all $x \in Y$ and $n \in \mathbb{N}$

Asymptotic stability revisited

A point x_* is called an equilibrium of $x^+ = g(x)$ if $g(x_*) = x_*$

A set $Y \subseteq X$ is called forward invariant for $x^+ = g(x)$ if $g(x) \in Y$ holds for each $x \in Y$

We say that x_* is asymptotically stable for $x^+ = g(x)$ on a forward invariant set Y if there exists $\beta \in \mathcal{KL}$ such that

$$\|x(n) - x_*\| \leq \beta(\|x(0) - x_*\|, n)$$

holds for all $x \in Y$ and $n \in \mathbb{N}$

How can we check whether this property holds?

UNIVERSITÄT BAYREUTH

Lyapunov function

Let $Y \subseteq X$ be a forward invariant set and $x_* \in X$. A function $V : Y \to \mathbb{R}_0^+$ is called a Lyapunov function for $x^+ = g(x)$ if the following two conditions hold for all $x \in Y$:

(i) There exists $\alpha_1, \alpha_2 \in \mathcal{K}_\infty$ such that

$$\alpha_1(\|x - x_*\|) \leq V(x) \leq \alpha_2(\|x - x_*\|)$$

(ii) There exists $\alpha_V \in \mathcal{K}$ such that

$$V(x^+) \leq V(x) - \alpha_V(\|x - x_*\|)$$

Stability theorem

Theorem: If the system $x^+ = g(x)$ admits a Lyapunov function V on a forward invariant set Y, then x_* is an asymptotically stable equilibrium on Y

Stability theorem

Theorem: If the system $x^+ = g(x)$ admits a Lyapunov function V on a forward invariant set Y, then x_* is an asymptotically stable equilibrium on Y

Idea of proof: $V(x^+) \leq V(x) - \alpha_V(\|x - x_*\|)$ implies that V is strictly decaying along solutions away from x_*

UNIVERSITÄT BAYREUTH

Stability theorem

Theorem: If the system $x^+ = g(x)$ admits a Lyapunov function V on a forward invariant set Y, then x_* is an asymptotically stable equilibrium on Y

Idea of proof: $V(x^+) \leq V(x) - \alpha_V(\|x - x_*\|)$ implies that V is strictly decaying along solutions away from x_*

This allows to construct $\tilde{\beta} \in \mathcal{KL}$ with $V(x(n)) \leq \tilde{\beta}(V(x(0)), n)$

Stability theorem

Theorem: If the system $x^+ = g(x)$ admits a Lyapunov function V on a forward invariant set Y, then x_* is an asymptotically stable equilibrium on Y

Idea of proof: $V(x^+) \le V(x) - \alpha_V(\|x - x_*\|)$ implies that V is strictly decaying along solutions away from x_*

This allows to construct $\tilde\beta \in \mathcal{KL}$ with $V(x(n)) \le \tilde\beta(V(x(0)), n)$

The bounds $\alpha_1(\|x - x_*\|) \le V(x) \le \alpha_2(\|x - x_*\|)$ imply that asymptotic stability holds with $\beta(r,t) = \alpha_1^{-1}(\tilde\beta(\alpha_2(r), t))$

Lyapunov functions — discussion

While the convergence $x(n) \to x_*$ is typically non-monotone for an asymptotically stable system, the convergence $V(x(n)) \to 0$ is strictly monotone

Lyapunov functions — discussion

While the convergence $x(n) \to x_*$ is typically non-monotone for an asymptotically stable system, the convergence $V(x(n)) \to 0$ is strictly monotone

It is hence sufficient to check the decay of V in one time step

UNIVERSITÄT BAYREUTH

Lyapunov functions — discussion

While the convergence $x(n) \to x_*$ is typically non-monotone for an asymptotically stable system, the convergence $V(x(n)) \to 0$ is strictly monotone

It is hence sufficient to check the decay of V in one time step

$\rightsquigarrow$ it is typically quite easy to check whether a given function is a Lyapunov function

Lyapunov functions — discussion

While the convergence $x(n) \to x_*$ is typically non-monotone for an asymptotically stable system, the convergence $V(x(n)) \to 0$ is strictly monotone

It is hence sufficient to check the decay of V in one time step

$\rightsquigarrow$ it is typically quite easy to check whether a given function is a Lyapunov function

But it is in general difficult to find a candidate for a Lyapunov function

Lyapunov functions — discussion

While the convergence $x(n) \to x_*$ is typically non-monotone for an asymptotically stable system, the convergence $V(x(n)) \to 0$ is strictly monotone

It is hence sufficient to check the decay of V in one time step

$\rightsquigarrow$ it is typically quite easy to check whether a given function is a Lyapunov function

But it is in general difficult to find a candidate for a Lyapunov function

For MPC, we will use the optimal value functions which we introduce in the next section

(2b) Background material: Dynamic Programming

Purpose of this section

We define the optimal value functions V_N for the optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

used within the MPC scheme (with $x_0 = x_{\mu_N}(n)$)

Purpose of this section

We define the optimal value functions V_N for the optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \;\; J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \;\; x_{\mathbf{u}}(0) = x_0$$

used within the MPC scheme (with $x_0 = x_{\mu_N}(n)$)

We present the dynamic programming principle, which establishes a relation for these functions and will eventually enable us to derive conditions under which V_N is a Lyapunov function

Optimal value functions

We define the optimal value function

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} J_N(x_0, \mathbf{u})$$

UNIVERSITÄT BAYREUTH

Optimal value functions

We define the optimal value function

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} J_N(x_0, \mathbf{u})$$

setting $V_N(x_0) := \infty$ if x_0 is not feasible, i.e., if there is no admissible $\mathbf{u}$

Optimal value functions

We define the optimal value function

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} J_N(x_0, \mathbf{u})$$

setting $V_N(x_0) := \infty$ if x_0 is not feasible, i.e., if there is no admissible $\mathbf{u}$ (recall: $\mathbf{u}$ admissible $\Leftrightarrow$ $x_{\mathbf{u}}(k) \in \mathbb{X}$, $\mathbf{u}(k) \in \mathbb{U}$)

Optimal value functions

We define the optimal value function

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} J_N(x_0, \mathbf{u})$$

setting $V_N(x_0) := \infty$ if x_0 is not feasible, i.e., if there is no admissible $\mathbf{u}$ (recall: $\mathbf{u}$ admissible $\Leftrightarrow$ $x_{\mathbf{u}}(k) \in \mathbb{X}$, $\mathbf{u}(k) \in \mathbb{U}$)

An admissible control sequence $\mathbf{u}^\star$ is called optimal, if

$$J_N(x_0, \mathbf{u}^\star) = V_N(x_0)$$

Optimal value functions

We define the optimal value function

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} J_N(x_0, \mathbf{u})$$

setting $V_N(x_0) := \infty$ if x_0 is not feasible, i.e., if there is no admissible $\mathbf{u}$ (recall: $\mathbf{u}$ admissible $\Leftrightarrow$ $x_{\mathbf{u}}(k) \in \mathbb{X}$, $\mathbf{u}(k) \in \mathbb{U}$)

An admissible control sequence $\mathbf{u}^\star$ is called optimal, if

$$J_N(x_0, \mathbf{u}^\star) = V_N(x_0)$$

Note: an optimal $\mathbf{u}^\star$ does not need to exist in general. In the sequel we assume that $\mathbf{u}^\star$ exists if x_0 is feasible

Dynamic Programming Principle

Theorem: (Dynamic Programming Principle) For any feasible $x_0 \in \mathbb{X}$ the optimal value function satisfies

$$V_N(x_0) = \inf_{\substack{u \in \mathbb{U} \\ f(x_0,u) \in \mathbb{X}}} \{\ell(x_0, u) + V_{N-1}(f(x_0, u))\}$$

Dynamic Programming Principle

Theorem: (Dynamic Programming Principle) For any feasible $x_0 \in \mathbb{X}$ the optimal value function satisfies

$$V_N(x_0) = \inf_{\substack{u \in \mathbb{U} \\ f(x_0,u) \in \mathbb{X}}} \{\ell(x_0, u) + V_{N-1}(f(x_0, u))\}$$

Moreover, if $\mathbf{u}^\star$ is an optimal control, then

$$V_N(x_0) = \ell(x_0, \mathbf{u}^*(0)) + V_{N-1}(f(x_0, \mathbf{u}^\star(0)))$$

holds.

Dynamic Programming Principle

Theorem: (Dynamic Programming Principle) For any feasible $x_0 \in \mathbb{X}$ the optimal value function satisfies

$$V_N(x_0) = \inf_{\substack{u \in \mathbb{U} \\ f(x_0,u) \in \mathbb{X}}} \{\ell(x_0,u) + V_{N-1}(f(x_0,u))\}$$

Moreover, if $\mathbf{u}^\star$ is an optimal control, then

$$V_N(x_0) = \ell(x_0, \mathbf{u}^*(0)) + V_{N-1}(f(x_0, \mathbf{u}^\star(0)))$$

holds.

Idea of Proof: Follows by taking infima in the identity

$$\begin{aligned} J_N(x_0, \mathbf{u}) &= \ell(x_\mathbf{u}(0), \mathbf{u}(0)) + \sum_{k=1}^{N-1} \ell(x_\mathbf{u}(k), \mathbf{u}(k)) \\ &= \ell(x_0, \mathbf{u}(0)) + J_{N-1}(f(x_0, \mathbf{u}(0)), \mathbf{u}(\cdot + 1)) \end{aligned}$$

UNIVERSITÄT BAYREUTH

Corollaries

Corollary: Let $x^\star$ be an optimal trajectory of length N with optimal control $u^\star$ and $x^\star(0) = x$.

Corollaries

Corollary: Let $x^\star$ be an optimal trajectory of length N with optimal control $u^\star$ and $x^\star(0) = x$. Then

(i) The "tail"

$$\big(x^\star(k), x^\star(k+1), \ldots, x^\star(N-1)\big)$$

is an optimal trajectory of length $N - k$.

Corollaries

Corollary: Let $x^\star$ be an optimal trajectory of length N with optimal control $u^\star$ and $x^\star(0) = x$. Then

(i) The "tail"

$$\big(x^\star(k), x^\star(k+1), \ldots, x^\star(N-1)\big)$$

is an optimal trajectory of length $N - k$.

(ii) The MPC feedback μ_N satisfies

$$\mu_N(x) = \operatorname*{argmin}_{u \in \mathbb{U}} \{\ell(x,u) + V_{N-1}(f(x,u))\}$$

(i.e., $u = \mu_N(x)$ minimizes this expression)

Corollaries

Corollary: Let $x^\star$ be an optimal trajectory of length N with optimal control $u^\star$ and $x^\star(0) = x$. Then

(i) The "tail"

$$\big(x^\star(k), x^\star(k+1), \ldots, x^\star(N-1)\big)$$

is an optimal trajectory of length $N - k$.

(ii) The MPC feedback μ_N satisfies

$$\mu_N(x) = \operatorname*{argmin}_{u \in \mathbb{U}} \{\ell(x,u) + V_{N-1}(f(x,u))\}$$

(i.e., $u = \mu_N(x)$ minimizes this expression),

$$V_N(x) = \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

Corollaries

Corollary: Let $x^\star$ be an optimal trajectory of length N with optimal control $u^\star$ and $x^\star(0) = x$. Then

(i) The "tail"

$$\big(x^\star(k), x^\star(k+1), \ldots, x^\star(N-1)\big)$$

is an optimal trajectory of length $N-k$.

(ii) The MPC feedback μ_N satisfies

$$\mu_N(x) = \operatorname*{argmin}_{u \in \mathbb{U}} \{\ell(x,u) + V_{N-1}(f(x,u))\}$$

(i.e., $u = \mu_N(x)$ minimizes this expression),

$$V_N(x) = \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

and

$$u^\star(k) = \mu_{N-k}(x^\star(k)), \quad k = 0, \ldots, N-1$$

Dynamic Programming Principle — discussion

We will see later, that under suitable conditions the optimal value function will play the role of a Lyapunov function for the MPC closed loop

Dynamic Programming Principle — discussion

We will see later, that under suitable conditions the optimal value function will play the role of a Lyapunov function for the MPC closed loop

The dynamic programming principle and its corollaries will prove to be important tools to establish this fact

Dynamic Programming Principle — discussion

We will see later, that under suitable conditions the optimal value function will play the role of a Lyapunov function for the MPC closed loop

The dynamic programming principle and its corollaries will prove to be important tools to establish this fact

In order to see why this can work, in the next section we briefly look at infinite horizon optimal control problems

Dynamic Programming Principle — discussion

We will see later, that under suitable conditions the optimal value function will play the role of a Lyapunov function for the MPC closed loop

The dynamic programming principle and its corollaries will prove to be important tools to establish this fact

In order to see why this can work, in the next section we briefly look at infinite horizon optimal control problems

Moreover, for simple systems the principle can be used for computing V_N and μ_N — we will see an example in the excercises

(2c) Background material:

Relaxed Dynamic Programming

Infinite horizon optimal control

Just like the finite horizon problem we can define the infinite horizon optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_\infty(x_0, \mathbf{u}) = \sum_{k=0}^{\infty} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

Infinite horizon optimal control

Just like the finite horizon problem we can define the infinite horizon optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_\infty(x_0,\mathbf{u}) = \sum_{k=0}^{\infty} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

and the corresponding optimal value function

$$V_\infty(x_0) := \inf_{\mathbf{u}\text{ admissible}} J_\infty(x_0,\mathbf{u})$$

Infinite horizon optimal control

Just like the finite horizon problem we can define the infinite horizon optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_\infty(x_0,\mathbf{u}) = \sum_{k=0}^{\infty} \ell(x_\mathbf{u}(k),\mathbf{u}(k)), \quad x_\mathbf{u}(0) = x_0$$

and the corresponding optimal value function

$$V_\infty(x_0) := \inf_{\mathbf{u}\text{ admissible}} J_\infty(x_0,\mathbf{u})$$

If we could compute an optimal feedback μ_∞ for this problem (which is — in contrast to computing μ_N — in general a very difficult problem), we would have solved the stabilization problem

Infinite horizon dynamic programming principle

Recall the corollary from the finite horizon dynamic programming principle

$$V_N(x) = \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

Infinite horizon dynamic programming principle

Recall the corollary from the finite horizon dynamic programming principle

$$V_N(x) = \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

The corresponding result which can be proved for the infinite horizon problem reads

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

Infinite horizon dynamic programming principle

Recall the corollary from the finite horizon dynamic programming principle

$$V_N(x) = \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

The corresponding result which can be proved for the infinite horizon problem reads

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

$\rightsquigarrow$ if $\ell(x, \mu_\infty(x)) \geq \alpha_V(\|x - x_*\|)$ holds, then we get

$$V_\infty(f(x, \mu_\infty(x))) \leq V_\infty(x) - \alpha_V(\|x - x_*\|)$$

UNIVERSITÄT BAYREUTH

Infinite horizon dynamic programming principle

Recall the corollary from the finite horizon dynamic programming principle

$$V_N(x) = \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

The corresponding result which can be proved for the infinite horizon problem reads

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

$\rightsquigarrow$ if $\ell(x, \mu_\infty(x)) \geq \alpha_V(\|x - x_*\|)$ holds, then we get

$$V_\infty(f(x, \mu_\infty(x))) \leq V_\infty(x) - \alpha_V(\|x - x_*\|)$$

and if in addition $\alpha_1(\|x - x_*\|) \leq V(x) \leq \alpha_2(\|x - x_*\|)$ holds, then V_∞ is a Lyapunov function

Infinite horizon dynamic programming principle

Recall the corollary from the finite horizon dynamic programming principle

$$V_N(x) = \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

The corresponding result which can be proved for the infinite horizon problem reads

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

$\rightsquigarrow$ if $\ell(x, \mu_\infty(x)) \geq \alpha_V(\|x - x_*\|)$ holds, then we get

$$V_\infty(f(x, \mu_\infty(x))) \leq V_\infty(x) - \alpha_V(\|x - x_*\|)$$

and if in addition $\alpha_1(\|x - x_*\|) \leq V(x) \leq \alpha_2(\|x - x_*\|)$ holds, then V_∞ is a Lyapunov function $\rightsquigarrow$ asymptotic stability

UNIVERSITÄT BAYREUTH

Relaxing dynamic programming

Unfortunately, an equation of the type

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

cannot be expected if we replace "∞" by "N" everywhere

Relaxing dynamic programming

Unfortunately, an equation of the type

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

cannot be expected if we replace "∞" by "N" everywhere (in fact, it would imply $V_N = V_\infty$)

Relaxing dynamic programming

Unfortunately, an equation of the type

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

cannot be expected if we replace "∞" by "N" everywhere (in fact, it would imply $V_N = V_\infty$)

However, we will see that we can establish relaxed versions of this inequality in which we

- relax "$=$" to "$\geq$"

Relaxing dynamic programming

Unfortunately, an equation of the type

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

cannot be expected if we replace "∞" by "N" everywhere (in fact, it would imply $V_N = V_\infty$)

However, we will see that we can establish relaxed versions of this inequality in which we

- relax "$=$" to "$\geq$"
- relax $\ell(x, \mu(x))$ to $\alpha\ell(x, \mu(x))$ for some $\alpha \in (0, 1]$

UNIVERSITÄT BAYREUTH

Relaxing dynamic programming

Unfortunately, an equation of the type

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

cannot be expected if we replace "∞" by "N" everywhere (in fact, it would imply $V_N = V_\infty$)

However, we will see that we can establish relaxed versions of this inequality in which we

- relax "$=$" to "$\geq$"
- relax $\ell(x, \mu(x))$ to $\alpha\ell(x, \mu(x))$ for some $\alpha \in (0, 1]$

$$\rightsquigarrow \quad V_N(x) \geq \alpha\ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

"relaxed dynamic programming inequality" [Rantzer et al. '06ff]

Relaxing dynamic programming

Unfortunately, an equation of the type

$$V_\infty(x) = \ell(x, \mu_\infty(x)) + V_\infty(f(x, \mu_\infty(x)))$$

cannot be expected if we replace "∞" by "N" everywhere (in fact, it would imply $V_N = V_\infty$)

However, we will see that we can establish relaxed versions of this inequality in which we

- relax "$=$" to "$\geq$"
- relax $\ell(x, \mu(x))$ to $\alpha\ell(x, \mu(x))$ for some $\alpha \in (0, 1]$

$$\rightsquigarrow \quad V_N(x) \geq \alpha\ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

"relaxed dynamic programming inequality" [Rantzer et al. '06ff]

What can we conclude from this inequality?

Relaxed dynamic programming

We define the infinite horizon performance of the MPC closed loop system $x^+ = f(x, \mu_N(x))$ as

$$J_\infty^{cl}(x_0, \mu_N) = \sum_{k=0}^{\infty} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))), \;\; x_{\mu_N}(0) = x_0$$

Relaxed dynamic programming

We define the infinite horizon performance of the MPC closed loop system $x^+ = f(x, \mu_N(x))$ as

$$J_\infty^{cl}(x_0, \mu_N) = \sum_{k=0}^{\infty} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))), \ \ x_{\mu_N}(0) = x_0$$

Theorem: [Gr./Rantzer '08, Gr./Pannek '11] Let $Y \subseteq \mathbb{X}$ be a forward invariant set for the MPC closed loop and assume that

$$V_N(x) \geq \alpha\ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

holds for all $x \in Y$ and some $N \in \mathbb{N}$ and $\alpha \in (0, 1]$

Relaxed dynamic programming

We define the infinite horizon performance of the MPC closed loop system $x^+ = f(x, \mu_N(x))$ as

$$J_\infty^{cl}(x_0, \mu_N) = \sum_{k=0}^{\infty} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))), \;\; x_{\mu_N}(0) = x_0$$

Theorem: [Gr./Rantzer '08, Gr./Pannek '11] Let $Y \subseteq \mathbb{X}$ be a forward invariant set for the MPC closed loop and assume that

$$V_N(x) \geq \alpha \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

holds for all $x \in Y$ and some $N \in \mathbb{N}$ and $\alpha \in (0, 1]$

Then for all $x \in Y$ the infinite horizon performance satisfies

$$J_\infty^{cl}(x_0, \mu_N) \leq V_N(x_0)/\alpha$$

UNIVERSITÄT BAYREUTH

Relaxed dynamic programming

Theorem (continued): If, moreover, there exists $\alpha_2, \alpha_3 \in \mathcal{K}_\infty$ such that the inequalities

$$V_N(x) \le \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x,u) \ge \alpha_3(\|x - x_*\|)$$

hold for all $x \in Y$, then the MPC closed loop is asymptotically stable on Y with Lyapunov function V_N.

Relaxed dynamic programming

Theorem (continued): If, moreover, there exists $\alpha_2, \alpha_3 \in \mathcal{K}_\infty$ such that the inequalities

$$V_N(x) \le \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x,u) \ge \alpha_3(\|x - x_*\|)$$

hold for all $x \in Y$, then the MPC closed loop is asymptotically stable on Y with Lyapunov function V_N.

Proof: The assumed inequalities immediately imply that $V = V_N$ is a Lyapunov function for $x^+ = g(x) = f(x, \mu_N(x))$ with

$$\alpha_1(r) = \alpha_3(r), \quad \alpha_V(r) = \alpha\, \alpha_3(r)$$

UNIVERSITÄT BAYREUTH

Relaxed dynamic programming

Theorem (continued): If, moreover, there exists $\alpha_2, \alpha_3 \in \mathcal{K}_\infty$ such that the inequalities

$$V_N(x) \le \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x,u) \ge \alpha_3(\|x - x_*\|)$$

hold for all $x \in Y$, then the MPC closed loop is asymptotically stable on Y with Lyapunov function V_N.

Proof: The assumed inequalities immediately imply that $V = V_N$ is a Lyapunov function for $x^+ = g(x) = f(x, \mu_N(x))$ with

$$\alpha_1(r) = \alpha_3(r), \quad \alpha_V(r) = \alpha\,\alpha_3(r)$$

$\Rightarrow$ asymptotic stability

UNIVERSITÄT BAYREUTH

Relaxed dynamic programming

For proving the performance estimate $J_\infty^{cl}(x_0, \mu_N) \leq V_N(x_0)/\alpha$, the relaxed dynamic programming inequality implies

$$
\begin{aligned}
& \alpha \sum_{n=0}^{K-1} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \\
\leq & \sum_{n=0}^{K-1} \Big(V_N(x_{\mu_N}(n)) - V_N(x_{\mu_N}(n+1)) \Big) \\
= & \; V_N(x_{\mu_N}(0)) - V_N(x_{\mu_N}(K)) \;\leq\; V_N(x_{\mu_N}(0))
\end{aligned}
$$

Relaxed dynamic programming

For proving the performance estimate $J_\infty^{cl}(x_0, \mu_N) \le V_N(x_0)/\alpha$, the relaxed dynamic programming inequality implies

$$\begin{aligned}
&\alpha \sum_{n=0}^{K-1} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \\
\le\ & \sum_{n=0}^{K-1} \Big(V_N(x_{\mu_N}(n)) - V_N(x_{\mu_N}(n+1)) \Big) \\
=\ & V_N(x_{\mu_N}(0)) - V_N(x_{\mu_N}(K)) \ \le\ V_N(x_{\mu_N}(0))
\end{aligned}$$

Since all summands are ≥ 0, this implies that the limit for $K \to \infty$ exists and we get

$$\alpha J_\infty^{cl}(x_0, \mu_N) = \alpha \sum_{n=0}^{\infty} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \le V_N(x_{\mu_N}(0))$$

Relaxed dynamic programming

For proving the performance estimate $J_\infty^{cl}(x_0, \mu_N) \le V_N(x_0)/\alpha$, the relaxed dynamic programming inequality implies

$$
\begin{aligned}
&\alpha \sum_{n=0}^{K-1} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \\
\le\ & \sum_{n=0}^{K-1} \Big(V_N(x_{\mu_N}(n)) - V_N(x_{\mu_N}(n+1)) \Big) \\
=\ & V_N(x_{\mu_N}(0)) - V_N(x_{\mu_N}(K)) \ \le\ V_N(x_{\mu_N}(0))
\end{aligned}
$$

Since all summands are ≥ 0, this implies that the limit for $K \to \infty$ exists and we get

$$\alpha J_\infty^{cl}(x_0, \mu_N) = \alpha \sum_{n=0}^{\infty} \ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \le V_N(x_{\mu_N}(0))$$

$\Rightarrow$ assertion

Summary of Section (2)

- Lyapunov functions are our central tool for verifying asymptotic stability

Summary of Section (2)

- Lyapunov functions are our central tool for verifying asymptotic stability
- Dynamic programming provides us with equations which will be heavily used in the subsequent analysis

Summary of Section (2)

- Lyapunov functions are our central tool for verifying asymptotic stability
- Dynamic programming provides us with equations which will be heavily used in the subsequent analysis
- Infinite horizon optimal control would solve the stabilization problem — if we could compute the feedback law μ_∞

Summary of Section (2)

- Lyapunov functions are our central tool for verifying asymptotic stability
- Dynamic programming provides us with equations which will be heavily used in the subsequent analysis
- Infinite horizon optimal control would solve the stabilization problem — if we could compute the feedback law μ_∞
- The performance of the MPC controller can be measured by looking at the infinite horizon value along the MPC closed loop trajectories

Summary of Section (2)

- Lyapunov functions are our central tool for verifying asymptotic stability
- Dynamic programming provides us with equations which will be heavily used in the subsequent analysis
- Infinite horizon optimal control would solve the stabilization problem — if we could compute the feedback law μ_∞
- The performance of the MPC controller can be measured by looking at the infinite horizon value along the MPC closed loop trajectories
- Relaxed dynamic programming gives us conditions under which both asymptotic stability and performance results can be derived

Application of background results

The main task will be to verify the assumptions of the relaxed dynamic programming theorem, i.e.,

$$V_N(x) \geq \alpha\ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

for some $\alpha \in (0, 1]$, and

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

for all x in a forward invariant set Y for $x^+ = f(x, \mu_N(x))$

Application of background results

The main task will be to verify the assumptions of the relaxed dynamic programming theorem, i.e.,

$$V_N(x) \geq \alpha \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

for some $\alpha \in (0, 1]$, and

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

for all x in a forward invariant set Y for $x^+ = f(x, \mu_N(x))$

To this end, we present two different approaches:

- modify the optimal control problem in the MPC loop by adding terminal constraints and costs

Application of background results

The main task will be to verify the assumptions of the relaxed dynamic programming theorem, i.e.,

$$V_N(x) \geq \alpha \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

for some $\alpha \in (0, 1]$, and

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

for all x in a forward invariant set Y for $x^+ = f(x, \mu_N(x))$

To this end, we present two different approaches:

- modify the optimal control problem in the MPC loop by adding terminal constraints and costs
- derive assumptions on f and ℓ under which MPC works without terminal constraints and costs

(3) Stability with stabilizing constraints

V_N as a Lyapunov Function

Problem: Prove that the MPC feedback law μ_N is stabilizing

V_N as a Lyapunov Function

Problem: Prove that the MPC feedback law μ_N is stabilizing

Approach: Verify the assumptions

$$V_N(x) \geq \alpha \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

for some $\alpha \in (0, 1]$, and

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

of the relaxed dynamic programming theorem for the optimal value function

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \ \ x_{\mathbf{u}}(0) = x_0$$

Why is this difficult?

Why is this difficult?

Let us first consider the inequality

$$V_N(x) \geq \alpha \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

Why is this difficult?

Let us first consider the inequality

$$V_N(x) \geq \alpha \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

The dynamic programming principle for V_N yields

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

Why is this difficult?

Let us first consider the inequality

$$V_N(x) \geq \alpha \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

The dynamic programming principle for V_N yields

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

$\rightsquigarrow$ we have V_{N-1} where we would like to have V_N

Why is this difficult?

Let us first consider the inequality

$$V_N(x) \geq \alpha\ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

The dynamic programming principle for V_N yields

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

$\rightsquigarrow$ we have V_{N-1} where we would like to have V_N

$\rightsquigarrow$ we would get the desired inequality if we could ensure

$$V_{N-1}(f(x, \mu_N(x))) \geq V_N(f(x, \mu_N(x))) + \text{“small error”}$$

Why is this difficult?

Let us first consider the inequality

$$V_N(x) \geq \alpha\ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

The dynamic programming principle for V_N yields

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

$\rightsquigarrow$ we have V_{N-1} where we would like to have V_N

$\rightsquigarrow$ we would get the desired inequality if we could ensure

$$V_{N-1}(f(x, \mu_N(x))) \geq V_N(f(x, \mu_N(x))) + \text{“small error”}$$

(where “small” means that the error can be compensated replacing $\ell(x, \mu_N(x))$ by $\alpha\ell(x, \mu_N(x))$ with $\alpha \in (0, 1)$)

Why is this difficult?

Task: Find conditions under which

$$V_{N-1}(f(x, \mu_N(x))) \geq V_N(f(x, \mu_N(x))) + \text{“small error”}$$

holds

Why is this difficult?

Task: Find conditions under which

$$V_{N-1}(f(x,\mu_N(x))) \geq V_N(f(x,\mu_N(x))) + \text{“small error”}$$

holds

For

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

this appeared to be out of reach until the mid 1990s

Why is this difficult?

Task: Find conditions under which

$$V_{N-1}(f(x,\mu_N(x))) \geq V_N(f(x,\mu_N(x))) + \text{“small error”}$$

holds

For

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \;\; x_{\mathbf{u}}(0) = x_0$$

this appeared to be out of reach until the mid 1990s

Note: $V_{N-1} \leq V_N$ by non-negativity of ℓ; typically with strict “$<$”

Why is this difficult?

Task: Find conditions under which

$$V_{N-1}(f(x,\mu_N(x))) \ge V_N(f(x,\mu_N(x))) + \text{“small error”}$$

holds

For

$$V_N(x_0) := \inf_{\mathbf{u} \text{ admissible}} \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \;\; x_{\mathbf{u}}(0) = x_0$$

this appeared to be out of reach until the mid 1990s

Note: $V_{N-1} \le V_N$ by non-negativity of ℓ; typically with strict “$<$”

$\rightsquigarrow$ additional stabilizing constraints were proposed

(3a) Equilibrium terminal constraint

Equilibrium terminal constraint

Optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0,\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

Equilibrium terminal constraint

Optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

Assumption: $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$

Equilibrium terminal constraint

Optimal control problem

$$\underset{\mathbf{u} \text{ admissible}}{\text{minimize}} \quad J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

Assumption: $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$

Idea: add equilibrium terminal constraint

$$x_{\mathbf{u}}(N) = x_*$$

[Keerthi/Gilbert '88, ...]

UNIVERSITÄT BAYREUTH

Equilibrium terminal constraint

Optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

Assumption: $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$

Idea: add equilibrium terminal constraint

$$x_{\mathbf{u}}(N) = x_*$$

[Keerthi/Gilbert '88, ...]

$\rightsquigarrow$ we now solve

$$\underset{\mathbf{u}\in\mathbb{U}^N_{x_*}(x_0)}{\text{minimize}} \quad J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

with $\mathbb{U}^N_{x_*}(x_0) := \{\mathbf{u} \in \mathbb{U}^N \text{ admissible and } x_{\mathbf{u}}(N) = x_*\}$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0)$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}_{x_*}^{N-1}(x_0) \quad \Rightarrow \quad x_{\tilde{\mathbf{u}}}(N-1) = x_*$

UNIVERSITÄT BAYREUTH

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0) \quad \Rightarrow \quad x_{\tilde{\mathbf{u}}}(N-1) = x_*$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \dots, N-2 \\ 0, & k = N-1 \end{cases}$

UNIVERSITÄT BAYREUTH

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0) \quad \Rightarrow \quad x_{\tilde{\mathbf{u}}}(N-1) = x_*$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \ldots, N-2 \\ 0, & k = N-1 \end{cases}$

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(x_*, 0) = x_*$$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0) \quad \Rightarrow \quad x_{\tilde{\mathbf{u}}}(N-1) = x_*$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \ldots, N-2 \\ 0, & k = N-1 \end{cases}$

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(x_*, 0) = x_*$$

$$\Rightarrow \quad \mathbf{u}_N \in \mathbb{U}^N_{x_*}(x_0)$$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0) \quad \Rightarrow \quad x_{\tilde{\mathbf{u}}}(N-1) = x_*$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \dots, N-2 \\ 0, & k = N-1 \end{cases}$

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(x_*, 0) = x_*$$

$$\Rightarrow \quad \mathbf{u}_N \in \mathbb{U}^N_{x_*}(x_0)$$

$\rightsquigarrow$ every $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0)$ can be prolonged to an $\mathbf{u}_N \in \mathbb{U}^N_{x_*}(x_0)$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0) \quad \Rightarrow \quad x_{\tilde{\mathbf{u}}}(N-1) = x_*$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \ldots, N-2 \\ 0, & k = N-1 \end{cases}$

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(x_*, 0) = x_*$$

$$\Rightarrow \quad \mathbf{u}_N \in \mathbb{U}^N_{x_*}(x_0)$$

$\rightsquigarrow$ every $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{x_*}(x_0)$ can be prolonged to an $\mathbf{u}_N \in \mathbb{U}^N_{x_*}(x_0)$

Moreover, since

$$\ell(x_{\mathbf{u}_N}(N-1), \mathbf{u}_N(N-1)) = \ell(x_*, 0) = 0,$$

the prolongation has zero stage cost

UNIVERSITÄT BAYREUTH

Reversal of $V_{N-1} \leq V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}_{x_*}^{N-1}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Reversal of $V_{N-1} \leq V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^N_{x_*}(x_0)$ its prolongation

Reversal of $V_{N-1} \leq V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) \;=\; J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Reversal of $V_{N-1} \leq V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) \; = \; J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) \; = \; \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

UNIVERSITÄT BAYREUTH

Reversal of $V_{N-1} \le V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) = \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

$$= \sum_{n=0}^{N-2} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + \underbrace{\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1))}_{=0}$$

Reversal of $V_{N-1} \leq V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) = \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

$$= \sum_{n=0}^{N-2} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + \underbrace{\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1))}_{=0}$$

$$= \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k))$$

Reversal of $V_{N-1} \le V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) = \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

$$= \sum_{n=0}^{N-2} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + \underbrace{\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1))}_{=0}$$

$$= \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) = J_N(x_0, \mathbf{u})$$

Reversal of $V_{N-1} \le V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) = \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

$$= \sum_{n=0}^{N-2} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + \underbrace{\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1))}_{=0}$$

$$= \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) = J_N(x_0, \mathbf{u}) \ge V_N(x_0)$$

Reversal of $V_{N-1} \leq V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^N_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) = \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

$$= \sum_{n=0}^{N-2} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + \underbrace{\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1))}_{=0}$$

$$= \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) = J_N(x_0, \mathbf{u}) \geq V_N(x_0)$$

$\rightsquigarrow$ The inequality $V_{N-1} \leq V_N$ is reversed to $V_{N-1} \geq V_N$

Reversal of $V_{N-1} \le V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^N_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) = \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

$$= \sum_{n=0}^{N-2} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + \underbrace{\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1))}_{=0}$$

$$= \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) = J_N(x_0, \mathbf{u}) \ge V_N(x_0)$$

$\rightsquigarrow$ The inequality $V_{N-1} \le V_N$ is reversed to $V_{N-1} \ge V_N$

Note: $V_{N-1} \le V_N$ does no longer hold now

Reversal of $V_{N-1} \le V_N$

Now, let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{x_*}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^N_{x_*}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) = \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k))$$

$$= \sum_{n=0}^{N-2} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + \underbrace{\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1))}_{=0}$$

$$= \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) = J_N(x_0, \mathbf{u}) \ge V_N(x_0)$$

$\rightsquigarrow$ The inequality $V_{N-1} \le V_N$ is reversed to $V_{N-1} \ge V_N$

Note: $V_{N-1} \le V_N$ does no longer hold now

But: the dynamic programming principle remains valid

Relaxed dynamic programming inequality

From the reversed inequality

$$V_{N-1}(x) \geq V_N(x)$$

and the dynamic programming principle

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

we immediately get

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

Relaxed dynamic programming inequality

From the reversed inequality

$$V_{N-1}(x) \geq V_N(x)$$

and the dynamic programming principle

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

we immediately get

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

This is exactly the desired relaxed dynamic programming inequality, even with $\alpha = 1$, since no "small error" occurs

Relaxed dynamic programming inequality

From the reversed inequality

$$V_{N-1}(x) \geq V_N(x)$$

and the dynamic programming principle

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_{N-1}(f(x, \mu_N(x)))$$

we immediately get

$$V_N(x) \geq \ell(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

This is exactly the desired relaxed dynamic programming inequality, even with $\alpha = 1$, since no "small error" occurs

$\rightsquigarrow$ stability follows if we can ensure the additional inequalities

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

Feasible sets

The inequality $\inf_{u \in \mathbb{U}} \ell(x,u) \geq \alpha_3(\|x - x_*\|)$ is easy to satisfy

Feasible sets

The inequality $\inf_{u\in\mathbb{U}} \ell(x,u) \geq \alpha_3(\|x - x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ will work (with $\alpha_3(r) = r^2$)

UNIVERSITÄT BAYREUTH

Feasible sets

The inequality $\inf_{u\in\mathbb{U}} \ell(x,u) \geq \alpha_3(\|x-x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x-x_*\|^2 + \lambda\|u\|^2$ will work (with $\alpha_3(r) = r^2$)

What about $V_N(x) \leq \alpha_2(\|x-x_*\|)$?

Feasible sets

The inequality $\inf_{u\in\mathbb{U}} \ell(x,u) \geq \alpha_3(\|x - x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ will work (with $\alpha_3(r) = r^2$)

What about $V_N(x) \leq \alpha_2(\|x - x_*\|)$?

Recall: by definition $V_N(x) = \infty$ if x is not feasible

Feasible sets

The inequality $\inf_{u \in \mathbb{U}} \ell(x,u) \geq \alpha_3(\|x - x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ will work (with $\alpha_3(r) = r^2$)

What about $V_N(x) \leq \alpha_2(\|x - x_*\|)$?

Recall: by definition $V_N(x) = \infty$ if x is not feasible, i.e., if there is no $\mathbf{u} \in \mathbb{U}^N_{x_*}(x)$

Feasible sets

The inequality $\inf_{u\in\mathbb{U}} \ell(x,u) \geq \alpha_3(\|x-x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x-x_*\|^2 + \lambda\|u\|^2$ will work (with $\alpha_3(r) = r^2$)

What about $V_N(x) \leq \alpha_2(\|x-x_*\|)$?

Recall: by definition $V_N(x) = \infty$ if x is not feasible, i.e., if there is no $\mathbf{u} \in \mathbb{U}^N_{x_*}(x)$

$\rightsquigarrow$ define the feasible set $\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \mathbb{U}^N_{x_*}(x) \neq \emptyset\}$

Feasible sets

The inequality $\inf_{u \in \mathbb{U}} \ell(x,u) \geq \alpha_3(\|x - x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x - x_*\|^2 + \lambda \|u\|^2$ will work (with $\alpha_3(r) = r^2$)

What about $V_N(x) \leq \alpha_2(\|x - x_*\|)$?

Recall: by definition $V_N(x) = \infty$ if x is not feasible, i.e., if there is no $\mathbf{u} \in \mathbb{U}^N_{x_*}(x)$

$\rightsquigarrow$ define the feasible set $\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \mathbb{U}^N_{x_*}(x) \neq \emptyset\}$

For $x \notin \mathbb{X}_N$ the inequality $V_N(x) \leq \alpha_2(\|x - x_*\|)$ cannot hold

Feasible sets

The inequality $\inf_{u\in\mathbb{U}} \ell(x,u) \geq \alpha_3(\|x-x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x-x_*\|^2 + \lambda\|u\|^2$ will work (with $\alpha_3(r) = r^2$)

What about $V_N(x) \leq \alpha_2(\|x-x_*\|)$?

Recall: by definition $V_N(x) = \infty$ if x is not feasible, i.e., if there is no $\mathbf{u} \in \mathbb{U}^N_{x_*}(x)$

$\rightsquigarrow$ define the feasible set $\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \mathbb{U}^N_{x_*}(x) \neq \emptyset\}$

For $x \notin \mathbb{X}_N$ the inequality $V_N(x) \leq \alpha_2(\|x-x_*\|)$ cannot hold

But: for all $x \in \mathbb{X}_N$ we can ensure this inequality under rather mild conditions (details can be given if desired)

UNIVERSITÄT BAYREUTH

Feasible sets

The inequality $\inf_{u\in\mathbb{U}} \ell(x,u) \ge \alpha_3(\|x-x_*\|)$ is easy to satisfy, e.g., $\ell(x,u) = \|x-x_*\|^2 + \lambda\|u\|^2$ will work (with $\alpha_3(r) = r^2$)

What about $V_N(x) \le \alpha_2(\|x-x_*\|)$?

Recall: by definition $V_N(x) = \infty$ if x is not feasible, i.e., if there is no $\mathbf{u} \in \mathbb{U}^N_{x_*}(x)$

$\rightsquigarrow$ define the feasible set $\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \mathbb{U}^N_{x_*}(x) \neq \emptyset\}$

For $x \notin \mathbb{X}_N$ the inequality $V_N(x) \le \alpha_2(\|x-x_*\|)$ cannot hold

But: for all $x \in \mathbb{X}_N$ we can ensure this inequality under rather mild conditions (details can be given if desired)

$\rightsquigarrow$ the feasible set $\mathbb{X}_N$ is the "natural" operating region of MPC with equilbrium terminal constraints

Stability theorem

Theorem: Consider the MPC scheme with equilibrium terminal constraint $x_{\mathbf{u}}(N) = x_*$ where x_* satisfies $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$.

Stability theorem

Theorem: Consider the MPC scheme with equilibrium terminal constraint $x_{\mathbf{u}}(N) = x_*$ where x_* satisfies $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$. Assume that

$$V_N(x) \le \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \ge \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

UNIVERSITÄT BAYREUTH

Stability theorem

Theorem: Consider the MPC scheme with equilibrium terminal constraint $x_{\mathbf{u}}(N) = x_*$ where x_* satisfies $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$. Assume that

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant

UNIVERSITÄT BAYREUTH

Stability theorem

Theorem: Consider the MPC scheme with equilibrium terminal constraint $x_{\mathbf{u}}(N) = x_*$ where x_* satisfies $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$. Assume that

$$V_N(x) \le \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \ge \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant, the MPC closed loop is asymptotically stable on $\mathbb{X}_N$

UNIVERSITÄT BAYREUTH

Stability theorem

Theorem: Consider the MPC scheme with equilibrium terminal constraint $x_{\mathbf{u}}(N) = x_*$ where x_* satisfies $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$. Assume that

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant, the MPC closed loop is asymptotically stable on $\mathbb{X}_N$ and the performance estimate

$$J_\infty^{cl}(x, \mu_N) \leq V_N(x)$$

holds.

Stability theorem

Theorem: Consider the MPC scheme with equilibrium terminal constraint $x_{\mathbf{u}}(N) = x_*$ where x_* satisfies $f(x_*, 0) = x_*$ and $\ell(x_*, 0) = 0$. Assume that

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant, the MPC closed loop is asymptotically stable on $\mathbb{X}_N$ and the performance estimate

$$J_\infty^{cl}(x, \mu_N) \leq V_N(x)$$

holds.

Note: The constraint $x_{\mathbf{u}}(N) = x_*$ does not imply $x_{\mu_N}(N) = x_*$

Stability theorem — sketch of proof

Sketch of proof: All assertions follow from the relaxed dynamic programming theorem if we prove forward invariance of $\mathbb{X}_N$ for the MPC closed loop system $x^+ = f(x, \mu_N(x))$

UNIVERSITÄT BAYREUTH

Stability theorem — sketch of proof

Sketch of proof: All assertions follow from the relaxed dynamic programming theorem if we prove forward invariance of $\mathbb{X}_N$ for the MPC closed loop system $x^+ = f(x, \mu_N(x))$

$\rightsquigarrow$ we need to prove $x \in \mathbb{X}_N \Rightarrow x^+ \in \mathbb{X}_N$

Stability theorem — sketch of proof

Sketch of proof: All assertions follow from the relaxed dynamic programming theorem if we prove forward invariance of $\mathbb{X}_N$ for the MPC closed loop system $x^+ = f(x, \mu_N(x))$

$\rightsquigarrow$ we need to prove $x \in \mathbb{X}_N \Rightarrow x^+ \in \mathbb{X}_N$

(1) The prolongation property implies $\mathbb{X}_{N-1} \subseteq \mathbb{X}_N$

UNIVERSITÄT BAYREUTH

Stability theorem — sketch of proof

Sketch of proof: All assertions follow from the relaxed dynamic programming theorem if we prove forward invariance of $\mathbb{X}_N$ for the MPC closed loop system $x^+ = f(x, \mu_N(x))$

$\rightsquigarrow$ we need to prove $x \in \mathbb{X}_N \Rightarrow x^+ \in \mathbb{X}_N$

(1) The prolongation property implies $\mathbb{X}_{N-1} \subseteq \mathbb{X}_N$

(2) For $x \in \mathbb{X}_N$, the definition $\mu_N(x) := \mathbf{u}^\star(0)$ implies

$$x^+ = f(x, \mu_N(x)) = f(x, u^\star(0)) = x^\star(1)$$

Stability theorem — sketch of proof

Sketch of proof: All assertions follow from the relaxed dynamic programming theorem if we prove forward invariance of $\mathbb{X}_N$ for the MPC closed loop system $x^+ = f(x, \mu_N(x))$

$\rightsquigarrow$ we need to prove $x \in \mathbb{X}_N \Rightarrow x^+ \in \mathbb{X}_N$

(1) The prolongation property implies $\mathbb{X}_{N-1} \subseteq \mathbb{X}_N$

(2) For $x \in \mathbb{X}_N$, the definition $\mu_N(x) := \mathbf{u}^\star(0)$ implies

$$x^+ = f(x, \mu_N(x)) = f(x, u^\star(0)) = x^\star(1)$$

and since $x^\star(N) = x_*$, the sequence $(x^\star(1), \ldots, x^\star(N))$ is an admissible trajectory of length $N-1$ from $x^\star(1) = x^+$ to $x^\star(N) = x_*$

(3) This implies $x^+ \in \mathbb{X}_{N-1}$

Stability theorem — sketch of proof

Sketch of proof: All assertions follow from the relaxed dynamic programming theorem if we prove forward invariance of $\mathbb{X}_N$ for the MPC closed loop system $x^+ = f(x, \mu_N(x))$

$\rightsquigarrow$ we need to prove $x \in \mathbb{X}_N \Rightarrow x^+ \in \mathbb{X}_N$

(1) The prolongation property implies $\mathbb{X}_{N-1} \subseteq \mathbb{X}_N$

(2) For $x \in \mathbb{X}_N$, the definition $\mu_N(x) := \mathbf{u}^\star(0)$ implies

$$x^+ = f(x, \mu_N(x)) = f(x, u^\star(0)) = x^\star(1)$$

and since $x^\star(N) = x_*$, the sequence $(x^\star(1), \ldots, x^\star(N))$ is an admissible trajectory of length $N-1$ from $x^\star(1) = x^+$ to $x^\star(N) = x_*$

(3) This implies $x^+ \in \mathbb{X}_{N-1} \subseteq \mathbb{X}_N$

Equilibrium terminal constraint — Discussion

The additional condition

$$x(N) = x_*$$

ensures asymptotic stability in a rigorously provable way

Equilibrium terminal constraint — Discussion

The additional condition

$$x(N) = x_*$$

ensures asymptotic stability in a rigorously provable way, but

- online optimization may become harder

UNIVERSITÄT BAYREUTH

Equilibrium terminal constraint — Discussion

The additional condition

$$x(N) = x_*$$

ensures asymptotic stability in a rigorously provable way, but

- online optimization may become harder
- if we want a large feasible set $\mathbb{X}_N$ we typically need a large optimization horizon N

Equilibrium terminal constraint — Discussion

The additional condition

$$x(N) = x_*$$

ensures asymptotic stability in a rigorously provable way, but

- online optimization may become harder
- if we want a large feasible set $\mathbb{X}_N$ we typically need a large optimization horizon N
  (see the car-and-mountains example)

UNIVERSITÄT BAYREUTH

Equilibrium terminal constraint — Discussion

The additional condition

$$x(N) = x_*$$

ensures asymptotic stability in a rigorously provable way, but

- online optimization may become harder
- if we want a large feasible set $\mathbb{X}_N$ we typically need a large optimization horizon N
  (see the car-and-mountains example)
- system needs to be controllable to x_* in finite time

Equilibrium terminal constraint — Discussion

The additional condition

$$x(N) = x_*$$

ensures asymptotic stability in a rigorously provable way, but

- online optimization may become harder
- if we want a large feasible set $\mathbb{X}_N$ we typically need a large optimization horizon N
  (see the car-and-mountains example)
- system needs to be controllable to x_* in finite time
- not very often used in industrial practice

UNIVERSITÄT
BAYREUTH

(3b) Regional terminal constraint and terminal cost

Regional constraint and terminal cost

Optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

Regional constraint and terminal cost

Optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

We want V_N to become a Lyapunov function

Regional constraint and terminal cost

Optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0,\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

We want V_N to become a Lyapunov function

Idea: add local Lyapunov function $F : \mathbb{X}_0 \to \mathbb{R}_0^+$ as terminal cost

$$J_N(x_0,u) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)) + F(x_{\mathbf{u}}(N))$$

Regional constraint and terminal cost

Optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0,\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0$$

We want V_N to become a Lyapunov function

Idea: add local Lyapunov function $F : \mathbb{X}_0 \to \mathbb{R}_0^+$ as terminal cost

$$J_N(x_0,u) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)) + F(x_{\mathbf{u}}(N))$$

F is defined on a region $\mathbb{X}_0$ around x_* which is imposed as terminal constraint $\quad x(N) \in \mathbb{X}_0$

[Chen & Allgöwer '98, Jadbabaie et al. '98 ...]

Regional constraint and terminal cost

We thus change the optimal control problem to

$$\underset{\mathbf{u}\in\mathbb{U}^N_{\mathbb{X}_0}(x_0)}{\text{minimize}} \quad J_N(x_0,\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)) \; + \; F(x_{\mathbf{u}}(N))$$

with

$$\mathbb{U}^N_{\mathbb{X}_0}(x_0) := \{\mathbf{u} \in \mathbb{U}^N \text{ admissible and } x_{\mathbf{u}}(N) \in \mathbb{X}_0\}$$

Regional constraint and terminal cost

We thus change the optimal control problem to

$$\underset{\mathbf{u}\in\mathbb{U}^N_{\mathbb{X}_0}(x_0)}{\text{minimize}} \;\; J_N(x_0,\mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_\mathbf{u}(k),\mathbf{u}(k)) \; + \; F(x_\mathbf{u}(N))$$

with

$$\mathbb{U}^N_{\mathbb{X}_0}(x_0) := \{\mathbf{u}\in\mathbb{U}^N \text{ admissible and } x_\mathbf{u}(N)\in\mathbb{X}_0\}$$

Which properties do we need for F and $\mathbb{X}_0$ in order to make this work?

Regional constraint and terminal cost

Assumptions on $F : \mathbb{X}_0 \to \mathbb{R}_0^+$ and $\mathbb{X}_0$

Regional constraint and terminal cost

Assumptions on $F : \mathbb{X}_0 \to \mathbb{R}_0^+$ and $\mathbb{X}_0$

There exists a controller $\kappa : \mathbb{X}_0 \to \mathbb{U}$ with the following properties:

Regional constraint and terminal cost

Assumptions on $F : \mathbb{X}_0 \to \mathbb{R}_0^+$ and $\mathbb{X}_0$

There exists a controller $\kappa : \mathbb{X}_0 \to \mathbb{U}$ with the following properties:

(i) $\mathbb{X}_0$ is forward invariant for $x^+ = f(x, \kappa(x))$:
for each $x \in \mathbb{X}_0$ we have $f(x, \kappa(x)) \in \mathbb{X}_0$

Regional constraint and terminal cost

Assumptions on $F : \mathbb{X}_0 \to \mathbb{R}_0^+$ and $\mathbb{X}_0$

There exists a controller $\kappa : \mathbb{X}_0 \to \mathbb{U}$ with the following properties:

(i) $\mathbb{X}_0$ is forward invariant for $x^+ = f(x, \kappa(x))$:
for each $x \in \mathbb{X}_0$ we have $f(x, \kappa(x)) \in \mathbb{X}_0$

(ii) F is a Lyapunov function for $x^+ = f(x, \kappa(x))$ on $\mathbb{X}_0$ which is compatible with the stage cost ℓ in the following sense:
for each $x \in \mathbb{X}_0$ the inequality

$$F(f(x, \kappa(x))) \le F(x) - \ell(x, \kappa(x))$$

holds

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0) \quad \Rightarrow \quad \tilde{x} := x_{\tilde{\mathbf{u}}}(N-1) \in \mathbb{X}_0$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0) \quad \Rightarrow \quad \tilde{x} := x_{\tilde{\mathbf{u}}}(N-1) \in \mathbb{X}_0$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \ldots, N-2 \\ \kappa(\tilde{x}), & k = N-1 \end{cases}$

with κ from (i)

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0) \quad \Rightarrow \quad \tilde{x} := x_{\tilde{\mathbf{u}}}(N-1) \in \mathbb{X}_0$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \ldots, N-2 \\ \kappa(\tilde{x}), & k = N-1 \end{cases}$

with κ from (i)

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(\tilde{x}, \kappa(\tilde{x})) \in \mathbb{X}_0$$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0) \quad \Rightarrow \quad \tilde{x} := x_{\tilde{\mathbf{u}}}(N-1) \in \mathbb{X}_0$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \dots, N-2 \\ \kappa(\tilde{x}), & k = N-1 \end{cases}$

with κ from (i)

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(\tilde{x}, \kappa(\tilde{x})) \in \mathbb{X}_0$$

$$\Rightarrow \quad \mathbf{u} \in \mathbb{U}^N_{\mathbb{X}_0}(x_0)$$

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0) \quad \Rightarrow \quad \tilde{x} := x_{\tilde{\mathbf{u}}}(N-1) \in \mathbb{X}_0$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \ldots, N-2 \\ \kappa(\tilde{x}), & k = N-1 \end{cases}$

with κ from (i)

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(\tilde{x}, \kappa(\tilde{x})) \in \mathbb{X}_0$$

$$\Rightarrow \quad \mathbf{u} \in \mathbb{U}^N_{\mathbb{X}_0}(x_0)$$

$\rightsquigarrow$ every $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ can be prolonged to an $\mathbf{u} \in \mathbb{U}^N_{\mathbb{X}_0}(x_0)$

UNIVERSITÄT BAYREUTH

Prolongation of control sequences

Let $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0) \quad \Rightarrow \quad \tilde{x} := x_{\tilde{\mathbf{u}}}(N-1) \in \mathbb{X}_0$

Define $\mathbf{u} \in \mathbb{U}^N$ as $\mathbf{u}(k) := \begin{cases} \tilde{\mathbf{u}}(k), & k = 0, \ldots, N-2 \\ \kappa(\tilde{x}), & k = N-1 \end{cases}$

with κ from (i)

$$\Rightarrow \quad x_{\mathbf{u}}(N) = f(x_{\tilde{\mathbf{u}}}(N-1), \mathbf{u}(N-1)) = f(\tilde{x}, \kappa(\tilde{x})) \in \mathbb{X}_0$$

$$\Rightarrow \quad \mathbf{u} \in \mathbb{U}^N_{\mathbb{X}_0}(x_0)$$

$\rightsquigarrow$ every $\tilde{\mathbf{u}} \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ can be prolonged to an $\mathbf{u} \in \mathbb{U}^N_{\mathbb{X}_0}(x_0)$

By (ii) the stage cost of the prolongation is bounded by

$$\ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1)) \leq F(x_{\mathbf{u}}(N-1)) - F(x_{\mathbf{u}}(N))$$

Reversal of $V_{N-1} \leq V_N$

Let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

UNIVERSITÄT BAYREUTH

Reversal of $V_{N-1} \leq V_N$

Let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{\mathbb{X}_0}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

$$= \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k)) + \qquad F(x_{\tilde{\mathbf{u}}^\star}(N-1))$$

Reversal of $V_{N-1} \le V_N$

Let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{\mathbb{X}_0}(x_0)$ its prolongation

$$\Rightarrow \quad V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$
$$= \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k)) + \underbrace{F(x_{\tilde{\mathbf{u}}^\star}(N-1))}_{\ge \ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1)) + F(x_{\mathbf{u}}(N))}$$

Reversal of $V_{N-1} \le V_N$

Let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{\mathbb{X}_0}(x_0)$ its prolongation

$$\begin{aligned}
\Rightarrow \qquad V_{N-1}(x_0) &= J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) \\
&= \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k)) + \underbrace{F(x_{\tilde{\mathbf{u}}^\star}(N-1))}_{\ge \ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1)) + F(x_{\mathbf{u}}(N))} \\
&\ge \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + F(x_{\mathbf{u}}(N))
\end{aligned}$$

Reversal of $V_{N-1} \leq V_N$

Let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^N_{\mathbb{X}_0}(x_0)$ its prolongation

$$\begin{aligned}
\Rightarrow \quad V_{N-1}(x_0) &= J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) \\
&= \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k)) + \underbrace{F(x_{\tilde{\mathbf{u}}^\star}(N-1))}_{\geq \ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1)) + F(x_{\mathbf{u}}(N))} \\
&\geq \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + F(x_{\mathbf{u}}(N)) \\
&= J_N(x_0, \mathbf{u}) \geq V_N(x_0)
\end{aligned}$$

Reversal of $V_{N-1} \le V_N$

Let $\tilde{\mathbf{u}}^\star \in \mathbb{U}^{N-1}_{\mathbb{X}_0}(x_0)$ be the optimal control for J_{N-1}, i.e.,

$$V_{N-1}(x_0) = J_{N-1}(x_0, \tilde{\mathbf{u}}^\star)$$

Denote by $\mathbf{u} \in \mathbb{U}^{N}_{\mathbb{X}_0}(x_0)$ its prolongation

$$\Rightarrow \quad \begin{aligned} V_{N-1}(x_0) &= J_{N-1}(x_0, \tilde{\mathbf{u}}^\star) \\ &= \sum_{k=0}^{N-2} \ell(x_{\tilde{\mathbf{u}}^\star}(k), \tilde{\mathbf{u}}^\star(k)) + \underbrace{F(x_{\tilde{\mathbf{u}}^\star}(N-1))}_{\ge \ell(x_{\mathbf{u}}(N-1), \mathbf{u}(N-1)) + F(x_{\mathbf{u}}(N))} \\ &\ge \sum_{n=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) + F(x_{\mathbf{u}}(N)) \\ &= J_N(x_0, \mathbf{u}) \ \ge \ V_N(x_0) \end{aligned}$$

$\rightsquigarrow$ again we get $V_{N-1} \ge V_N$

Feasible sets

Define the feasible set

$$\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \mathbb{U}^N_{\mathbb{X}_0}(x) \neq \emptyset\}$$

Feasible sets

Define the feasible set

$$\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \mathbb{U}^N_{\mathbb{X}_0}(x) \neq \emptyset\}$$

Like in the equilibrium constrained case, on $\mathbb{X}_N$ one can ensure the inequality

$$V_N(x) \leq \alpha_2(\|x - x_*\|)$$

for some $\alpha_2 \in \mathcal{K}_\infty$ under mild conditions

Feasible sets

Define the feasible set

$$\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \mathbb{U}^N_{\mathbb{X}_0}(x) \neq \emptyset\}$$

Like in the equilibrium constrained case, on $\mathbb{X}_N$ one can ensure the inequality

$$V_N(x) \leq \alpha_2(\|x - x_*\|)$$

for some $\alpha_2 \in \mathcal{K}_\infty$ under mild conditions, while outside $\mathbb{X}_N$ we get $V_N(x) = \infty$

Stability theorem

Theorem: Consider the MPC scheme with regional terminal constraint $x_{\mathbf{u}}(N) \in \mathbb{X}_0$ and Lyapunov function terminal cost F compatible with ℓ.

Stability theorem

Theorem: Consider the MPC scheme with regional terminal constraint $x_{\mathbf{u}}(N) \in \mathbb{X}_0$ and Lyapunov function terminal cost F compatible with ℓ. Assume that

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

UNIVERSITÄT BAYREUTH

Stability theorem

Theorem: Consider the MPC scheme with regional terminal constraint $x_{\mathbf{u}}(N) \in \mathbb{X}_0$ and Lyapunov function terminal cost F compatible with ℓ. Assume that

$$V_N(x) \le \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x,u) \ge \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant

UNIVERSITÄT BAYREUTH

Stability theorem

Theorem: Consider the MPC scheme with regional terminal constraint $x_{\mathbf{u}}(N) \in \mathbb{X}_0$ and Lyapunov function terminal cost F compatible with ℓ. Assume that

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x,u) \geq \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant, the MPC closed loop is asymptotically stable on $\mathbb{X}_N$

Stability theorem

Theorem: Consider the MPC scheme with regional terminal constraint $x_{\mathbf{u}}(N) \in \mathbb{X}_0$ and Lyapunov function terminal cost F compatible with ℓ. Assume that

$$V_N(x) \leq \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x, u) \geq \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant, the MPC closed loop is asymptotically stable on $\mathbb{X}_N$ and the performance estimate

$$J_\infty^{cl}(x, \mu_N) \leq V_N(x)$$

holds.

Stability theorem

Theorem: Consider the MPC scheme with regional terminal constraint $x_{\mathbf{u}}(N) \in \mathbb{X}_0$ and Lyapunov function terminal cost F compatible with ℓ. Assume that

$$V_N(x) \le \alpha_2(\|x - x_*\|), \quad \inf_{u \in \mathbb{U}} \ell(x,u) \ge \alpha_3(\|x - x_*\|)$$

holds for all $x \in \mathbb{X}_N$.

Then $\mathbb{X}_N$ is forward invariant, the MPC closed loop is asymptotically stable on $\mathbb{X}_N$ and the performance estimate

$$J_\infty^{cl}(x, \mu_N) \le V_N(x)$$

holds.

Proof: Almost identical to the equilibrium constrained case

UNIVERSITÄT BAYREUTH

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems
- yields larger feasible sets

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems
- yields larger feasible sets
- does not need exact controllability to x_*

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems
- yields larger feasible sets
- does not need exact controllability to x_*

But:

- large feasible set still needs a large optimization horizon N

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems
- yields larger feasible sets
- does not need exact controllability to x_*

But:

- large feasible set still needs a large optimization horizon N (see again the car-and-mountains example)

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems
- yields larger feasible sets
- does not need exact controllability to x_*

But:

- large feasible set still needs a large optimization horizon N (see again the car-and-mountains example)
- additional analytical effort for computing F

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems
- yields larger feasible sets
- does not need exact controllability to x_*

But:

- large feasible set still needs a large optimization horizon N (see again the car-and-mountains example)
- additional analytical effort for computing F
- hardly ever used in industrial practice

Regional constraint and terminal cost — Discussion

Compared to the equilibrium constraint, the regional constraint

- yields easier online optimization problems
- yields larger feasible sets
- does not need exact controllability to x_*

But:

- large feasible set still needs a large optimization horizon N (see again the car-and-mountains example)
- additional analytical effort for computing F
- hardly ever used in industrial practice

In Section (5) we will see how stability can be proved without stabilizing terminal constraints

Summary of Section (3)

- terminal constraints yield that the usual inequality $V_{N-1} \leq V_N$ is reversed to $V_{N-1} \geq V_N$

UNIVERSITÄT BAYREUTH

Summary of Section (3)

- terminal constraints yield that the usual inequality $V_{N-1} \leq V_N$ is reversed to $V_{N-1} \geq V_N$
- this enables us to derive the relaxed dynamic programming inequality (with $\alpha = 1$) from the dynamic programming principle

Summary of Section (3)

- terminal constraints yield that the usual inequality $V_{N-1} \leq V_N$ is reversed to $V_{N-1} \geq V_N$
- this enables us to derive the relaxed dynamic programming inequality (with $\alpha = 1$) from the dynamic programming principle
- equilibrium constraints demand more properties of the system than regional constraints but do not require a Lyapunov function terminal cost

Summary of Section (3)

- terminal constraints yield that the usual inequality $V_{N-1} \leq V_N$ is reversed to $V_{N-1} \geq V_N$
- this enables us to derive the relaxed dynamic programming inequality (with $\alpha = 1$) from the dynamic programming principle
- equilibrium constraints demand more properties of the system than regional constraints but do not require a Lyapunov function terminal cost
- in both cases, the operating region is restricted to the feasible set $\mathbb{X}_N$

(4) Inverse optimality and suboptimality

Performance of μ_N

Once stability can be guaranteed, we can investigate the performance of the MPC feedback law μ_N

Performance of μ_N

Once stability can be guaranteed, we can investigate the performance of the MPC feedback law μ_N

As already mentioned, we measure the performance of the feedback $\mu_N : X \to U$ via the infinite horizon functional

$$J_\infty^{cl}(x_0, \mu_N) := \sum_{n=0}^{\infty} \ell(x_{\mu_N}(n), \mu_N(x_{\mu_N}(n)))$$

Performance of μ_N

Once stability can be guaranteed, we can investigate the performance of the MPC feedback law μ_N

As already mentioned, we measure the performance of the feedback $\mu_N : X \to U$ via the infinite horizon functional

$$J_\infty^{cl}(x_0, \mu_N) := \sum_{n=0}^{\infty} \ell(x_{\mu_N}(n), \mu_N(x_{\mu_N}(n)))$$

Recall: the optimal feedback μ_∞ satisfies $J_\infty^{cl}(x_0, \mu_\infty) = V_\infty(x_0)$

UNIVERSITÄT BAYREUTH

Performance of μ_N

Once stability can be guaranteed, we can investigate the performance of the MPC feedback law μ_N

As already mentioned, we measure the performance of the feedback $\mu_N : X \to U$ via the infinite horizon functional

$$J_\infty^{cl}(x_0, \mu_N) := \sum_{n=0}^{\infty} \ell(x_{\mu_N}(n), \mu_N(x_{\mu_N}(n)))$$

Recall: the optimal feedback μ_∞ satisfies $J_\infty^{cl}(x_0, \mu_\infty) = V_\infty(x_0)$

In the literature, two different concepts can be found:

- Inverse Optimality: show that μ_N is optimal for an altered running cost $\tilde{\ell} \neq \ell$

Performance of μ_N

Once stability can be guaranteed, we can investigate the performance of the MPC feedback law μ_N

As already mentioned, we measure the performance of the feedback $\mu_N : X \to U$ via the infinite horizon functional

$$J_\infty^{cl}(x_0, \mu_N) := \sum_{n=0}^{\infty} \ell(x_{\mu_N}(n), \mu_N(x_{\mu_N}(n)))$$

Recall: the optimal feedback μ_∞ satisfies $J_\infty^{cl}(x_0, \mu_\infty) = V_\infty(x_0)$

In the literature, two different concepts can be found:

- Inverse Optimality: show that μ_N is optimal for an altered running cost $\tilde{\ell} \neq \ell$
- Suboptimality: derive upper bounds for $J_\infty^{cl}(x_0, \mu_N)$

Inverse optimality

Theorem: [Poubelle/Bitmead/Gevers '88, Magni/Sepulchre '97]

For both types of terminal constraints, μ_N is optimal for

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \ \widetilde{J}_\infty(x_0,\mathbf{u}) = \sum_{k=0}^{\infty} \tilde{\ell}(x_\mathbf{u}(n),\mathbf{u}(n)), \ \ x_\mathbf{u}(0) = x_0$$

with $\tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$

Inverse optimality

Theorem: [Poubelle/Bitmead/Gevers '88, Magni/Sepulchre '97]

For both types of terminal constraints, μ_N is optimal for

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad \widetilde{J}_\infty(x_0, \mathbf{u}) = \sum_{k=0}^{\infty} \tilde{\ell}(x_{\mathbf{u}}(n), \mathbf{u}(n)), \quad x_{\mathbf{u}}(0) = x_0$$

with $\quad \tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$

Note: $\tilde{\ell} \geq \ell$

UNIVERSITÄT BAYREUTH

Inverse optimality

Theorem: [Poubelle/Bitmead/Gevers '88, Magni/Sepulchre '97]

For both types of terminal constraints, μ_N is optimal for

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad \widetilde{J}_\infty(x_0, \mathbf{u}) = \sum_{k=0}^{\infty} \tilde{\ell}(x_{\mathbf{u}}(n), \mathbf{u}(n)), \quad x_{\mathbf{u}}(0) = x_0$$

with $\tilde{\ell}(x, u) := \ell(x, u) + V_{N-1}(f(x, u)) - V_N(f(x, u))$

Note: $\tilde{\ell} \geq \ell$

Idea of proof: By the dynamic programming principle

$$V_N(x) = \inf_{u \in \mathbb{U}} \{\ell(x, u) + V_{N-1}(f(x, u))\}$$

Inverse optimality

Theorem: [Poubelle/Bitmead/Gevers '88, Magni/Sepulchre '97]

For both types of terminal constraints, μ_N is optimal for

$$\underset{\mathbf{u} \text{ admissible}}{\text{minimize}} \quad \widetilde{J}_\infty(x_0, \mathbf{u}) = \sum_{k=0}^{\infty} \tilde{\ell}(x_{\mathbf{u}}(n), \mathbf{u}(n)), \quad x_{\mathbf{u}}(0) = x_0$$

with $\tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$

Note: $\tilde{\ell} \geq \ell$

Idea of proof: By the dynamic programming principle

$$\begin{aligned} V_N(x) &= \inf_{u \in \mathbb{U}} \{\ell(x,u) + V_{N-1}(f(x,u))\} \\ &= \inf_{u \in \mathbb{U}} \{\tilde{\ell}(x,u) + V_N(f(x,u))\} \end{aligned}$$

UNIVERSITÄT BAYREUTH

Inverse optimality

Theorem: [Poubelle/Bitmead/Gevers '88, Magni/Sepulchre '97]

For both types of terminal constraints, μ_N is optimal for

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad \widetilde{J}_\infty(x_0,\mathbf{u}) = \sum_{k=0}^{\infty} \tilde{\ell}(x_{\mathbf{u}}(n),\mathbf{u}(n)), \quad x_{\mathbf{u}}(0) = x_0$$

with $\tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$

Note: $\tilde{\ell} \geq \ell$

Idea of proof: By the dynamic programming principle

$$\begin{aligned} V_N(x) &= \inf_{u\in\mathbb{U}}\{\ell(x,u) + V_{N-1}(f(x,u))\} \\ &= \inf_{u\in\mathbb{U}}\{\tilde{\ell}(x,u) + V_N(f(x,u))\} \end{aligned}$$

and $$V_N(x) = \tilde{\ell}(x,\mu_N(x)) + V_N(f(x,\mu_N(x)))$$

Inverse optimality

Theorem: [Poubelle/Bitmead/Gevers '88, Magni/Sepulchre '97]

For both types of terminal constraints, μ_N is optimal for

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad \widetilde{J}_\infty(x_0, \mathbf{u}) = \sum_{k=0}^{\infty} \tilde{\ell}(x_{\mathbf{u}}(n), \mathbf{u}(n)), \quad x_{\mathbf{u}}(0) = x_0$$

with $\tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$

Note: $\tilde{\ell} \geq \ell$

Idea of proof: By the dynamic programming principle

$$\begin{aligned} V_N(x) &= \inf_{u \in \mathbb{U}} \{\ell(x,u) + V_{N-1}(f(x,u))\} \\ &= \inf_{u \in \mathbb{U}} \{\tilde{\ell}(x,u) + V_N(f(x,u))\} \end{aligned}$$

and
$$V_N(x) = \tilde{\ell}(x, \mu_N(x)) + V_N(f(x, \mu_N(x)))$$

$\Rightarrow V_N$ and μ_N satisfy the principle for $\tilde{\ell}$

Inverse optimality

Theorem: [Poubelle/Bitmead/Gevers '88, Magni/Sepulchre '97]

For both types of terminal constraints, μ_N is optimal for

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad \widetilde{J}_\infty(x_0,\mathbf{u}) = \sum_{k=0}^{\infty} \tilde{\ell}(x_{\mathbf{u}}(n),\mathbf{u}(n)), \quad x_{\mathbf{u}}(0) = x_0$$

with $\tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$

Note: $\tilde{\ell} \geq \ell$

Idea of proof: By the dynamic programming principle

$$\begin{aligned} V_N(x) &= \inf_{u\in\mathbb{U}}\{\ell(x,u) + V_{N-1}(f(x,u))\} \\ &= \inf_{u\in\mathbb{U}}\{\tilde{\ell}(x,u) + V_N(f(x,u))\} \end{aligned}$$

and $$V_N(x) = \tilde{\ell}(x,\mu_N(x)) + V_N(f(x,\mu_N(x)))$$

$\Rightarrow$ V_N and μ_N satisfy the principle for $\tilde{\ell}$ $\Rightarrow$ optimality

Inverse optimality

Inverse optimality

- shows that μ_N is an infinite horizon optimal feedback law

Inverse optimality

Inverse optimality

- shows that μ_N is an infinite horizon optimal feedback law
- thus implies inherent robustness against perturbations (sector margin $(1/2, \infty)$)

Inverse optimality

Inverse optimality

- shows that μ_N is an infinite horizon optimal feedback law
- thus implies inherent robustness against perturbations (sector margin $(1/2, \infty)$)

But

- the running cost

$$\tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$$

is unknown and difficult to compute

UNIVERSITÄT BAYREUTH

Inverse optimality

Inverse optimality

- shows that μ_N is an infinite horizon optimal feedback law
- thus implies inherent robustness against perturbations (sector margin $(1/2, \infty)$)

But

- the running cost

$$\tilde{\ell}(x,u) := \ell(x,u) + V_{N-1}(f(x,u)) - V_N(f(x,u))$$

  is unknown and difficult to compute
- knowing that μ_N is optimal for $\widetilde{J}_\infty(x_0, u)$ doesn't give us a simple way to estimate $J_\infty^{cl}(x_0, \mu_N)$

UNIVERSITÄT BAYREUTH

Suboptimality

Recall: For both stabilizing terminal constraints the relaxed dynamic programming theorem yields the estimate

$$J_\infty^{cl}(x_0, \mu_N) \leq V_N(x_0)$$

Suboptimality

Recall: For both stabilizing terminal constraints the relaxed dynamic programming theorem yields the estimate

$$J_\infty^{cl}(x_0, \mu_N) \leq V_N(x_0)$$

But: How large is V_N ?

Suboptimality

Recall: For both stabilizing terminal constraints the relaxed dynamic programming theorem yields the estimate

$$J_\infty^{cl}(x_0, \mu_N) \leq V_N(x_0)$$

But: How large is V_N ?

Without terminal constraints, the inequality $V_N \leq V_\infty$ is immediate

Suboptimality

Recall: For both stabilizing terminal constraints the relaxed dynamic programming theorem yields the estimate

$$J_\infty^{cl}(x_0, \mu_N) \leq V_N(x_0)$$

But: How large is V_N ?

Without terminal constraints, the inequality $V_N \leq V_\infty$ is immediate

However, the terminal constraints also reverse this inequality, i.e., we have $V_N \geq V_\infty$ and the gap is very difficult to estimate

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

UNIVERSITÄT BAYREUTH

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

Example 1: $x^+ = x + u, \quad \ell(x, u) = x^2 + u^2$

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

Example 1: $x^+ = x + u, \quad \ell(x, u) = x^2 + u^2$

Terminal constraints $\quad x_{\mathbf{u}}(N) = x_* = 0$

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

Example 1: $x^+ = x + u, \quad \ell(x, u) = x^2 + u^2$

Terminal constraints $\quad x_{\mathbf{u}}(N) = x_* = 0$

Example 2: as Example 1, but with $\quad \ell(x, u) = x^2 + u^4$

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

Example 1: $x^+ = x + u$, $\ell(x,u) = x^2 + u^2$

Terminal constraints $x_{\mathbf{u}}(N) = x_* = 0$

$V_\infty(x) \approx 1.618x^2$, $J_\infty^{cl}(x, \mu_2) = 1.625x^2$

Example 2: as Example 1, but with $\ell(x,u) = x^2 + u^4$

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

Example 1: $x^+ = x + u$, $\ell(x, u) = x^2 + u^2$

Terminal constraints $x_{\mathbf{u}}(N) = x_* = 0$

$V_\infty(x) \approx 1.618x^2$, $J_\infty^{cl}(x, \mu_2) = 1.625x^2$

Example 2: as Example 1, but with $\ell(x, u) = x^2 + u^4$

$V_\infty(20) \leq 1726$, $J_\infty^{cl}(x, \mu_2) \approx 11240$

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

Example 1: $x^+ = x + u$, $\ell(x, u) = x^2 + u^2$

Terminal constraints $x_{\mathbf{u}}(N) = x_* = 0$

$V_\infty(x) \approx 1.618x^2$, $J_\infty^{cl}(x, \mu_2) = 1.625x^2$

Example 2: as Example 1, but with $\ell(x, u) = x^2 + u^4$

$V_\infty(20) \leq 1726$, $J_\infty^{cl}(x, \mu_2) \approx 11240$

General estimates for fixed N appear difficult to obtain.

Suboptimality — example

We consider two examples with $\mathbb{X} = \mathbb{R}$, $\mathbb{U} = \mathbb{R}$ for $N = 2$

Example 1: $x^+ = x + u, \quad \ell(x,u) = x^2 + u^2$

Terminal constraints $\quad x_{\mathbf{u}}(N) = x_* = 0$

$V_\infty(x) \approx 1.618x^2, \quad J_\infty^{cl}(x, \mu_2) = 1.625x^2$

Example 2: as Example 1, but with $\quad \ell(x,u) = x^2 + u^4$

$V_\infty(20) \leq 1726, \quad J_\infty^{cl}(x, \mu_2) \approx 11240$

General estimates for fixed N appear difficult to obtain. But we can give an asymptotic result for $N \to \infty$

Asymptotic Suboptimality

Theorem: For both types of terminal constraints the assumptions of the stability theorems ensure

$$V_N(x) \to V_\infty(x)$$

and thus

$$J_\infty^{cl}(x, \mu_N) \to V_\infty(x)$$

as $N \to \infty$ uniformly on compact subsets of the feasible sets

Asymptotic Suboptimality

Theorem: For both types of terminal constraints the assumptions of the stability theorems ensure

$$V_N(x) \to V_\infty(x)$$

and thus

$$J_\infty^{cl}(x, \mu_N) \to V_\infty(x)$$

as $N \to \infty$ uniformly on compact subsets of the feasible sets, i.e., the MPC performance converges to the optimal one

Asymptotic Suboptimality

Theorem: For both types of terminal constraints the assumptions of the stability theorems ensure

$$V_N(x) \to V_\infty(x)$$

and thus

$$J_\infty^{cl}(x, \mu_N) \to V_\infty(x)$$

as $N \to \infty$ uniformly on compact subsets of the feasible sets, i.e., the MPC performance converges to the optimal one

Idea of proof: uses that any approximately optimal trajectory for J_∞ converges to x_* and can thus be modified to meet the constraints with only moderately changing its value

Summary of Section (4)

- μ_N is infinite horizon optimal for a suitably altered running cost

Summary of Section (4)

- μ_N is infinite horizon optimal for a suitably altered running cost
- the infinite horizon functional along the μ_N-controlled trajectory is bounded by V_N, i.e.,

$$J_\infty^{cl}(x, \mu_N) \leq V_N(x)$$

Summary of Section (4)

- μ_N is infinite horizon optimal for a suitably altered running cost
- the infinite horizon functional along the μ_N-controlled trajectory is bounded by V_N, i.e.,

$$J_\infty^{cl}(x, \mu_N) \leq V_N(x)$$

- $V_N \gg V_\infty$ is possible under terminal constraints

UNIVERSITÄT BAYREUTH

Summary of Section (4)

- μ_N is infinite horizon optimal for a suitably altered running cost
- the infinite horizon functional along the μ_N-controlled trajectory is bounded by V_N, i.e.,

$$J_\infty^{cl}(x, \mu_N) \leq V_N(x)$$

- $V_N \gg V_\infty$ is possible under terminal constraints
- $V_N \to V_\infty$ holds for $N \to \infty$

(5) Stability and suboptimality without stabilizing constraints

MPC without stabilizing terminal constraints

We return to the basic MPC formulation

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0,u) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k),\mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0 = x_{\mu_N}(n)$$

without any stabilizing terminal constraints and costs

MPC without stabilizing terminal constraints

We return to the basic MPC formulation

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_0, u) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_0 = x_{\mu_N}(n)$$

without any stabilizing terminal constraints and costs

In order to motivate why we want to avoid terminal constraints and costs, we consider an example of P double integrators in the plane

UNIVERSITÄT BAYREUTH

A motivating example for avoiding terminal constraints

Example: [Jahn '10] Consider P 4-dimensional systems

$$\dot{x}_i = f(x_i, u_i) := (x_{i2}, u_{i1}, x_{i4}, u_{i2})^T, \quad i = 1, \ldots, P$$

Interpretation: $(x_{i1}, x_{i3})^T =$ position, $(x_{i2}, x_{i4})^T =$ velocity

A motivating example for avoiding terminal constraints

Example: [Jahn '10] Consider P 4-dimensional systems

$$\dot{x}_i = f(x_i, u_i) := (x_{i2}, u_{i1}, x_{i4}, u_{i2})^T, \quad i = 1, \ldots, P$$

Interpretation: $(x_{i1}, x_{i3})^T$ = position, $(x_{i2}, x_{i4})^T$ = velocity

Stage cost: $\ell(x,u) = \sum_{i=1}^{P} \|(x_{i1}, x_{i3})^T - x_d\| + \|(x_{i2}, x_{i4})^T\|/50$

with $x_d = (0,0)^T$ until $t = 20s$ and $x_d = (3,0)^T$ afterwards

A motivating example for avoiding terminal constraints

Example: [Jahn '10] Consider P 4-dimensional systems

$$\dot{x}_i = f(x_i, u_i) := (x_{i2}, u_{i1}, x_{i4}, u_{i2})^T, \quad i = 1, \ldots, P$$

Interpretation: $(x_{i1}, x_{i3})^T$ = position, $(x_{i2}, x_{i4})^T$ = velocity

Stage cost: $\ell(x,u) = \sum_{i=1}^{P} \|(x_{i1}, x_{i3})^T - x_d\| + \|(x_{i2}, x_{i4})^T\|/50$

with $x_d = (0,0)^T$ until $t = 20s$ and $x_d = (3,0)^T$ afterwards

Constraints: no collision, obstacles, limited speed and control

UNIVERSITÄT BAYREUTH

A motivating example for avoiding terminal constraints

Example: [Jahn '10] Consider P 4-dimensional systems

$$\dot{x}_i = f(x_i, u_i) := (x_{i2}, u_{i1}, x_{i4}, u_{i2})^T, \quad i = 1, \dots, P$$

Interpretation: $(x_{i1}, x_{i3})^T$ = position, $(x_{i2}, x_{i4})^T$ = velocity

Stage cost: $\ell(x,u) = \sum_{i=1}^{P} \|(x_{i1}, x_{i3})^T - x_d\| + \|(x_{i2}, x_{i4})^T\|/50$

with $x_d = (0,0)^T$ until $t = 20s$ and $x_d = (3,0)^T$ afterwards

Constraints: no collision, obstacles, limited speed and control

The simulation shows MPC for $P = 128$ ($\rightsquigarrow$ system dimension 512) with sampling time $T = 0.02s$ and horizon $N = 6$

Stabilizing NMPC without terminal constraint

(Some) stability and performance results known in the literature:

[Alamir/Bornard '95]

[Shamma/Xiong '97, Primbs/Nevistić '00]

[Jadbabaie/Hauser '05]

[Grimm/Messina/Tuna/Teel '05, Tuna/Messina/Teel '06,
Gr./Rantzer '08, Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

Stabilizing NMPC without terminal constraint

(Some) stability and performance results known in the literature:

[Alamir/Bornard '95]

use a controllability condition for all $x \in \mathbb{X}$

[Shamma/Xiong '97, Primbs/Nevistić '00]

[Jadbabaie/Hauser '05]

[Grimm/Messina/Tuna/Teel '05, Tuna/Messina/Teel '06, Gr./Rantzer '08, Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

Stabilizing NMPC without terminal constraint

(Some) stability and performance results known in the literature:

[Alamir/Bornard '95]
use a controllability condition for all $x \in \mathbb{X}$

[Shamma/Xiong '97, Primbs/Nevistić '00]
use knowledge of optimal value functions

[Jadbabaie/Hauser '05]

[Grimm/Messina/Tuna/Teel '05, Tuna/Messina/Teel '06, Gr./Rantzer '08, Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

Stabilizing NMPC without terminal constraint

(Some) stability and performance results known in the literature:

[Alamir/Bornard '95]
  use a controllability condition for all $x \in \mathbb{X}$

[Shamma/Xiong '97, Primbs/Nevistić '00]
  use knowledge of optimal value functions

[Jadbabaie/Hauser '05]
  use controllability of linearization in x_*

[Grimm/Messina/Tuna/Teel '05, Tuna/Messina/Teel '06, Gr./Rantzer '08, Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

Stabilizing NMPC without terminal constraint

(Some) stability and performance results known in the literature:

[Alamir/Bornard '95]
use a controllability condition for all $x \in \mathbb{X}$

[Shamma/Xiong '97, Primbs/Nevistić '00]
use knowledge of optimal value functions

[Jadbabaie/Hauser '05]
use controllability of linearization in x_*

[Grimm/Messina/Tuna/Teel '05, Tuna/Messina/Teel '06, Gr./Rantzer '08, Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]
use bounds on optimal value functions

Stabilizing NMPC without terminal constraint

(Some) stability and performance results known in the literature:

[Alamir/Bornard '95]
 use a controllability condition for all $x \in \mathbb{X}$

[Shamma/Xiong '97, Primbs/Nevistić '00]
 use knowledge of optimal value functions

[Jadbabaie/Hauser '05]
 use controllability of linearization in x_*

[Grimm/Messina/Tuna/Teel '05, Tuna/Messina/Teel '06, Gr./Rantzer '08, Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]
 use bounds on optimal value functions

Here we explain the last approach

Bounds on the optimal value function

Recall the definition of the optimal value function

$$V_N(x) := \inf_{\mathbf{u} \text{ admissible}} \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k,x), \mathbf{u}(k))$$

Boundedness assumption: there exists $\gamma > 0$ with

$$V_N(x) \le \gamma \ell^\star(x) \quad \text{for all } x \in \mathbb{X}, N \in \mathbb{N}$$

where $\ell^\star(x) := \min_{u \in \mathbb{U}} \ell(x,u)$

Bounds on the optimal value function

Recall the definition of the optimal value function

$$V_N(x) := \inf_{\mathbf{u} \text{ admissible}} \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k,x), \mathbf{u}(k))$$

Boundedness assumption: there exists $\gamma > 0$ with

$$V_N(x) \leq \gamma \ell^\star(x) \quad \text{for all } x \in \mathbb{X}, N \in \mathbb{N}$$

where $\ell^\star(x) := \min_{u \in \mathbb{U}} \ell(x,u)$

(sufficient conditions for and relaxations of this bound will be discussed later)

Stability and performance index

We choose ℓ, such that

$$\alpha_3(\|x - x_*\|) \leq \ell^\star(x) \leq \alpha_4(\|x - x_*\|)$$

holds for $\alpha_3, \alpha_4 \in \mathcal{K}_\infty$ (again, $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ works)

Stability and performance index

We choose ℓ, such that

$$\alpha_3(\|x - x_*\|) \leq \ell^\star(x) \leq \alpha_4(\|x - x_*\|)$$

holds for $\alpha_3, \alpha_4 \in \mathcal{K}_\infty$ (again, $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ works)

Then, the only inequality left to prove in order to apply the relaxed dynamic programming theorem is

$$V_N(f(x, \mu_N(x))) \leq V_N(x) - \alpha_N \ell(x, \mu_N(x))$$

for some $\alpha_N \in (0,1)$ and all $x \in \mathbb{X}$

Stability and performance index

We choose ℓ, such that

$$\alpha_3(\|x - x_*\|) \le \ell^\star(x) \le \alpha_4(\|x - x_*\|)$$

holds for $\alpha_3, \alpha_4 \in \mathcal{K}_\infty$ (again, $\ell(x,u) = \|x - x_*\|^2 + \lambda\|u\|^2$ works)

Then, the only inequality left to prove in order to apply the relaxed dynamic programming theorem is

$$V_N(f(x, \mu_N(x))) \le V_N(x) - \alpha_N \ell(x, \mu_N(x))$$

for some $\alpha_N \in (0,1)$ and all $x \in \mathbb{X}$

We can compute α_N from the bound $V_N(x) \le \gamma \ell^\star(x)$

Computing α_N

We assume $\quad V_N(x) \leq \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

We want $\quad V_N(f(x, \mu_N(x))) \leq V_N(x) - \alpha_N \ell(x, \mu_N(x))$

UNIVERSITÄT BAYREUTH

Computing α_N

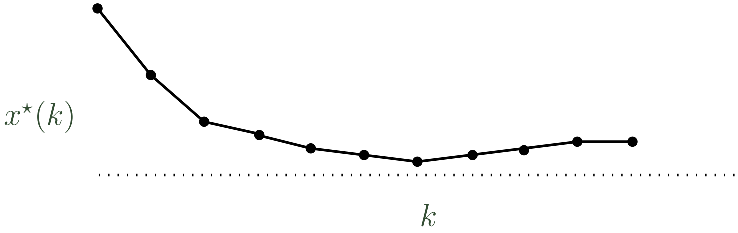
We assume $\quad V_N(x) \le \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

Computing α_N

We assume $\quad V_N(x) \le \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

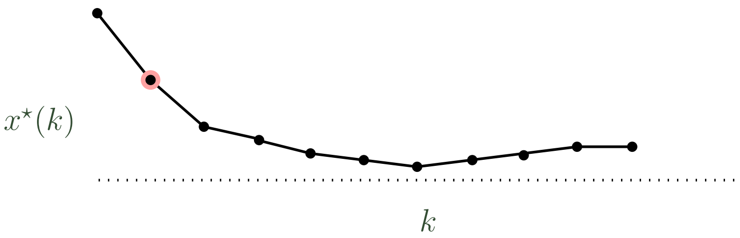
We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$



Computing α_N

We assume $\quad V_N(x) \le \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

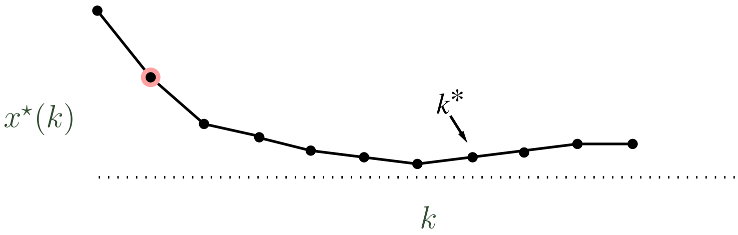


Computing α_N

We assume $\quad V_N(x) \le \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

- use $(*)$ to find $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$

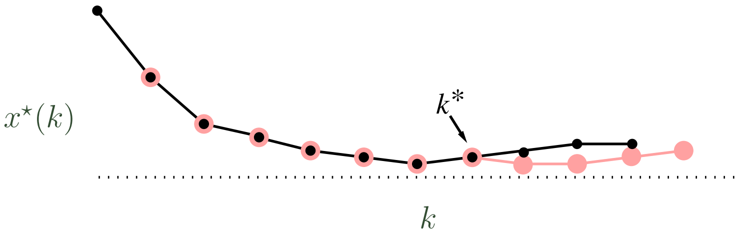


Computing α_N

We assume $\quad V_N(x) \le \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

- use $(*)$ to find $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$
- concatenate $x^\star(1), \ldots, x^\star(k^\star)$ and the optimal trajectory starting in $x^\star(k^\star)$

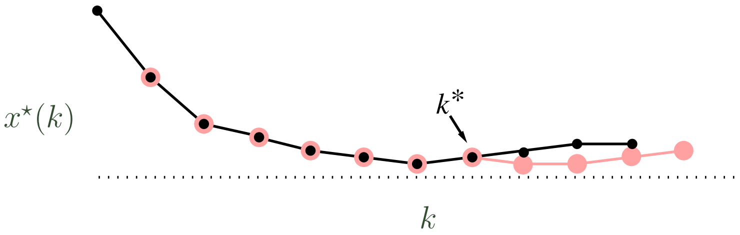


Computing α_N

We assume $\quad V_N(x) \le \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

- use $(*)$ to find $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$
- concatenate $x^\star(1), \ldots, x^\star(k^\star)$ and the optimal trajectory starting in $x^\star(k^\star) \quad \rightsquigarrow \quad \tilde{x}(\cdot),\ \tilde{\mathbf{u}}(\cdot)$



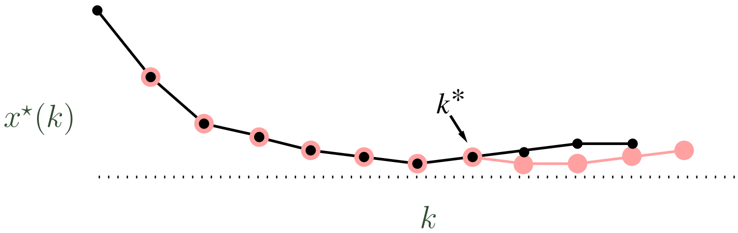
Computing α_N

We assume $\quad V_N(x) \le \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

- use $(*)$ to find $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$
- concatenate $x^\star(1), \ldots, x^\star(k^\star)$ and the optimal trajectory starting in $x^\star(k^\star) \quad \rightsquigarrow \quad \tilde{x}(\cdot),\ \tilde{\mathbf{u}}(\cdot)$

$$\Rightarrow\ V_N(x^\star(1)) \le J_N(x^\star(1), \tilde{\mathbf{u}}) \le V_N(x^\star(0)) - (1 - \gamma\eta_N)\, \ell(x^\star(0), \mathbf{u}^\star(0))$$



UNIVERSITÄT BAYREUTH

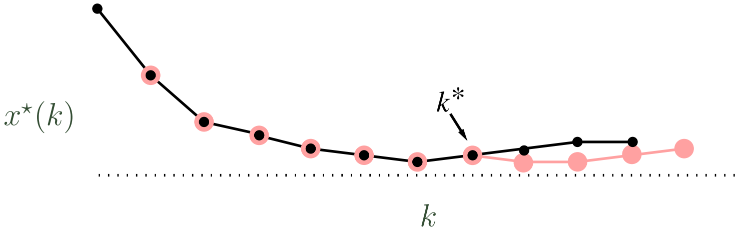
Computing α_N

We assume $\quad V_N(x) \le \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

- use $(*)$ to find $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$
- concatenate $x^\star(1), \ldots, x^\star(k^\star)$ and the optimal trajectory starting in $x^\star(k^\star) \quad \rightsquigarrow \quad \tilde{x}(\cdot)$, $\tilde{\mathbf{u}}(\cdot)$

$$\Rightarrow \; V_N(x^\star(1)) \le J_N(x^\star(1), \tilde{\mathbf{u}}) \le V_N(x^\star(0)) - (1 - \underbrace{\gamma\eta_N)\,\ell(x^\star(0), \mathbf{u}^\star(0))}_{=\text{“small error”}}$$



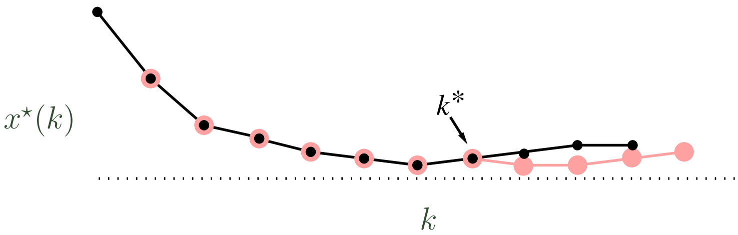
Computing α_N

We assume $\quad V_N(x) \leq \gamma \ell^\star(x) \quad$ for all $\quad x \in \mathbb{X},\ N \in \mathbb{N} \quad (*)$

We want $\quad V_N(x^\star(1)) \leq V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$

- use $(*)$ to find $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$
- concatenate $x^\star(1), \ldots, x^\star(k^\star)$ and the optimal trajectory starting in $x^\star(k^\star) \quad \rightsquigarrow \quad \tilde{x}(\cdot)$, $\tilde{\mathbf{u}}(\cdot)$

$$\Rightarrow \ V_N(x^\star(1)) \leq J_N(x^\star(1), \tilde{\mathbf{u}}) \leq V_N(x^\star(0)) - \underbrace{(1 - \gamma\eta_N)}_{=\alpha_N} \ell(x^\star(0), \mathbf{u}^\star(0))$$



Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 1 [Grimm/Messina/Tuna/Teel '05]

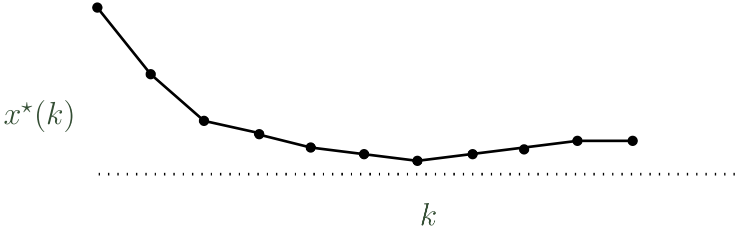
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 1 [Grimm/Messina/Tuna/Teel '05]

$V_N(x) \leq \gamma \ell^\star(x)$



UNIVERSITÄT BAYREUTH

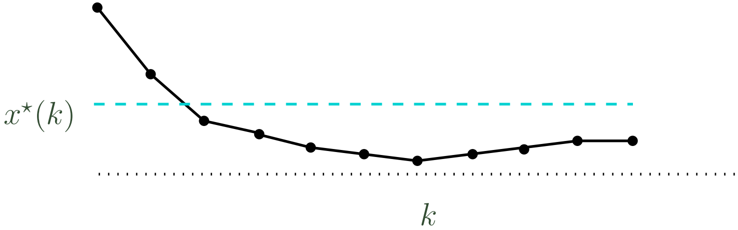
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 1 [Grimm/Messina/Tuna/Teel '05]

$V_N(x) \leq \gamma \ell^\star(x) \quad \Rightarrow \quad \ell(x^\star(k), u^\star(k)) \leq \gamma \ell^\star(x)/N$ for at least one $k^\star$



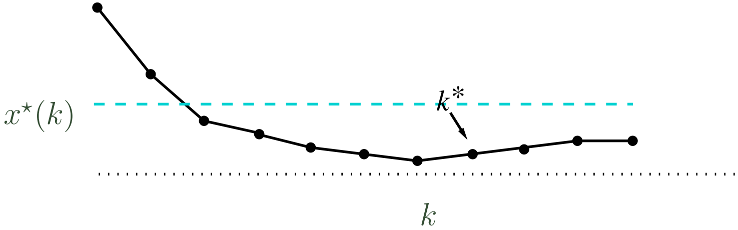
Decay of the optimal trajectory

We assume $V_N(x) \le \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$

Variant 1 [Grimm/Messina/Tuna/Teel '05]

$V_N(x) \le \gamma \ell^\star(x) \quad \Rightarrow \quad \ell(x^\star(k), u^\star(k)) \le \gamma \ell^\star(x)/N$ for at least one $k^\star$



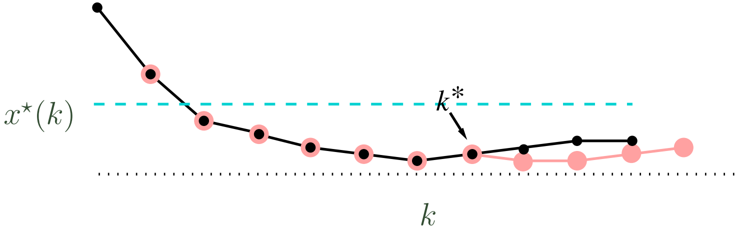
Decay of the optimal trajectory

We assume $V_N(x) \le \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$

Variant 1 [Grimm/Messina/Tuna/Teel '05]

$V_N(x) \le \gamma \ell^\star(x) \quad \Rightarrow \quad \ell(x^\star(k), u^\star(k)) \le \gamma \ell^\star(x)/N$ for at least one $k^\star$



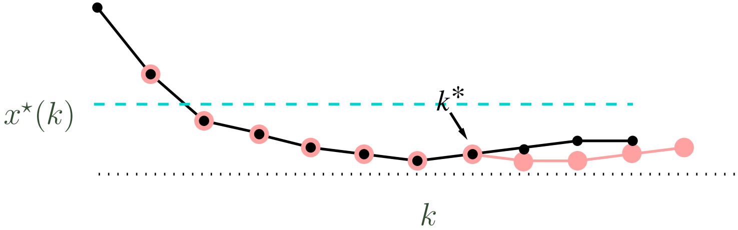
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 1 [Grimm/Messina/Tuna/Teel '05]

$V_N(x) \leq \gamma \ell^\star(x) \Rightarrow \ell(x^\star(k), u^\star(k)) \leq \gamma \ell^\star(x)/N$ for at least one $k^\star$ $\Rightarrow \alpha_N = 1 - \gamma(\gamma - 1)/N$



Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 2 [Tuna/Messina/Teel '06, Gr./Rantzer '08]

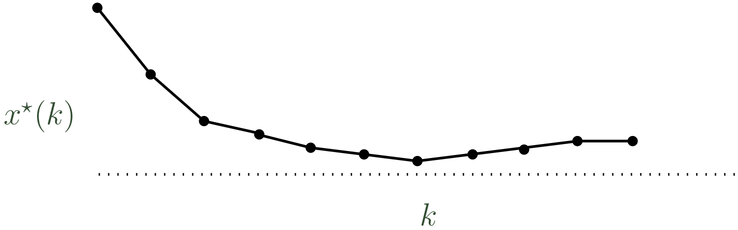
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 2 [Tuna/Messina/Teel '06, Gr./Rantzer '08]

$V_N(x) \leq \gamma \ell^\star(x)$



UNIVERSITÄT BAYREUTH

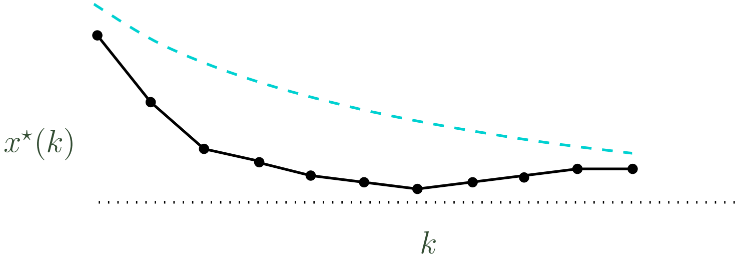
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 2 [Tuna/Messina/Teel '06, Gr./Rantzer '08]

$$V_N(x) \leq \gamma \ell^\star(x) \quad \Rightarrow \quad \ell(x^\star(k), u^\star(k)) \leq \gamma \left(\frac{\gamma-1}{\gamma}\right)^k \ell^\star(x)$$



Decay of the optimal trajectory

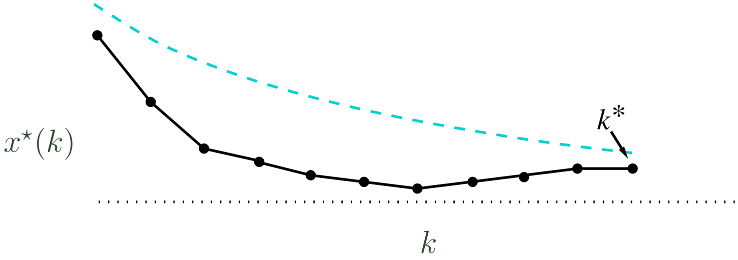
We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 2 [Tuna/Messina/Teel '06, Gr./Rantzer '08]

$$V_N(x) \leq \gamma \ell^\star(x) \quad \Rightarrow \quad \ell(x^\star(k), u^\star(k)) \leq \gamma \left(\frac{\gamma-1}{\gamma}\right)^k \ell^\star(x)$$

$$\Rightarrow \quad k^\star = N-1$$



Decay of the optimal trajectory

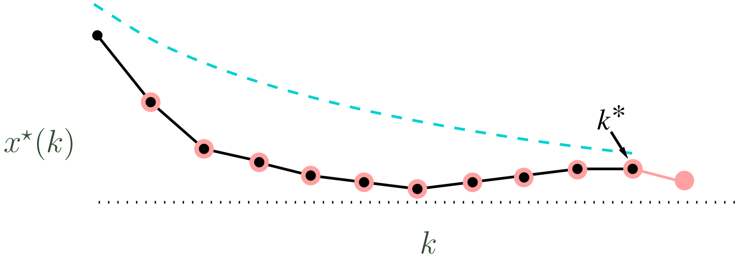
We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 2 [Tuna/Messina/Teel '06, Gr./Rantzer '08]

$$V_N(x) \leq \gamma \ell^\star(x) \quad \Rightarrow \quad \ell(x^\star(k), u^\star(k)) \leq \gamma \left(\frac{\gamma-1}{\gamma}\right)^k \ell^\star(x)$$

$$\Rightarrow \quad k^\star = N-1$$



Decay of the optimal trajectory

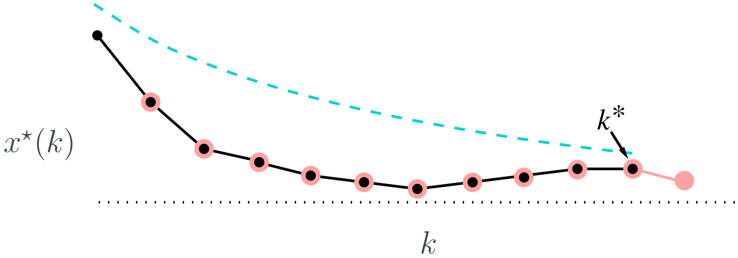
We assume $V_N(x) \le \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$

Variant 2 [Tuna/Messina/Teel '06, Gr./Rantzer '08]

$$V_N(x) \le \gamma \ell^\star(x) \quad \Rightarrow \quad \ell(x^\star(k), u^\star(k)) \le \gamma \left(\frac{\gamma-1}{\gamma}\right)^k \ell^\star(x)$$

$$\Rightarrow \quad k^\star = N-1 \quad \Rightarrow \quad \alpha_N = 1 - (\gamma-1)^N/\gamma^{N-2}$$



Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 3 [Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

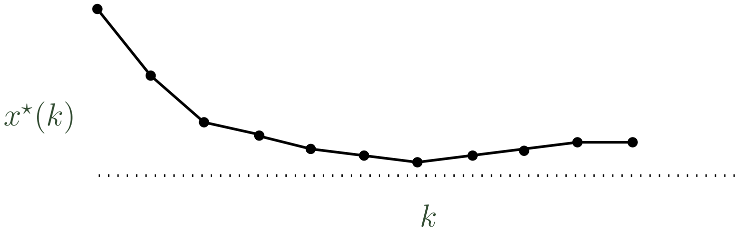
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 3 [Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

$V_N(x) \leq \gamma \ell^\star(x)$



UNIVERSITÄT BAYREUTH

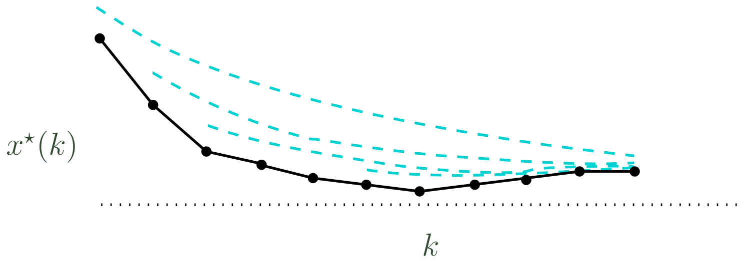
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 3 [Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

$V_N(x) \leq \gamma \ell^\star(x)$ $\Rightarrow$ formulate all constraints



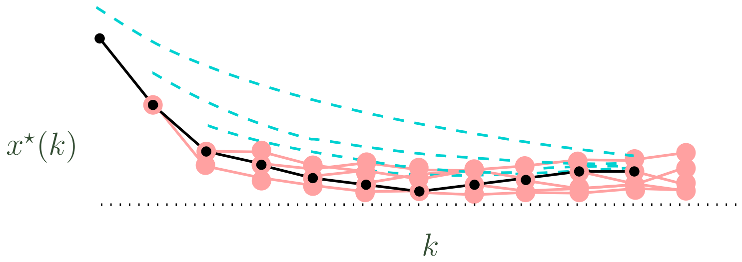
Decay of the optimal trajectory

We assume $V_N(x) \leq \gamma\ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \geq 1$ with $\ell^\star(x^\star(k^\star)) \leq \eta_N \ell^\star(x^\star(0))$

Variant 3 [Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

$V_N(x) \leq \gamma\ell^\star(x) \quad \Rightarrow \quad$ formulate all constraints and trajectories



Decay of the optimal trajectory

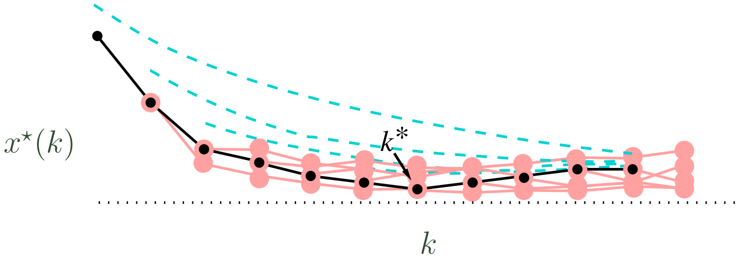
We assume $V_N(x) \le \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$

Variant 3 [Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

$V_N(x) \le \gamma \ell^\star(x)$ $\Rightarrow$ formulate all constraints and trajectories

$\Rightarrow$ optimize for α_N



Decay of the optimal trajectory

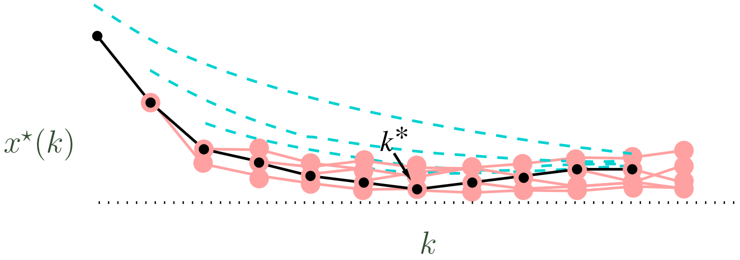
We assume $V_N(x) \le \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$

We want $\eta_N > 0$, $k^\star \ge 1$ with $\ell^\star(x^\star(k^\star)) \le \eta_N \ell^\star(x^\star(0))$

Variant 3 [Gr. '09, Gr./Pannek/Seehafer/Worthmann '10]

$V_N(x) \le \gamma \ell^\star(x)$ $\Rightarrow$ formulate all constraints and trajectories

$\Rightarrow$ optimize for α_N $\Rightarrow$ $\alpha_N = 1 - \frac{(\gamma-1)^N}{\gamma^{N-1}-(\gamma-1)^{N-2}}$



Optimization approach to compute α_N

We explain the optimization approach (Variant 3) in more detail. We want α_N such that

$$V_N(x^\star(1)) \leq V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$$

holds for all optimal trajectories $x^\star(n), \mathbf{u}^\star(n)$ for V_N

Optimization approach to compute α_N

We explain the optimization approach (Variant 3) in more detail. We want α_N such that

$$V_N(x^\star(1)) \leq V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$$

holds for all optimal trajectories $x^\star(n), \mathbf{u}^\star(n)$ for V_N

The bound and the dynamic programming principle imply:

$$V_N(x^\star(1)) \quad \leq \quad \gamma \ell^\star(x^\star(1))$$

UNIVERSITÄT BAYREUTH

Optimization approach to compute α_N

We explain the optimization approach (Variant 3) in more detail. We want α_N such that

$$V_N(x^\star(1)) \leq V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$$

holds for all optimal trajectories $x^\star(n), \mathbf{u}^\star(n)$ for V_N

The bound and the dynamic programming principle imply:

$$V_N(x^\star(1)) \leq \gamma \ell^\star(x^\star(1))$$

$$V_N(x^\star(1)) \leq \ell(x^\star(1), \mathbf{u}^\star(1)) + \gamma \ell^\star(x^\star(2))$$

Optimization approach to compute α_N

We explain the optimization approach (Variant 3) in more detail. We want α_N such that

$$V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$$

holds for all optimal trajectories $x^\star(n), \mathbf{u}^\star(n)$ for V_N

The bound and the dynamic programming principle imply:

$$\begin{aligned}
V_N(x^\star(1)) &\le \gamma \ell^\star(x^\star(1)) \\
V_N(x^\star(1)) &\le \ell(x^\star(1), \mathbf{u}^\star(1)) + \gamma \ell^\star(x^\star(2)) \\
V_N(x^\star(1)) &\le \ell(x^\star(1), \mathbf{u}^\star(1)) + \ell(x^\star(2), \mathbf{u}^\star(2)) + \gamma \ell^\star(x^\star(3))
\end{aligned}$$

UNIVERSITÄT BAYREUTH

Optimization approach to compute α_N

We explain the optimization approach (Variant 3) in more detail. We want α_N such that

$$V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0))$$

holds for all optimal trajectories $x^\star(n), \mathbf{u}^\star(n)$ for V_N

The bound and the dynamic programming principle imply:

$$\begin{aligned}
V_N(x^\star(1)) &\le \gamma \ell^\star(x^\star(1)) \\
V_N(x^\star(1)) &\le \ell(x^\star(1), \mathbf{u}^\star(1)) + \gamma \ell^\star(x^\star(2)) \\
V_N(x^\star(1)) &\le \ell(x^\star(1), \mathbf{u}^\star(1)) + \ell(x^\star(2), \mathbf{u}^\star(2)) + \gamma \ell^\star(x^\star(3)) \\
\vdots \quad & \quad \vdots \quad \quad \vdots
\end{aligned}$$

Optimization approach to compute α_N

$\rightsquigarrow$ $V_N(x^\star(1))$ is bounded by sums over $\ell(x^\star(n), \mathbf{u}^\star(n))$

For sums of these values, in turn, we get bounds from the dynamic programming principle and the bound

Optimization approach to compute α_N

$\rightsquigarrow V_N(x^\star(1))$ is bounded by sums over $\ell(x^\star(n), \mathbf{u}^\star(n))$

For sums of these values, in turn, we get bounds from the dynamic programming principle and the bound:

$$\sum_{n=0}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) \;=\; V_N(x^\star(0)) \qquad \leq \; \gamma \ell^\star(x^\star(0))$$

Optimization approach to compute α_N

$\rightsquigarrow V_N(x^\star(1))$ is bounded by sums over $\ell(x^\star(n), \mathbf{u}^\star(n))$

For sums of these values, in turn, we get bounds from the dynamic programming principle and the bound:

$$\sum_{n=0}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) = V_N(x^\star(0)) \leq \gamma \ell^\star(x^\star(0))$$

$$\sum_{n=1}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) = V_{N-1}(x^\star(1)) \leq \gamma \ell^\star(x^\star(1))$$

UNIVERSITÄT BAYREUTH

Optimization approach to compute α_N

$\rightsquigarrow$ $V_N(x^\star(1))$ is bounded by sums over $\ell(x^\star(n), \mathbf{u}^\star(n))$

For sums of these values, in turn, we get bounds from the dynamic programming principle and the bound:

$$\begin{aligned}
\sum_{n=0}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) &= V_N(x^\star(0)) &\leq \gamma \ell^\star(x^\star(0)) \\
\sum_{n=1}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) &= V_{N-1}(x^\star(1)) &\leq \gamma \ell^\star(x^\star(1)) \\
\sum_{n=2}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) &= V_{N-2}(x^\star(2)) &\leq \gamma \ell^\star(x^\star(2))
\end{aligned}$$

Optimization approach to compute α_N

$\rightsquigarrow V_N(x^\star(1))$ is bounded by sums over $\ell(x^\star(n), \mathbf{u}^\star(n))$

For sums of these values, in turn, we get bounds from the dynamic programming principle and the bound:

$$\sum_{n=0}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) = V_N(x^\star(0)) \leq \gamma \ell^\star(x^\star(0))$$

$$\sum_{n=1}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) = V_{N-1}(x^\star(1)) \leq \gamma \ell^\star(x^\star(1))$$

$$\sum_{n=2}^{N-1} \ell(x^\star(n), \mathbf{u}^\star(n)) = V_{N-2}(x^\star(2)) \leq \gamma \ell^\star(x^\star(2))$$

$$\vdots \qquad\qquad \vdots$$

Verifying the relaxed Lyapunov inequality

Find α_N, such that for all optimal trajectories $x^\star$, $\mathbf{u}^\star$:

$$V_N(x^\star(1)) \leq V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0)) \qquad (*)$$

Verifying the relaxed Lyapunov inequality

Find α_N, such that for all optimal trajectories $x^\star$, $\mathbf{u}^\star$:

$$V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0)) \qquad (*)$$

Define $\qquad \lambda_n := \ell(x^\star(n), \mathbf{u}^\star(n)), \quad \nu := V_N(x^\star(1))$

UNIVERSITÄT BAYREUTH

Verifying the relaxed Lyapunov inequality

Find α_N, such that for all optimal trajectories $x^\star$, $\mathbf{u}^\star$:

$$V_N(x^\star(1)) \leq V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0)) \qquad (*)$$

Define $\qquad \lambda_n := \ell(x^\star(n), \mathbf{u}^\star(n)), \quad \nu := V_N(x^\star(1))$

Then: $\quad (*) \;\Leftrightarrow\; \nu \leq \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0$

Verifying the relaxed Lyapunov inequality

Find α_N, such that for all optimal trajectories $x^\star$, $\mathbf{u}^\star$:

$$V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0)) \qquad (*)$$

Define $\qquad \lambda_n := \ell(x^\star(n), \mathbf{u}^\star(n)), \quad \nu := V_N(x^\star(1))$

Then: $\quad (*) \;\Leftrightarrow\; \nu \le \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0$

The inequalities from the last slides translate to

$$\sum_{n=k}^{N-1} \lambda_n \le \gamma \lambda_k, \quad k = 0, \ldots, N-2 \qquad (1)$$

$$\nu \le \sum_{n=1}^{j} \lambda_n + \gamma \lambda_{j+1}, \quad j = 0, \ldots, N-2 \qquad (2)$$

UNIVERSITÄT BAYREUTH

Verifying the relaxed Lyapunov inequality

Find α_N, such that for all optimal trajectories $x^\star$, $\mathbf{u}^\star$:

$$V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0)) \qquad (*)$$

Define $\qquad \lambda_n := \ell(x^\star(n), \mathbf{u}^\star(n)), \quad \nu := V_N(x^\star(1))$

Then: $\quad (*) \;\Leftrightarrow\; \nu \le \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0$

The inequalities from the last slides translate to

$$\sum_{n=k}^{N-1} \lambda_n \le \gamma \lambda_k, \quad k = 0, \ldots, N-2 \qquad (1)$$

$$\nu \le \sum_{n=1}^{j} \lambda_n + \gamma \lambda_{j+1}, \quad j = 0, \ldots, N-2 \qquad (2)$$

We call $\lambda_0, \ldots, \lambda_{N-1}, \nu \ge 0$ with (1), (2) admissible

Verifying the relaxed Lyapunov inequality

Find α_N, such that for all optimal trajectories $x^\star$, $\mathbf{u}^\star$:

$$V_N(x^\star(1)) \le V_N(x^\star(0)) - \alpha_N \ell(x^\star(0), \mathbf{u}^\star(0)) \qquad (*)$$

Define $\quad \lambda_n := \ell(x^\star(n), \mathbf{u}^\star(n)), \quad \nu := V_N(x^\star(1))$

Then: $\quad (*) \quad \Leftrightarrow \quad \nu \le \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0$

The inequalities from the last slides translate to

$$\sum_{n=k}^{N-1} \lambda_n \le \gamma \lambda_k, \quad k = 0, \ldots, N-2 \qquad (1)$$

$$\nu \le \sum_{n=1}^{j} \lambda_n + \gamma \lambda_{j+1}, \quad j = 0, \ldots, N-2 \qquad (2)$$

We call $\lambda_0, \ldots, \lambda_{N-1}, \nu \ge 0$ with (1), (2) admissible

Optimization problem

$\Rightarrow$ if α_N is such that the inequality

$$\nu \leq \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0$$

holds for all admissible λ_n and ν, then the desired inequality will hold for all optimal trajectories

Optimization problem

$\Rightarrow$ if α_N is such that the inequality

$$\nu \leq \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0 \;\Leftrightarrow\; \alpha_N \leq \frac{\sum_{n=0}^{N-1} \lambda_n - \nu}{\lambda_0}$$

holds for all admissible λ_n and ν, then the desired inequality will hold for all optimal trajectories

Optimization problem

$\Rightarrow$ if α_N is such that the inequality

$$\nu \le \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0 \;\Leftrightarrow\; \alpha_N \le \frac{\sum_{n=0}^{N-1} \lambda_n - \nu}{\lambda_0}$$

holds for all admissible λ_n and ν, then the desired inequality will hold for all optimal trajectories

The largest α_N satisfying this condition is

$$\alpha_N := \min_{\lambda_n,\, \nu \text{ admissible}} \frac{\sum_{n=0}^{N-1} \lambda_n - \nu}{\lambda_0}$$

Optimization problem

$\Rightarrow$ if α_N is such that the inequality

$$\nu \leq \sum_{n=0}^{N-1} \lambda_n - \alpha_N \lambda_0 \Leftrightarrow \alpha_N \leq \frac{\sum_{n=0}^{N-1} \lambda_n - \nu}{\lambda_0}$$

holds for all admissible λ_n and ν, then the desired inequality will hold for all optimal trajectories

The largest α_N satisfying this condition is

$$\alpha_N := \min_{\lambda_n, \nu \text{ admissible}} \frac{\sum_{n=0}^{N-1} \lambda_n - \nu}{\lambda_0}$$

This is a linear optimization problem whose solution can be computed explicitly (which is nontrivial) and reads

$$\alpha_N = 1 - \frac{(\gamma - 1)^N}{\gamma^{N-1} - (\gamma - 1)^{N-1}}$$

Stability and performance theorem

Theorem: [Gr./Pannek/Seehafer/Worthmann '10]: Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$. If

$$\alpha_N > 0$$

then the NMPC closed loop is asymptotically stable with Lyapunov function V_N

Stability and performance theorem

Theorem: [Gr./Pannek/Seehafer/Worthmann '10]: Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$. If

$$\alpha_N > 0$$

then the NMPC closed loop is asymptotically stable with Lyapunov function V_N and we get the performance estimate $J_\infty^{cl}(x, \mu_N) \leq V_\infty(x)/\alpha_N$ with

$$\alpha_N = 1 - \frac{(\gamma - 1)^N}{\gamma^{N-1} - (\gamma - 1)^{N-1}}$$

Stability and performance theorem

Theorem: [Gr./Pannek/Seehafer/Worthmann '10]: Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$. If

$$\alpha_N > 0 \;\Leftrightarrow\; N > 2 + \frac{\ln(\gamma - 1)}{\ln \gamma - \ln(\gamma - 1)}$$

then the NMPC closed loop is asymptotically stable with Lyapunov function V_N and we get the performance estimate $J_\infty^{cl}(x, \mu_N) \leq V_\infty(x)/\alpha_N$ with

$$\alpha_N = 1 - \frac{(\gamma - 1)^N}{\gamma^{N-1} - (\gamma - 1)^{N-1}}$$

UNIVERSITÄT BAYREUTH

Stability and performance theorem

Theorem: [Gr./Pannek/Seehafer/Worthmann '10]: Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$. If

$$\alpha_N > 0 \;\Leftrightarrow\; N > 2 + \frac{\ln(\gamma - 1)}{\ln\gamma - \ln(\gamma - 1)} \;\sim\; \gamma \ln \gamma$$

then the NMPC closed loop is asymptotically stable with Lyapunov function V_N and we get the performance estimate $J_\infty^{cl}(x, \mu_N) \leq V_\infty(x)/\alpha_N$ with

$$\alpha_N = 1 - \frac{(\gamma - 1)^N}{\gamma^{N-1} - (\gamma - 1)^{N-1}}$$

Stability and performance theorem

Theorem: [Gr./Pannek/Seehafer/Worthmann '10]: Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$. If

$$\alpha_N > 0 \;\Leftrightarrow\; N > 2 + \frac{\ln(\gamma - 1)}{\ln\gamma - \ln(\gamma - 1)} \;\sim\; \gamma \ln \gamma$$

then the NMPC closed loop is asymptotically stable with Lyapunov function V_N and we get the performance estimate $J_\infty^{cl}(x, \mu_N) \leq V_\infty(x)/\alpha_N$ with

$$\alpha_N = 1 - \frac{(\gamma - 1)^N}{\gamma^{N-1} - (\gamma - 1)^{N-1}} \to 1 \quad \text{as} \quad N \to \infty$$

Stability and performance theorem

Theorem: [Gr./Pannek/Seehafer/Worthmann '10]: Assume $V_N(x) \leq \gamma\ell^\star(x)$ for all $x \in \mathbb{X}$, $N \in \mathbb{N}$. If

$$\alpha_N > 0 \Leftrightarrow N > 2 + \frac{\ln(\gamma - 1)}{\ln\gamma - \ln(\gamma - 1)} \sim \gamma \ln \gamma$$

then the NMPC closed loop is asymptotically stable with Lyapunov function V_N and we get the performance estimate $J_\infty^{cl}(x, \mu_N) \leq V_\infty(x)/\alpha_N$ with

$$\alpha_N = 1 - \frac{(\gamma - 1)^N}{\gamma^{N-1} - (\gamma - 1)^{N-1}} \to 1 \quad \text{as} \quad N \to \infty$$

Conversely, if $N < 2 + \frac{\ln(\gamma-1)}{\ln\gamma-\ln(\gamma-1)}$, then there exists a system for which $V_N(x) \leq \gamma\ell^\star(x)$ holds but the NMPC closed loop is not asymptotically stable.

Horizon dependent γ-values

The theorem remains valid if we replace the bound condition

$$V_N(x) \leq \gamma \ell^\star(x)$$

by

$$V_N(x) \leq \gamma_N \ell^\star(x)$$

for horizon-dependent bounded values $\gamma_N \in \mathbb{R}$, $N \in \mathbb{N}$

Horizon dependent γ-values

The theorem remains valid if we replace the bound condition

$$V_N(x) \le \gamma \ell^\star(x)$$

by

$$V_N(x) \le \gamma_N \ell^\star(x)$$

for horizon-dependent bounded values $\gamma_N \in \mathbb{R}$, $N \in \mathbb{N}$

$$\rightsquigarrow \quad \alpha_N = 1 - \frac{(\gamma_N - 1) \prod_{i=2}^{N} (\gamma_i - 1)}{\prod_{i=2}^{N} \gamma_i - \prod_{i=2}^{N} (\gamma_i - 1)}$$

Horizon dependent γ-values

The theorem remains valid if we replace the bound condition

$$V_N(x) \le \gamma \ell^\star(x)$$

by

$$V_N(x) \le \gamma_N \ell^\star(x)$$

for horizon-dependent bounded values $\gamma_N \in \mathbb{R}$, $N \in \mathbb{N}$

$$\rightsquigarrow \quad \alpha_N = 1 - \frac{(\gamma_N - 1)\prod_{i=2}^{N}(\gamma_i - 1)}{\prod_{i=2}^{N}\gamma_i - \prod_{i=2}^{N}(\gamma_i - 1)}$$

This allows for tighter bounds and a refined analysis

Controllability condition

A refined analysis can be performed if we compute γ_N from a controllability condition

Controllability condition

A refined analysis can be performed if we compute γ_N from a controllability condition, e.g., exponential controllability:

Assume that for each $x_0 \in \mathbb{X}$ there exists an admissible control $\mathbf{u}$ such that

$$\ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) \leq C\sigma^k \ell^\star(x_0), \quad k = 0, 1, 2, \ldots$$

for given overshoot constant $C > 0$ and decay rate $\sigma \in (0, 1)$

Controllability condition

A refined analysis can be performed if we compute γ_N from a controllability condition, e.g., exponential controllability:

Assume that for each $x_0 \in \mathbb{X}$ there exists an admissible control $\mathbf{u}$ such that

$$\ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) \leq C\sigma^k \ell^\star(x_0), \quad k = 0, 1, 2, \ldots$$

for given overshoot constant $C > 0$ and decay rate $\sigma \in (0, 1)$

$$\rightsquigarrow \quad V_N(x) \leq \gamma_N \ell^\star(x) \quad \text{for} \quad \gamma_N = \sum_{k=0}^{N-1} C\sigma^k$$

Controllability condition

A refined analysis can be performed if we compute γ_N from a controllability condition, e.g., exponential controllability:

Assume that for each $x_0 \in \mathbb{X}$ there exists an admissible control $\mathbf{u}$ such that

$$\ell(x_{\mathbf{u}}(k), \mathbf{u}(k)) \leq C\sigma^k \ell^\star(x_0), \quad k = 0, 1, 2, \ldots$$

for given overshoot constant $C > 0$ and decay rate $\sigma \in (0, 1)$

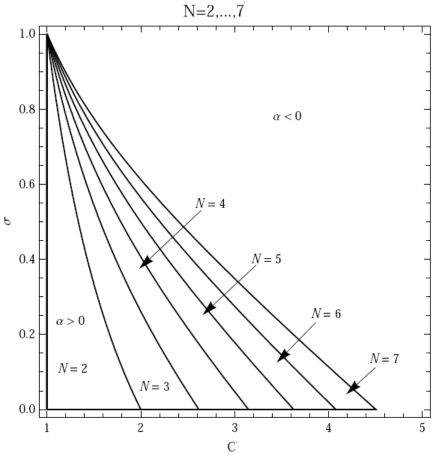
$$\rightsquigarrow \quad V_N(x) \leq \gamma_N \ell^\star(x) \quad \text{for} \quad \gamma_N = \sum_{k=0}^{N-1} C\sigma^k$$

This allows to compute the minimal stabilizing horizon

$$\min\{N \in \mathbb{N} \,|\, \alpha_N > 0\}$$

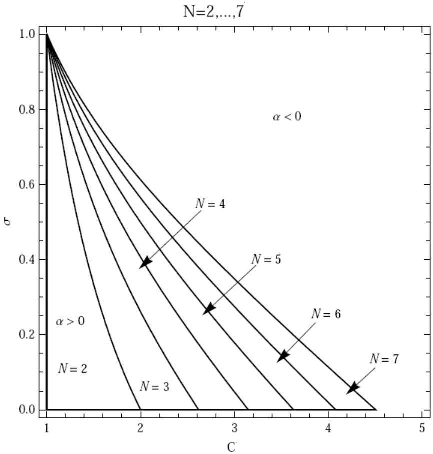
depending on C and σ

Stability chart for C and σ



(Figure: Harald Voit)

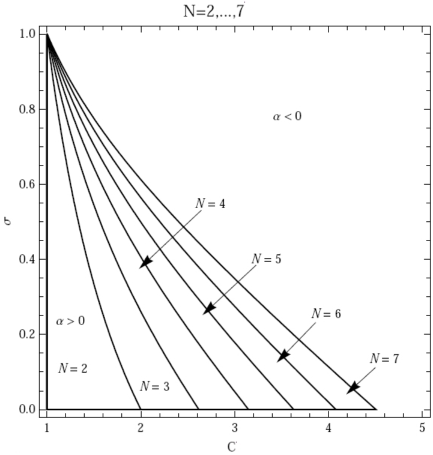
Stability chart for C and σ



(Figure: Harald Voit)

Conclusion: for short optimization horizon N it is
more important: small C ("small overshoot")
less important: small σ ("fast decay")

Stability chart for C and σ



(Figure: Harald Voit)

Conclusion: for short optimization horizon N it is
more important: small C ("small overshoot")
less important: small σ ("fast decay")

(we will see in the next section how to use this information)

Comments and extensions

- for unconstrained linear quadratic problems:

Comments and extensions

- for unconstrained linear quadratic problems:
  existence of $\gamma \quad \Leftrightarrow \quad (A, B)$ stabilizable

Comments and extensions

- for unconstrained linear quadratic problems:
  existence of $\gamma \quad \Leftrightarrow \quad (A, B)$ stabilizable
- additional weights on the last term can be incorporated into the analysis [Gr./Pannek/Seehafer/Worthmann '10]

Comments and extensions

- for unconstrained linear quadratic problems:
  existence of $\gamma \quad \Leftrightarrow \quad (A, B)$ stabilizable
- additional weights on the last term can be incorporated into the analysis [Gr./Pannek/Seehafer/Worthmann '10]
- instead of using γ, α can be estimated numerically online along the closed loop [Pannek et al. '10ff]

UNIVERSITÄT BAYREUTH

Comments and extensions

- for unconstrained linear quadratic problems:
  existence of $\gamma \quad \Leftrightarrow \quad (A, B)$ stabilizable
- additional weights on the last term can be incorporated into the analysis [Gr./Pannek/Seehafer/Worthmann '10]
- instead of using γ, α can be estimated numerically online along the closed loop [Pannek et al. '10ff]
- positive definiteness of ℓ can be replaced by a detectability condition [Grimm/Messina/Tuna/Teel '05]

Comments and extensions

- for unconstrained linear quadratic problems:
  existence of $\gamma \quad \Leftrightarrow \quad (A, B)$ stabilizable
- additional weights on the last term can be incorporated into the analysis [Gr./Pannek/Seehafer/Worthmann '10]
- instead of using γ, α can be estimated numerically online along the closed loop [Pannek et al. '10ff]
- positive definiteness of ℓ can be replaced by a detectability condition [Grimm/Messina/Tuna/Teel '05]
- under appropriate uniformity assumptions, the results are easily carried over to tracking time variant references $x_{\text{ref}}(n)$ instead of an equilibrium x_* [Gr./Pannek '11]

Comments and extensions

The "linear" inequality $V_N(x) \leq \gamma\ell^\star(x)$ may be too demanding for nonlinear systems under constraints

Comments and extensions

The "linear" inequality $V_N(x) \leq \gamma \ell^\star(x)$ may be too demanding for nonlinear systems under constraints

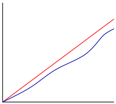
Generalization: $V_N(x) \leq \rho(\ell^\star(x)), \quad \rho \in \mathcal{K}_\infty$

Comments and extensions

The "linear" inequality $V_N(x) \leq \gamma \ell^\star(x)$ may be too demanding for nonlinear systems under constraints

Generalization: $\quad V_N(x) \leq \rho(\ell^\star(x)), \quad \rho \in \mathcal{K}_\infty$

- there is $\gamma > 0$ with $\rho(r) \leq \gamma r$ for all $r \in [0, \infty]$



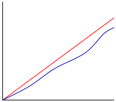
UNIVERSITÄT BAYREUTH

Comments and extensions

The "linear" inequality $V_N(x) \leq \gamma \ell^\star(x)$ may be too demanding for nonlinear systems under constraints

Generalization: $V_N(x) \leq \rho(\ell^\star(x)), \quad \rho \in \mathcal{K}_\infty$

- there is $\gamma > 0$ with $\rho(r) \leq \gamma r$ for all $r \in [0, \infty]$
  $\Rightarrow$ global asymptotic stability

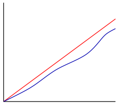


Comments and extensions

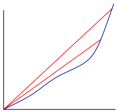
The "linear" inequality $V_N(x) \le \gamma \ell^\star(x)$ may be too demanding for nonlinear systems under constraints

Generalization: $V_N(x) \le \rho(\ell^\star(x)), \quad \rho \in \mathcal{K}_\infty$

- there is $\gamma > 0$ with $\rho(r) \le \gamma r$ for all $r \in [0, \infty]$ $\Rightarrow$ global asymptotic stability



- for each $R > 0$ there is $\gamma_R > 0$ with $\rho(r) \le \gamma_R r$ for all $r \in [0, R]$



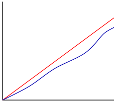
UNIVERSITÄT BAYREUTH

Comments and extensions

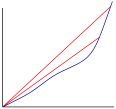
The "linear" inequality $V_N(x) \leq \gamma \ell^\star(x)$ may be too demanding for nonlinear systems under constraints

Generalization: $V_N(x) \leq \rho(\ell^\star(x)), \quad \rho \in \mathcal{K}_\infty$

- there is $\gamma > 0$ with $\rho(r) \leq \gamma r$ for all $r \in [0, \infty]$
  $\Rightarrow$ global asymptotic stability



- for each $R > 0$
  there is $\gamma_R > 0$ with $\rho(r) \leq \gamma_R r$ for all $r \in [0, R]$
  $\Rightarrow$ semiglobal asymptotic stability

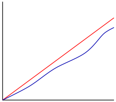


Comments and extensions

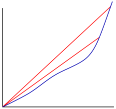
The "linear" inequality $V_N(x) \leq \gamma \ell^\star(x)$ may be too demanding for nonlinear systems under constraints

Generalization: $\quad V_N(x) \leq \rho(\ell^\star(x)), \quad \rho \in \mathcal{K}_\infty$

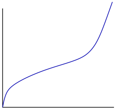
- there is $\gamma > 0$ with $\rho(r) \leq \gamma r$ for all $r \in [0, \infty]$
  $\Rightarrow$ global asymptotic stability



- for each $R > 0$
  there is $\gamma_R > 0$ with $\rho(r) \leq \gamma_R r$ for all $r \in [0, R]$
  $\Rightarrow$ semiglobal asymptotic stability



- $\rho \in \mathcal{K}_\infty$ arbitrary

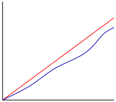


Comments and extensions

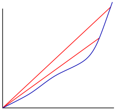
The "linear" inequality $V_N(x) \le \gamma \ell^\star(x)$ may be too demanding for nonlinear systems under constraints

Generalization: $V_N(x) \le \rho(\ell^\star(x)), \quad \rho \in \mathcal{K}_\infty$

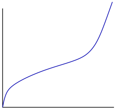
- there is $\gamma > 0$ with $\rho(r) \le \gamma r$ for all $r \in [0, \infty]$
  $\Rightarrow$ global asymptotic stability



- for each $R > 0$
  there is $\gamma_R > 0$ with $\rho(r) \le \gamma_R r$ for all $r \in [0, R]$
  $\Rightarrow$ semiglobal asymptotic stability



- $\rho \in \mathcal{K}_\infty$ arbitrary
  $\Rightarrow$ semiglobal practical asymptotic stability



[Grimm/Messina/Tuna/Teel '05, Gr./Pannek '11]

Summary of Section (5)

- Stability and performance of MPC without terminal constraints can be ensured by suitable bounds on V_N

Summary of Section (5)

- Stability and performance of MPC without terminal constraints can be ensured by suitable bounds on V_N
- An optimization approach allows to compute the best possible α_N in the relaxed dynamic programming theorem

Summary of Section (5)

- Stability and performance of MPC without terminal constraints can be ensured by suitable bounds on V_N
- An optimization approach allows to compute the best possible α_N in the relaxed dynamic programming theorem
- The γ or γ_N can be computed from controllability properties, e.g., exponential controllability

Summary of Section (5)

- Stability and performance of MPC without terminal constraints can be ensured by suitable bounds on V_N
- An optimization approach allows to compute the best possible α_N in the relaxed dynamic programming theorem
- The γ or γ_N can be computed from controllability properties, e.g., exponential controllability
- The overshoot bound $C > 0$ plays a crucial role or obtaining small stabilizing horizons

(6) Examples for the design of MPC schemes

Design of “good” MPC running costs ℓ

We want small overshoot C in the estimate

$$\ell(x_{\mathbf{u}}(n), \mathbf{u}(n)) \leq C\sigma^n \ell^\star(x_0)$$

Design of “good” MPC running costs ℓ

We want small overshoot C in the estimate

$$\ell(x_{\mathbf{u}}(n), \mathbf{u}(n)) \leq C\sigma^n \ell^\star(x_0)$$

The trajectories $x_{\mathbf{u}}(n)$ are given

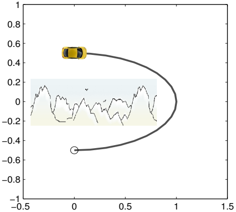
Design of “good” MPC running costs ℓ

We want small overshoot C in the estimate

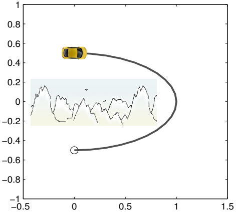
$$\ell(x_{\mathbf{u}}(n), \mathbf{u}(n)) \leq C\sigma^n \ell^\star(x_0)$$

The trajectories $x_{\mathbf{u}}(n)$ are given, but we can use the running cost ℓ as design parameter

The car-and-mountains example reloaded



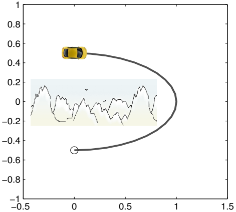
The car-and-mountains example reloaded



MPC with $\ell(x,u) = \|x - x_*\|^2 + |u|^2$ and $u_{\max} = 0.2$

$\rightsquigarrow$ asymptotic stability for $N = 11$ but not for $N \leq 10$

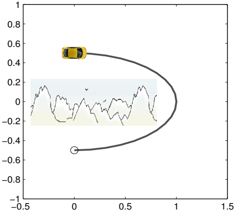
The car-and-mountains example reloaded



MPC with $\ell(x,u) = \|x - x_*\|^2 + |u|^2$ and $u_{\max} = 0.2$
$\rightsquigarrow$ asymptotic stability for $N = 11$ but not for $N \leq 10$

Reason: detour around mountains causes large overshoot C

The car-and-mountains example reloaded



MPC with $\ell(x,u) = \|x - x_*\|^2 + |u|^2$ and $u_{\max} = 0.2$

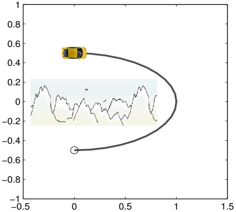
$\rightsquigarrow$ asymptotic stability for $N = 11$ but not for $N \leq 10$

Reason: detour around mountains causes large overshoot C

Remedy: put larger weight on x_2:

$$\ell(x,u) = (x_1 - x_{*,1})^2 + 5(x_2 - x_{*,2})^2 + |u|^2$$

The car-and-mountains example reloaded



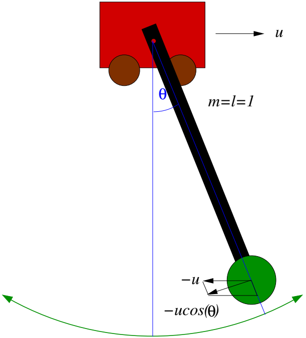
MPC with $\ell(x,u) = \|x - x_*\|^2 + |u|^2$ and $u_{\max} = 0.2$
$\rightsquigarrow$ asymptotic stability for $N = 11$ but not for $N \le 10$

Reason: detour around mountains causes large overshoot C

Remedy: put larger weight on x_2:

$\ell(x,u) = (x_1 - x_{*,1})^2 + 5(x_2 - x_{*,2})^2 + |u|^2$ $\rightsquigarrow$ as. stab. for $N = 2$

Example: pendulum on a cart



$x_1 = \theta =$ angle
$x_2 =$ angular velocity
$x_3 =$ cart position
$x_4 =$ cart velocity
$u \;=$ cart acceleration

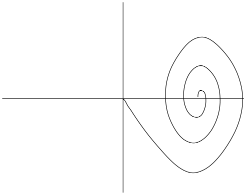
$\rightsquigarrow$ control system

$$\begin{aligned}
\dot{x}_1 &= x_2(t) \\
\dot{x}_2 &= -g\sin(x_1) - kx_2 \\
&\quad -u\cos(x_1) \\
\dot{x}_3 &= x_4 \\
\dot{x}_4 &= u
\end{aligned}$$

Example: Inverted Pendulum

Reducing overshoot for swingup of the pendulum on a cart:

$$\dot{x}_1 = x_2, \qquad \dot{x}_2 = g\sin(x_1) - kx_2 + u\cos(x_1)$$
$$\dot{x}_3 = x_4, \qquad \dot{x}_4 = u$$



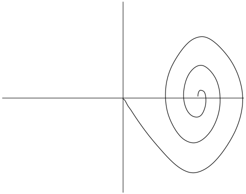
Typical swingup trajectory
x_1 and x_2 component

Example: Inverted Pendulum

Reducing overshoot for swingup of the pendulum on a cart:

$$\dot{x}_1 = x_2, \qquad \dot{x}_2 = g\sin(x_1) - kx_2 + u\cos(x_1)$$
$$\dot{x}_3 = x_4, \qquad \dot{x}_4 = u$$

Let $\ell(x) = \sqrt{\ell_1(x_1, x_2) + x_3^2 + x_4^2}$



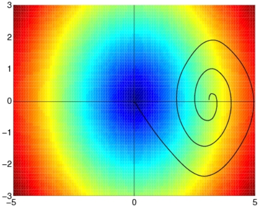
Typical swingup trajectory
x_1 and x_2 component

Example: Inverted Pendulum

Reducing overshoot for swingup of the pendulum on a cart:

$$\begin{aligned} \dot{x}_1 &= x_2, & \dot{x}_2 &= g\sin(x_1) - kx_2 + u\cos(x_1) \\ \dot{x}_3 &= x_4, & \dot{x}_4 &= u \end{aligned}$$

Let $\ell(x) = \sqrt{\ell_1(x_1, x_2) + x_3^2 + x_4^2}$ with



$\ell_1(x_1, x_2) = x_1^2 + x_2^2$

$N = 15$

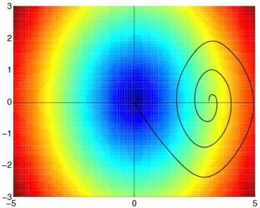
sampling time $T = 0.15$

Example: Inverted Pendulum

Reducing overshoot for swingup of the pendulum on a cart:

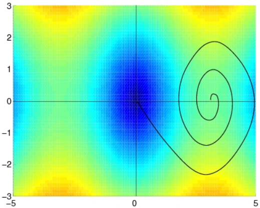
$$\dot{x}_1 = x_2, \qquad \dot{x}_2 = g\sin(x_1) - kx_2 + u\cos(x_1)$$
$$\dot{x}_3 = x_4, \qquad \dot{x}_4 = u$$

Let $\ell(x) = \sqrt{\ell_1(x_1, x_2) + x_3^2 + x_4^2}$ with



$\ell_1(x_1, x_2) = x_1^2 + x_2^2$

$N = 15$



$4(1 - \cos x_1) + x_2^2$

$N = 10$

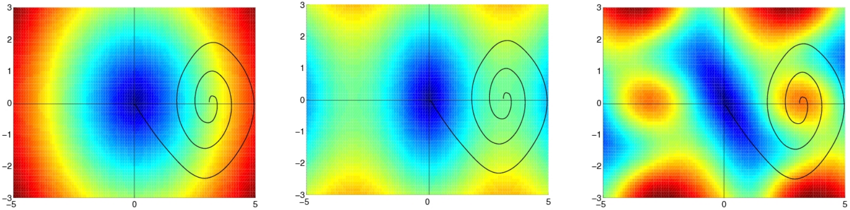
sampling time $T = 0.15$

Example: Inverted Pendulum

Reducing overshoot for swingup of the pendulum on a cart:

$$\dot{x}_1 = x_2, \qquad \dot{x}_2 = g\sin(x_1) - kx_2 + u\cos(x_1)$$
$$\dot{x}_3 = x_4, \qquad \dot{x}_4 = u$$

Let $\ell(x) = \sqrt{\ell_1(x_1, x_2) + x_3^2 + x_4^2}$ with



$\ell_1(x_1, x_2) = x_1^2 + x_2^2$ | $4(1 - \cos x_1) + x_2^2$ | $(\sin x_1, x_2)P(\sin x_1, x_2)^T + 2((1 - \cos x_1)(1 - \cos x_2)^2)^2$

$N = 15$ | $N = 10$ | $N = 4$ (swingup only)

sampling time $T = 0.15$

UNIVERSITÄT BAYREUTH

A PDE example

We illustrate this with the 1d controlled PDE

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

with

domain $\Omega = [0, 1]$

solution $y = y(t, x)$

boundary conditions $y(t, 0) = y(t, 1) = 0$

parameters $\nu = 0.1$ and $\mu = 10$

and distributed control $u : \mathbb{R} \times \Omega \to \mathbb{R}$

A PDE example

We illustrate this with the 1d controlled PDE

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

with

domain $\Omega = [0, 1]$

solution $y = y(t, x)$

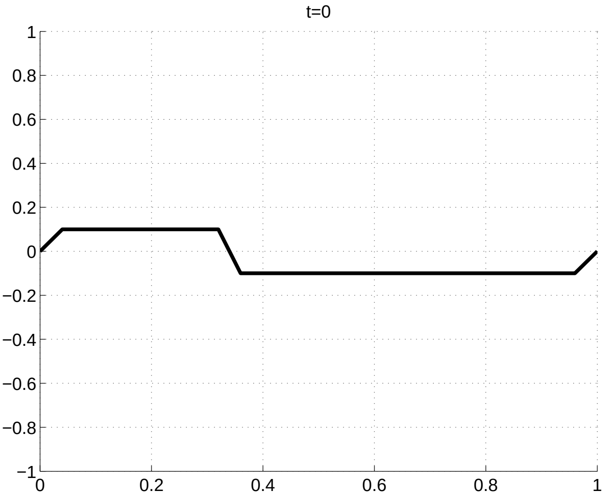
boundary conditions $y(t, 0) = y(t, 1) = 0$

parameters $\nu = 0.1$ and $\mu = 10$

and distributed control $u : \mathbb{R} \times \Omega \to \mathbb{R}$

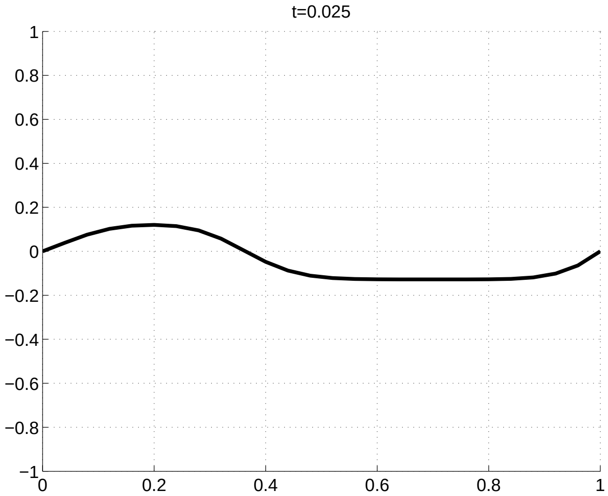
Discrete time system: $y(n) = y(nT, \cdot)$, sampling time $T = 0.025$

The uncontrolled PDE



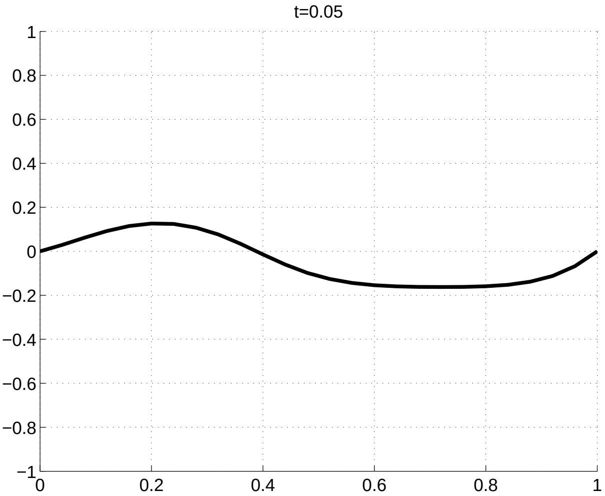
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



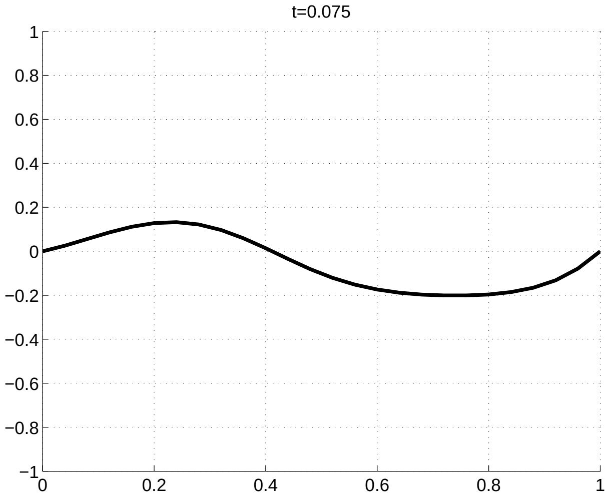
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



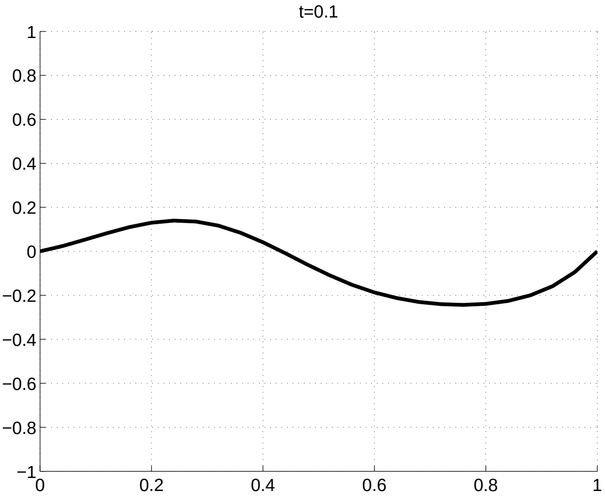
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



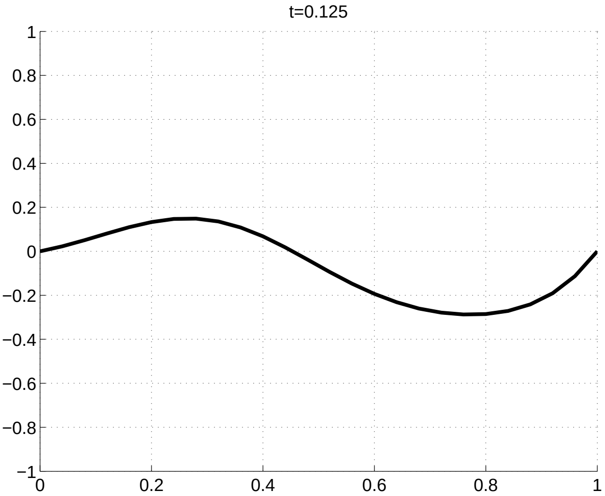
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



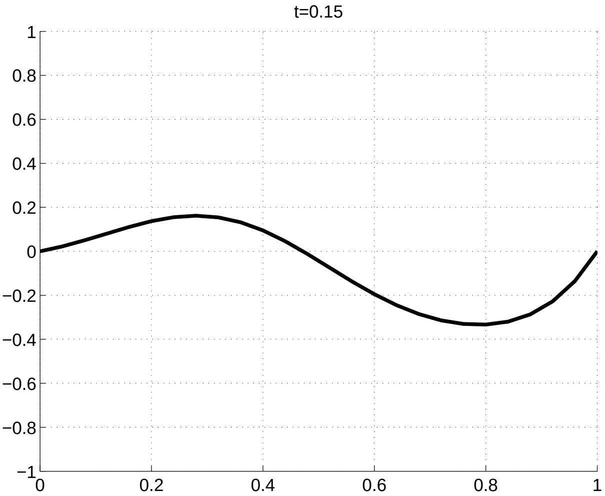
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



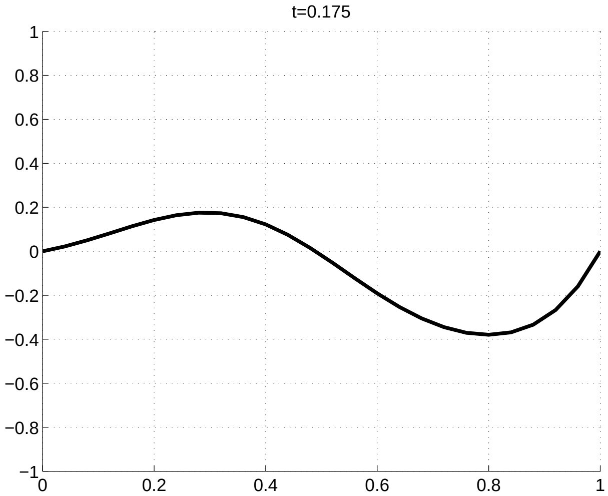
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



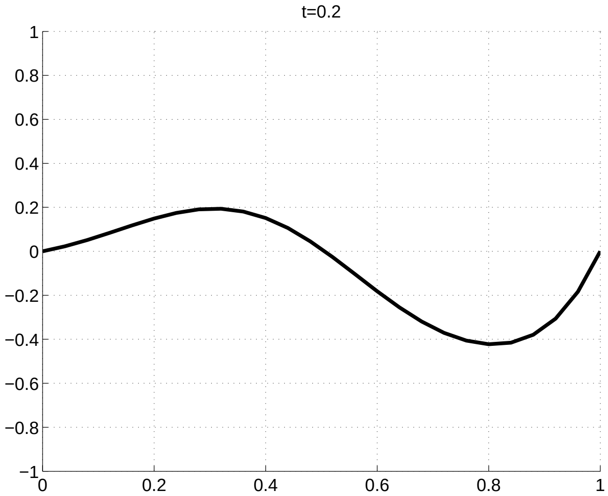
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



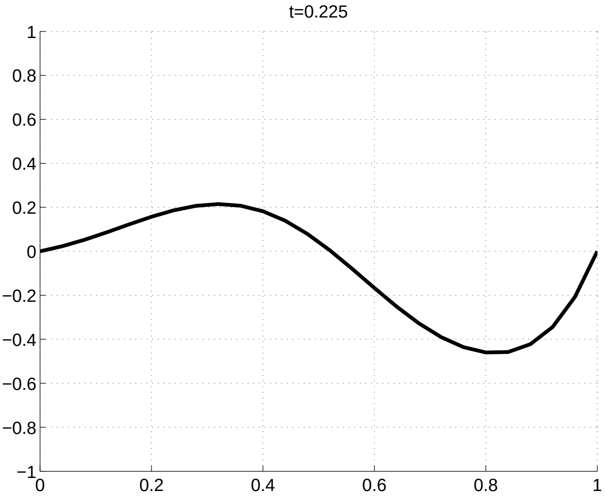
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



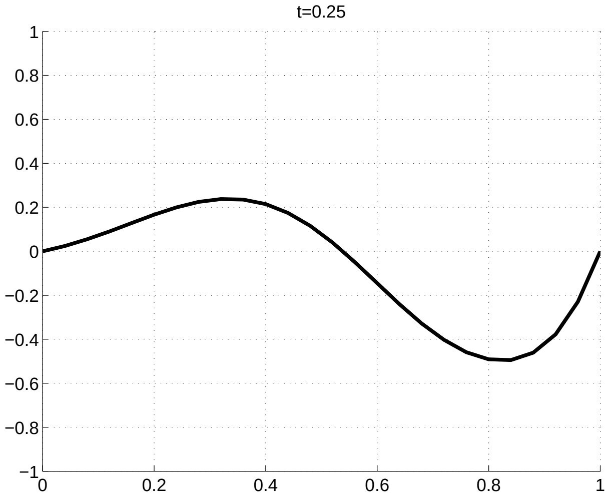
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



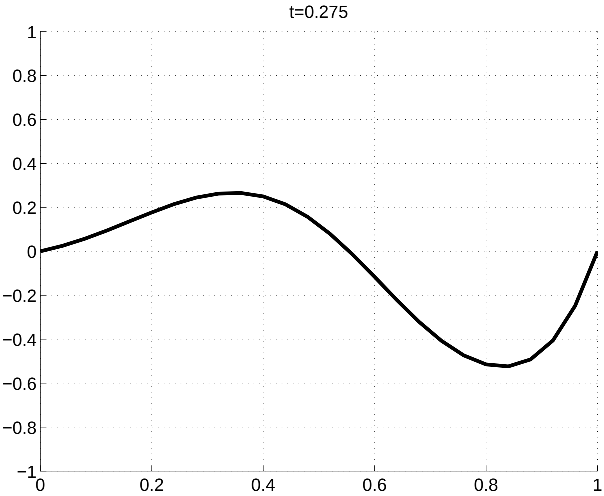
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



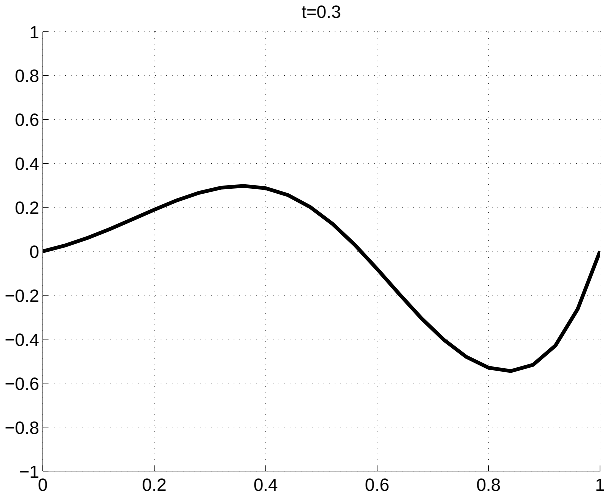
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



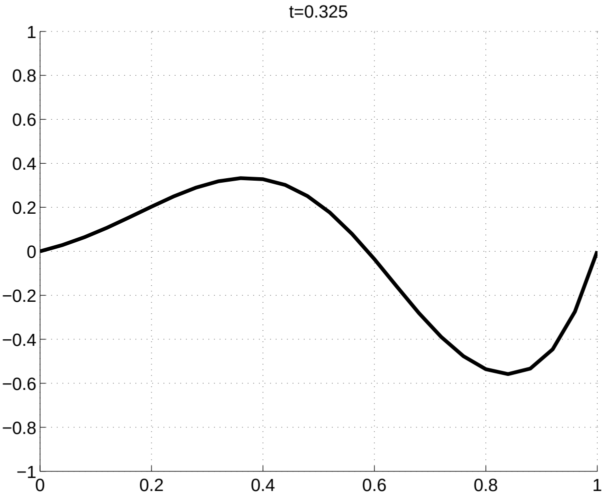
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



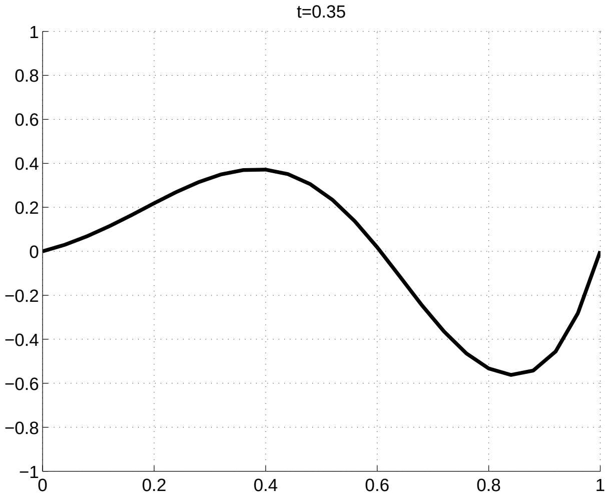
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



uncontrolled $(u \equiv 0)$

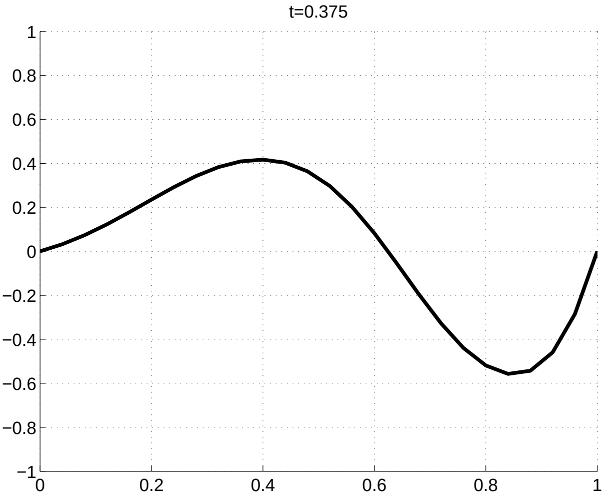
The uncontrolled PDE



uncontrolled $(u \equiv 0)$

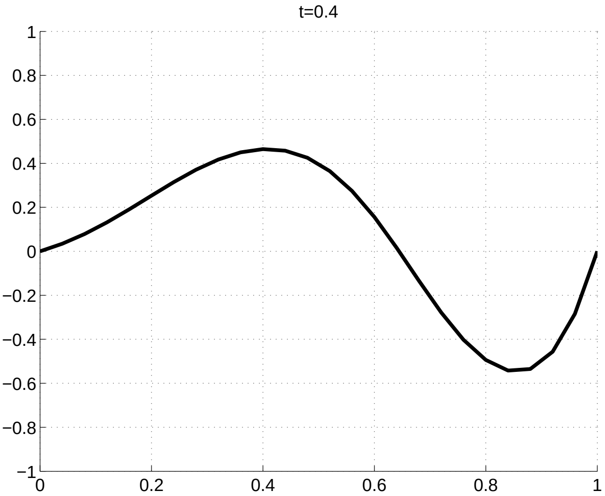
UNIVERSITÄT BAYREUTH

The uncontrolled PDE



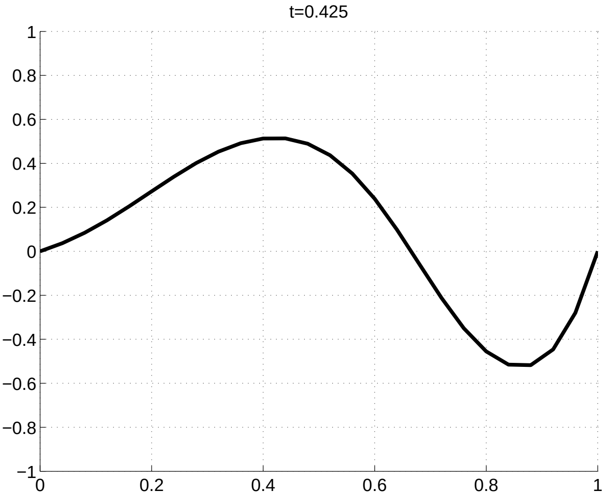
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



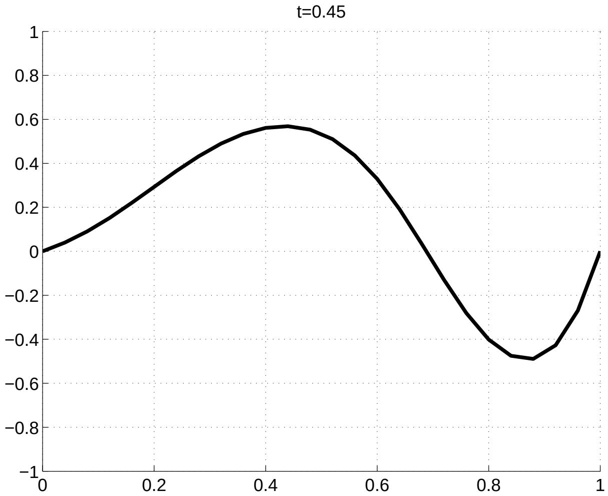
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



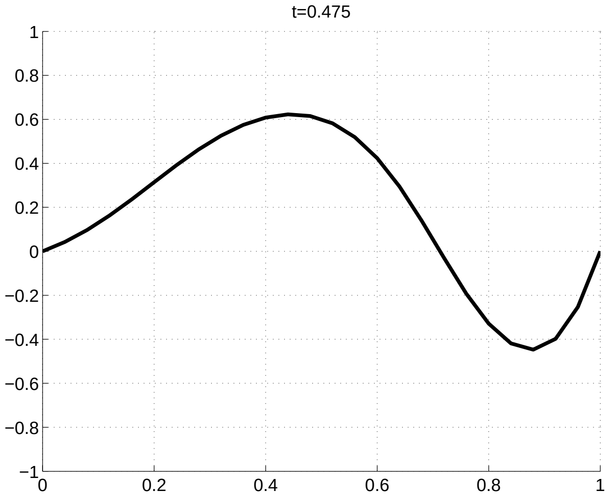
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



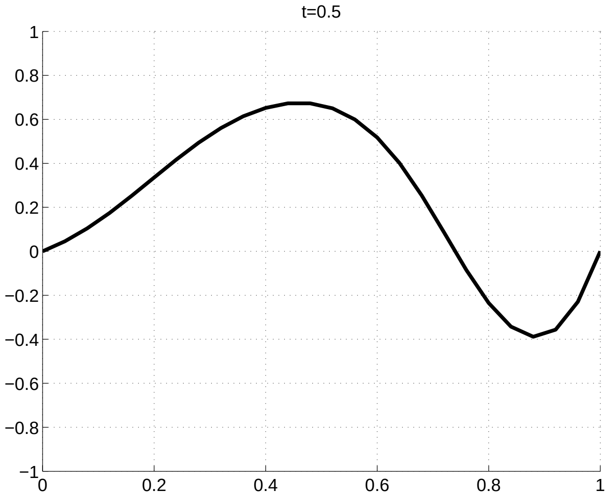
uncontrolled $(u \equiv 0)$

The uncontrolled PDE



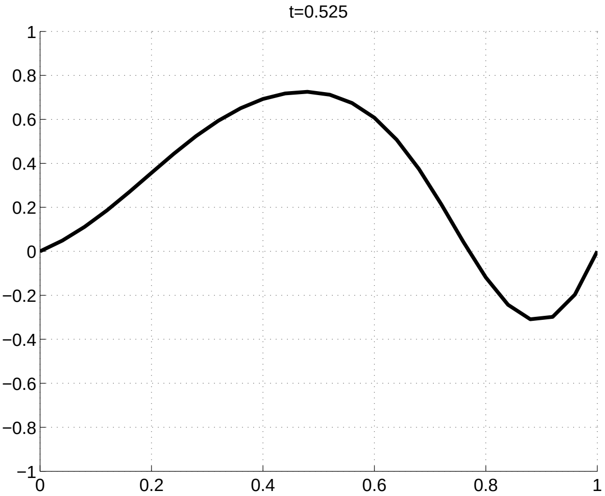
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



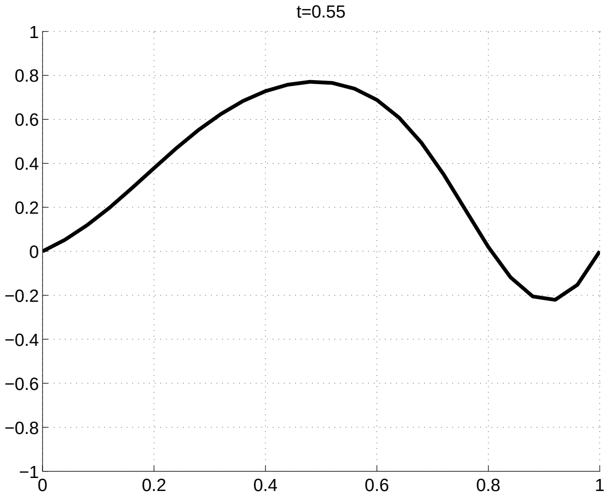
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



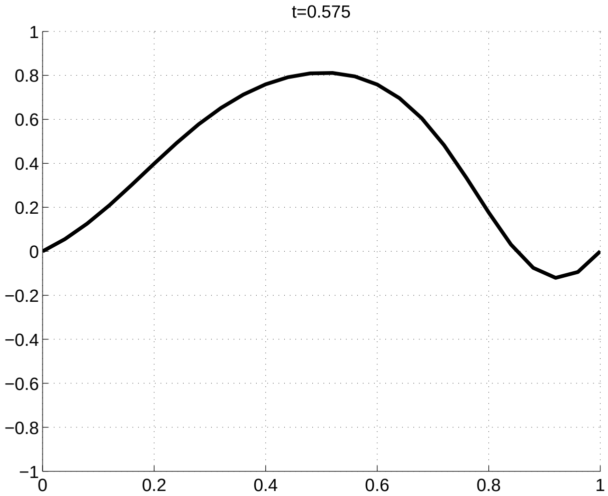
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



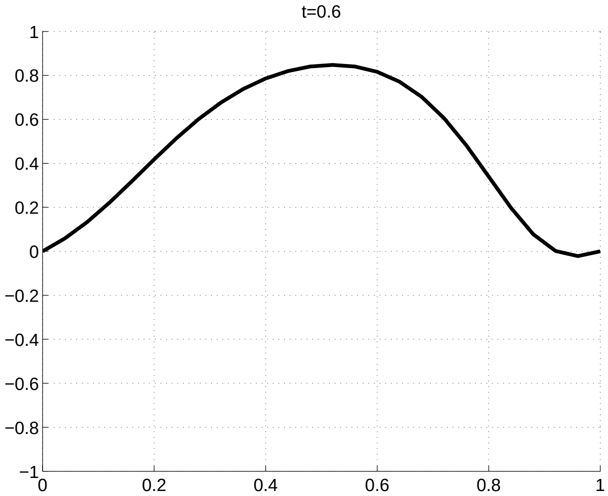
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



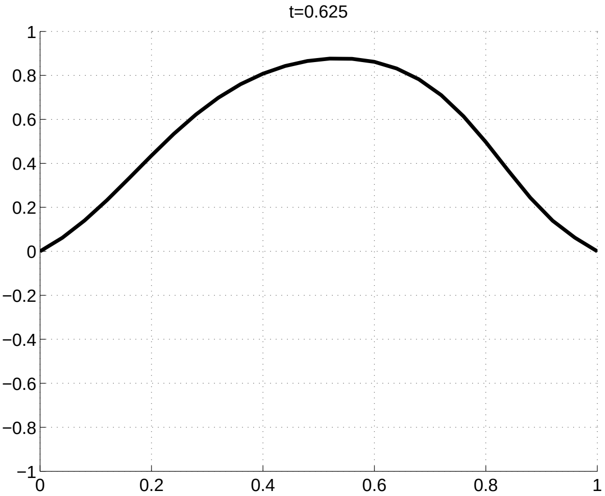
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



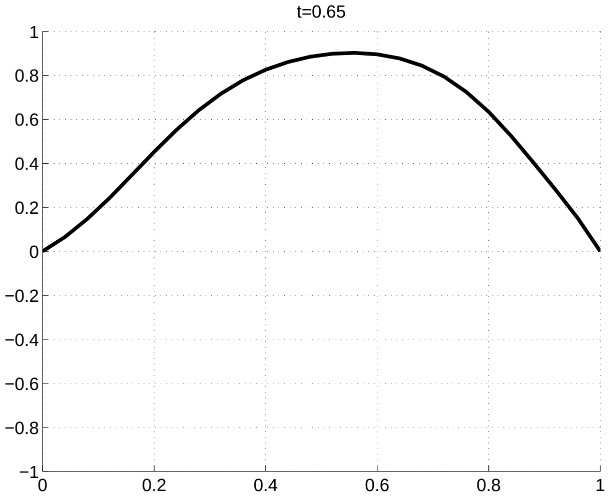
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



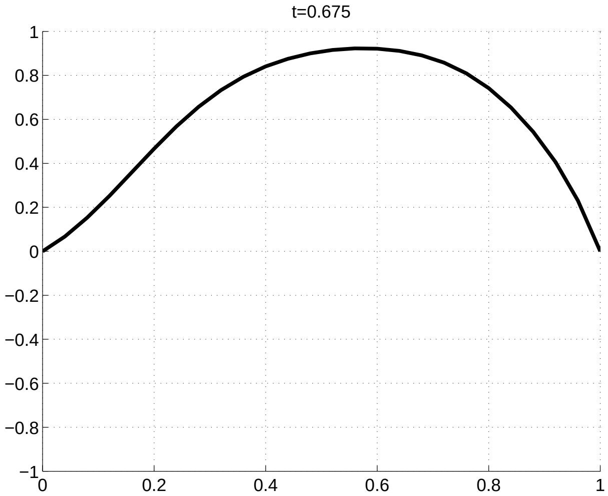
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



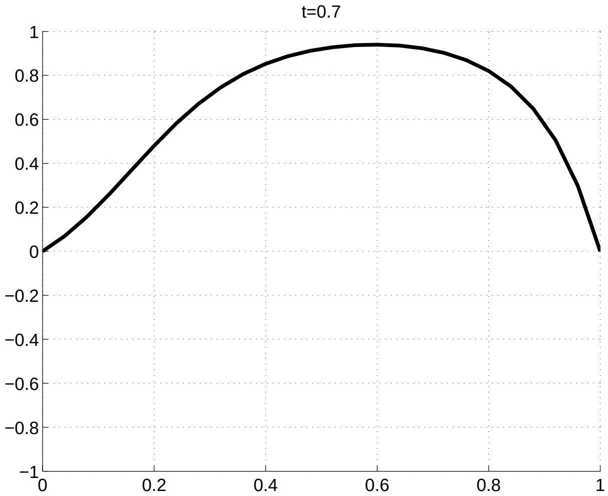
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



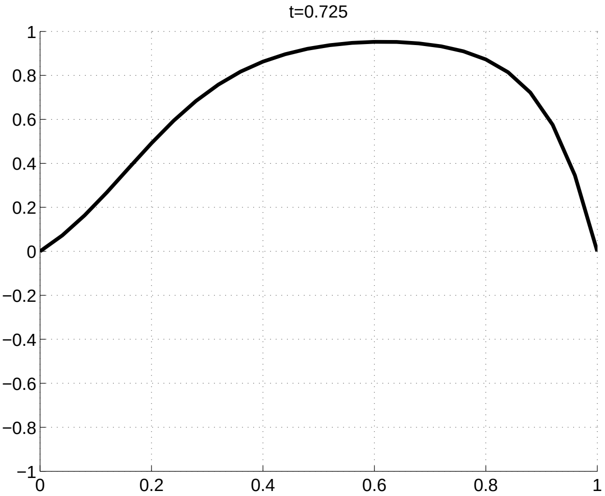
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



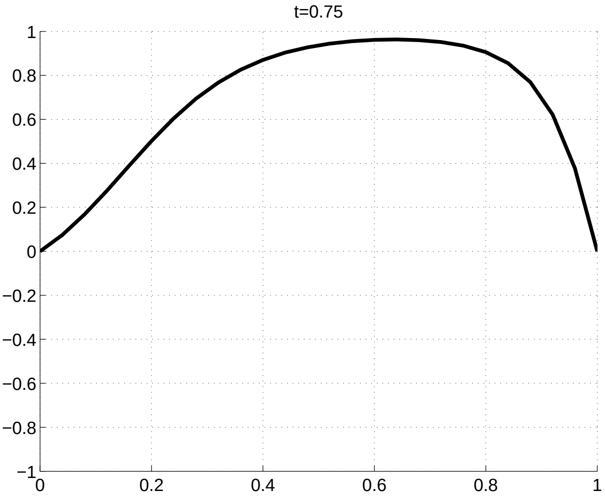
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



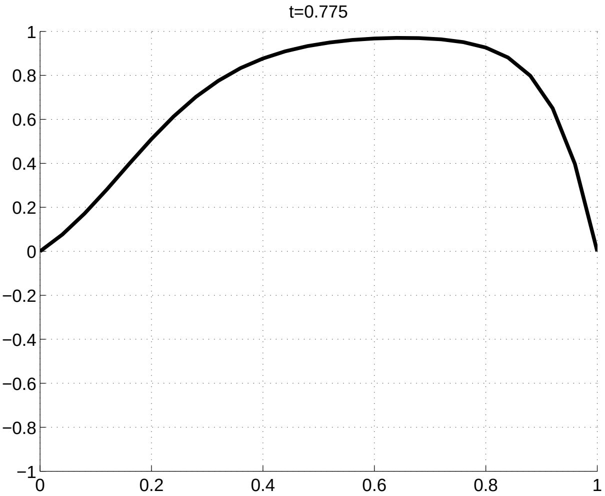
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



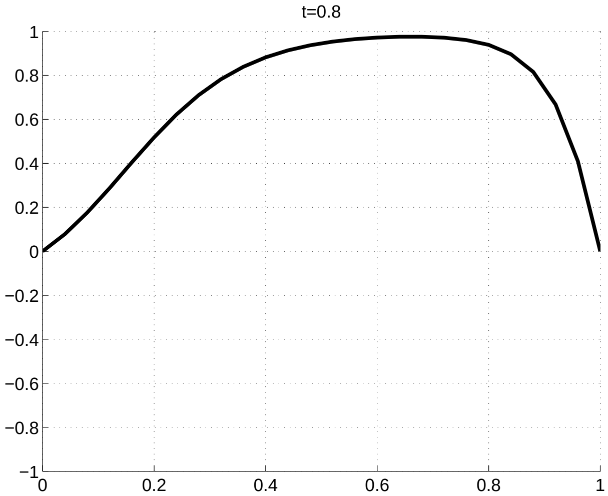
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



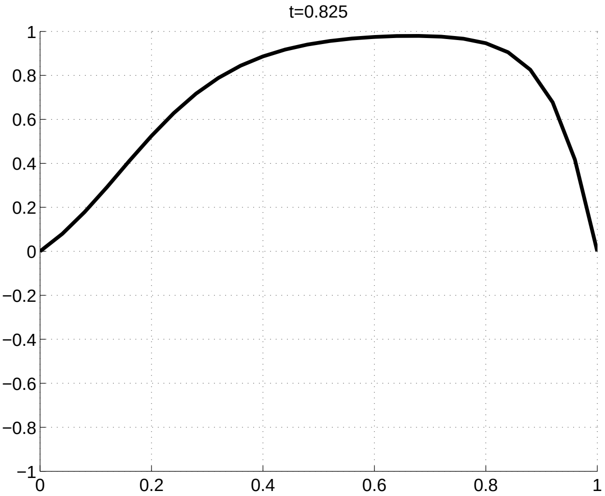
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



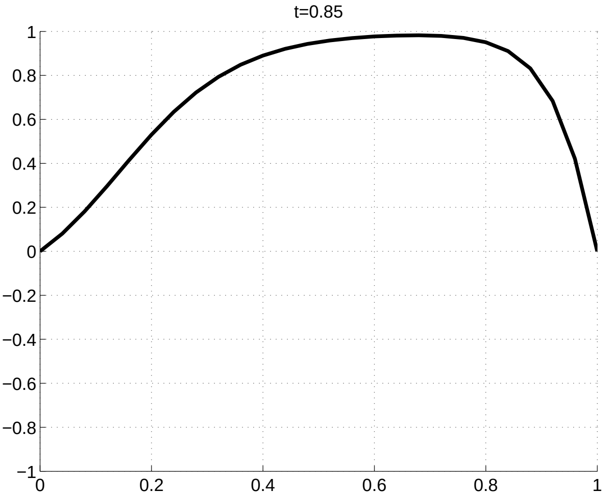
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



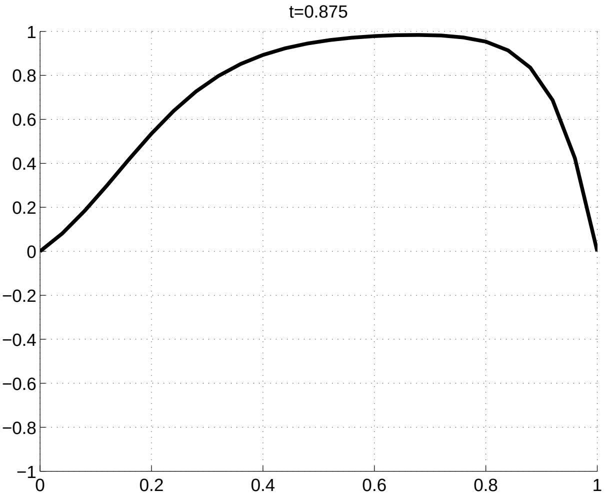
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



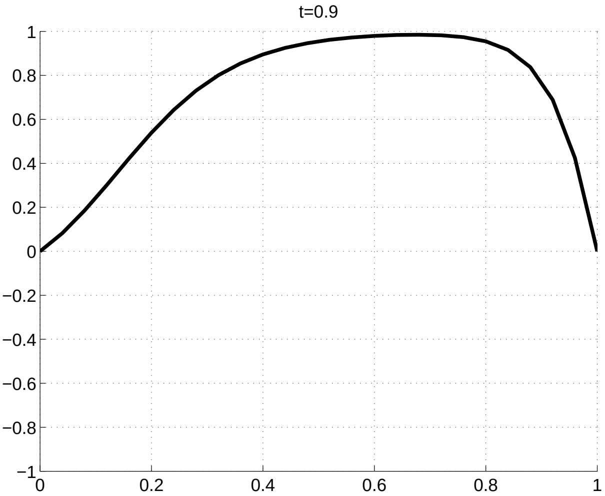
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



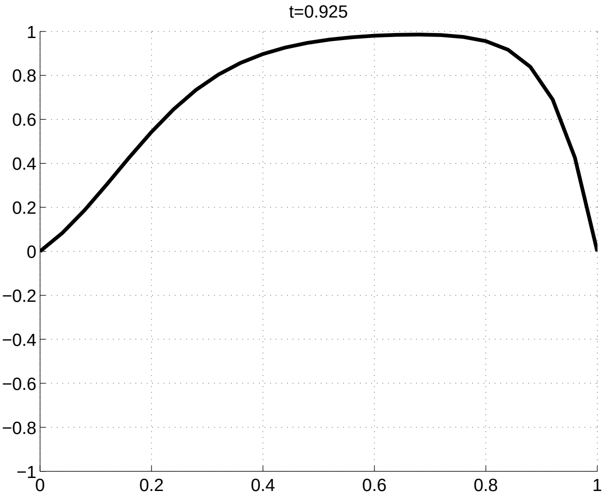
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



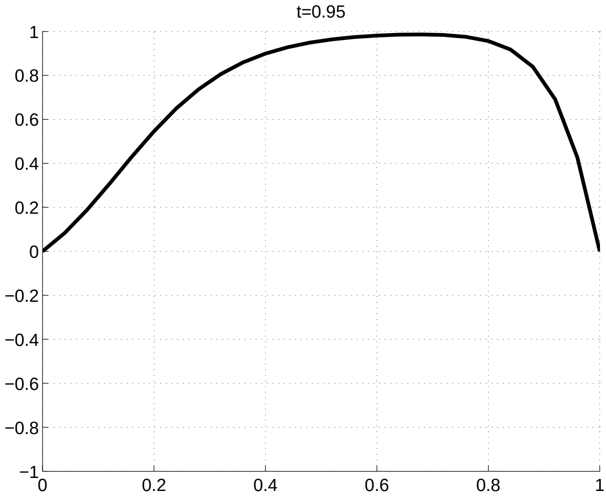
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



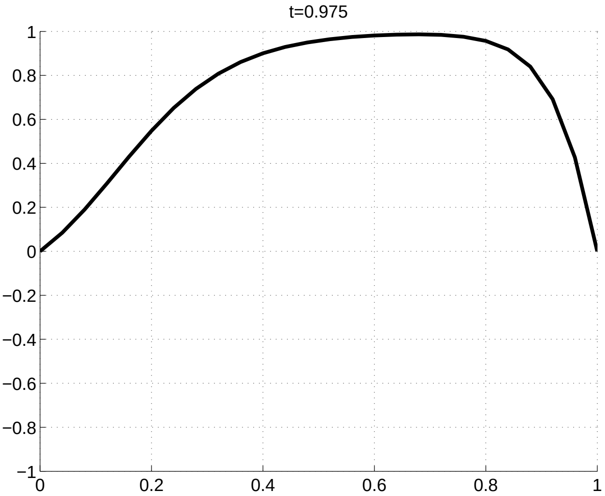
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



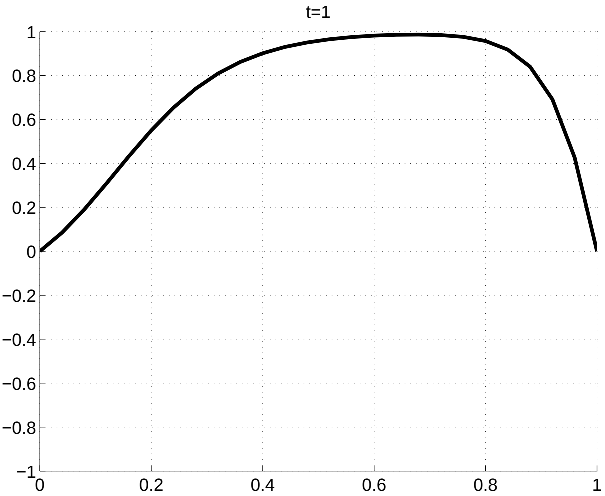
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



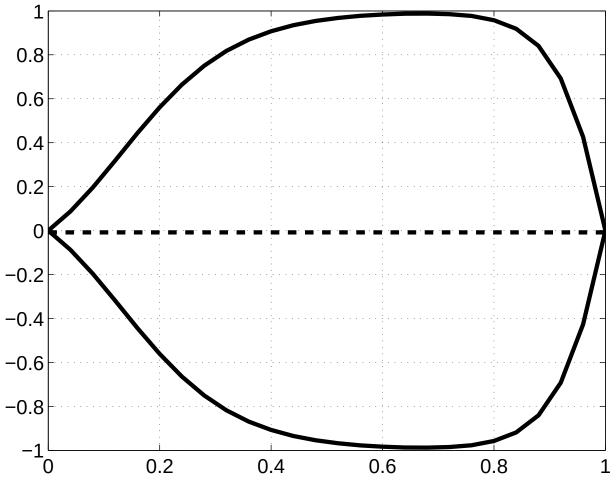
uncontrolled ($u \equiv 0$)

The uncontrolled PDE



uncontrolled $(u \equiv 0)$

The uncontrolled PDE



all equilibrium solutions

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

Goal: stabilize the sampled data system $y(n)$ at $y \equiv 0$

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

Goal: stabilize the sampled data system $y(n)$ at $y \equiv 0$

Usual approach: quadratic L^2 cost

$$\ell(y(n), u(n)) = \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2$$

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

Goal: stabilize the sampled data system $y(n)$ at $y \equiv 0$

Usual approach: quadratic L^2 cost

$$\ell(y(n), u(n)) = \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2$$

For $y \approx 0$ the control u must compensate for $y_x \rightsquigarrow u \approx -y_x$

UNIVERSITÄT BAYREUTH

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

Goal: stabilize the sampled data system $y(n)$ at $y \equiv 0$

Usual approach: quadratic L^2 cost

$$\ell(y(n), u(n)) = \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2$$

For $y \approx 0$ the control u must compensate for $y_x \rightsquigarrow u \approx -y_x$

$\rightsquigarrow$ controllability condition

$$\ell(y(n), u(n)) \quad \leq \quad C\sigma^n \ell^*(y(0))$$

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

Goal: stabilize the sampled data system $y(n)$ at $y \equiv 0$

Usual approach: quadratic L^2 cost

$$\ell(y(n), u(n)) = \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2$$

For $y \approx 0$ the control u must compensate for $y_x \rightsquigarrow u \approx -y_x$

$\rightsquigarrow$ controllability condition

$$\begin{aligned} \ell(y(n), u(n)) &\leq C\sigma^n \ell^*(y(0)) \\ \Leftrightarrow \quad \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2 &\leq C\sigma^n \|y(0)\|_{L^2}^2 \end{aligned}$$

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

Goal: stabilize the sampled data system $y(n)$ at $y \equiv 0$

Usual approach: quadratic L^2 cost

$$\ell(y(n), u(n)) = \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2$$

For $y \approx 0$ the control u must compensate for $y_x \rightsquigarrow u \approx -y_x$

$\rightsquigarrow$ controllability condition

$$\begin{aligned} & \ell(y(n), u(n)) & \le & \; C\sigma^n \ell^*(y(0)) \\ \Leftrightarrow \quad & \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2 & \le & \; C\sigma^n \|y(0)\|_{L^2}^2 \\ \approx \quad & \|y(n)\|_{L^2}^2 + \lambda \|y_x(n)\|_{L^2}^2 & \le & \; C\sigma^n \|y(0)\|_{L^2}^2 \end{aligned}$$

MPC for the PDE example

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y) + u$$

Goal: stabilize the sampled data system $y(n)$ at $y \equiv 0$

Usual approach: quadratic L^2 cost

$$\ell(y(n), u(n)) = \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2$$

For $y \approx 0$ the control u must compensate for $y_x \rightsquigarrow u \approx -y_x$

$\rightsquigarrow$ controllability condition

$$\begin{array}{rrcl} & \ell(y(n), u(n)) & \leq & C\sigma^n \ell^*(y(0)) \\ \Leftrightarrow & \|y(n)\|_{L^2}^2 + \lambda \|u(n)\|_{L^2}^2 & \leq & C\sigma^n \|y(0)\|_{L^2}^2 \\ \approx & \|y(n)\|_{L^2}^2 + \lambda \|y_x(n)\|_{L^2}^2 & \leq & C\sigma^n \|y(0)\|_{L^2}^2 \end{array}$$

for $\|y_x\|_{L^2} \gg \|y\|_{L^2}$ this can only hold if $C \gg 0$

UNIVERSITÄT BAYREUTH

MPC for the PDE example

Conclusion: because of

$$\|y(n)\|_{L^2}^2 + \lambda\|y_x(n)\|_{L^2}^2 \leq C\sigma^n\|y(0)\|_{L^2}^2$$

the controllability condition may only hold for very large C

MPC for the PDE example

Conclusion: because of

$$\|y(n)\|_{L^2}^2 + \lambda\|y_x(n)\|_{L^2}^2 \le C\sigma^n\|y(0)\|_{L^2}^2$$

the controllability condition may only hold for very large C

Remedy: use H^1 cost

$$\ell(y(n),u(n)) = \underbrace{\|y(n)\|_{L^2}^2 + \|y_x(n)\|_{L^2}^2}_{=\|y(n)\|_{H^1}^2} + \lambda\|u(n)\|_{L^2}^2.$$

MPC for the PDE example

Conclusion: because of

$$\|y(n)\|_{L^2}^2 + \lambda\|y_x(n)\|_{L^2}^2 \le C\sigma^n\|y(0)\|_{L^2}^2$$

the controllability condition may only hold for very large C

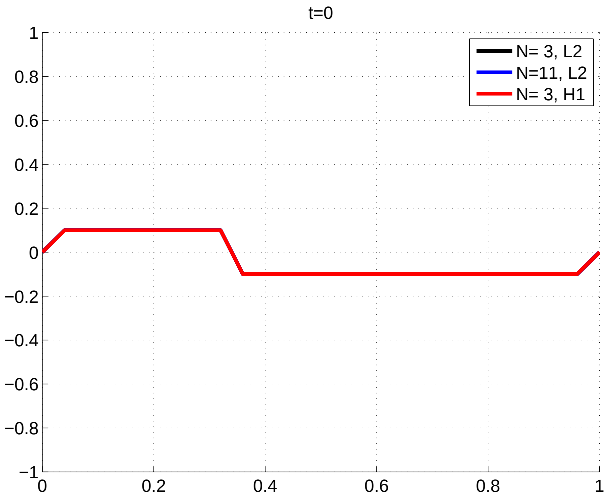
Remedy: use H^1 cost

$$\ell(y(n),u(n)) = \underbrace{\|y(n)\|_{L^2}^2 + \|y_x(n)\|_{L^2}^2}_{=\|y(n)\|_{H^1}^2} + \lambda\|u(n)\|_{L^2}^2.$$

Then an analogous computation yields

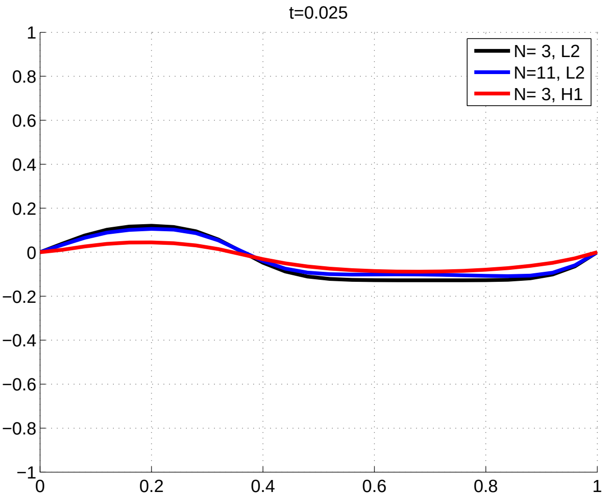
$$\|y(n)\|_{L^2}^2 + (1+\lambda)\|y_x(n)\|_{L^2}^2 \le C\sigma^n\Big(\|y(0)\|_{L^2}^2 + \|y_x(0)\|_{L^2}^2\Big)$$

MPC with L_2 vs. H_1 cost



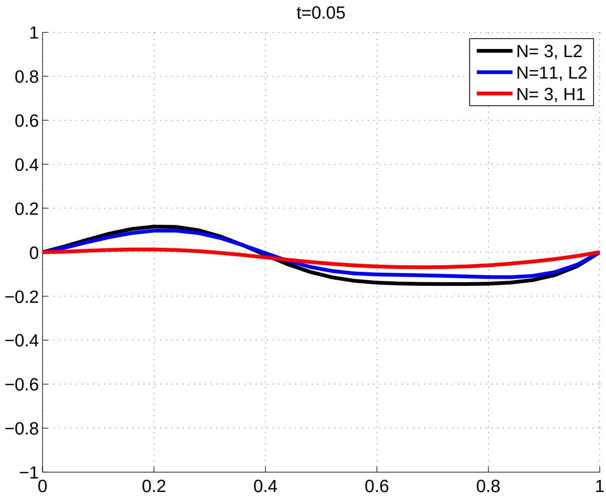
MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



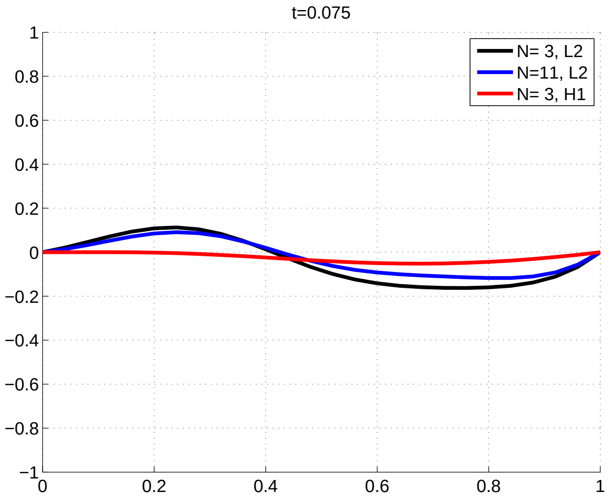
MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



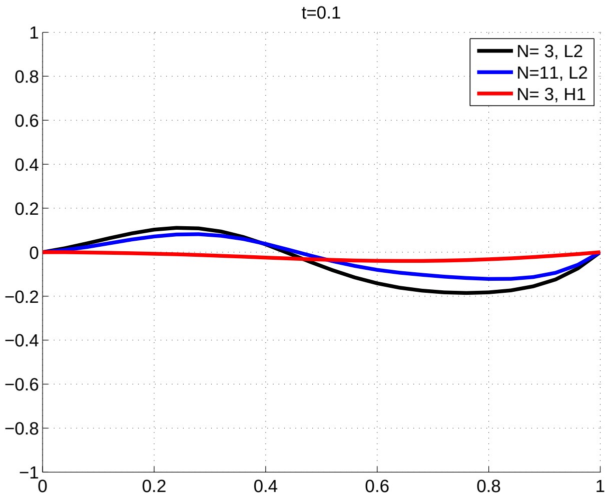
MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



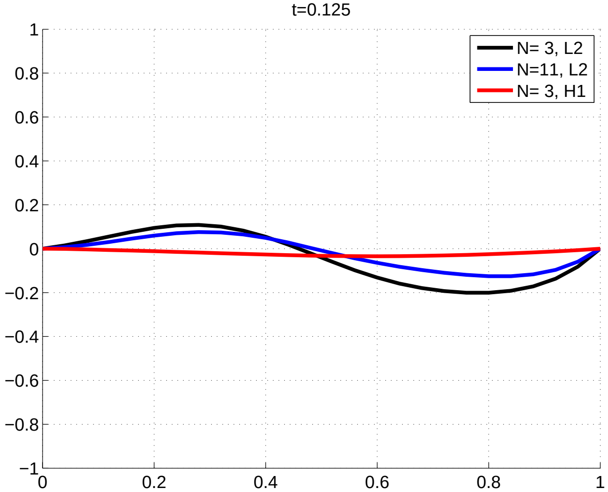
MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

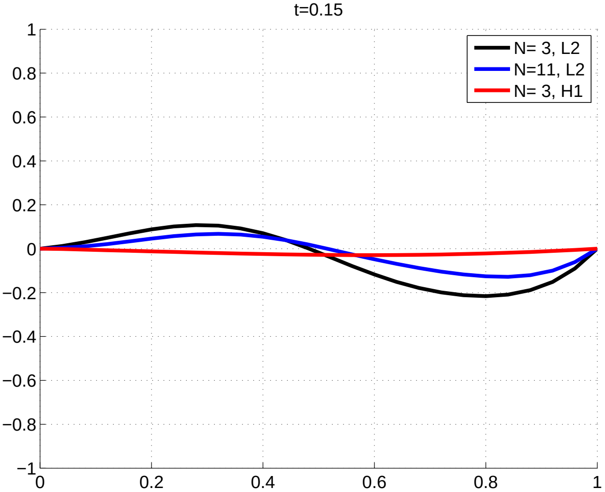
MPC with L_2 vs. H_1 cost



MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

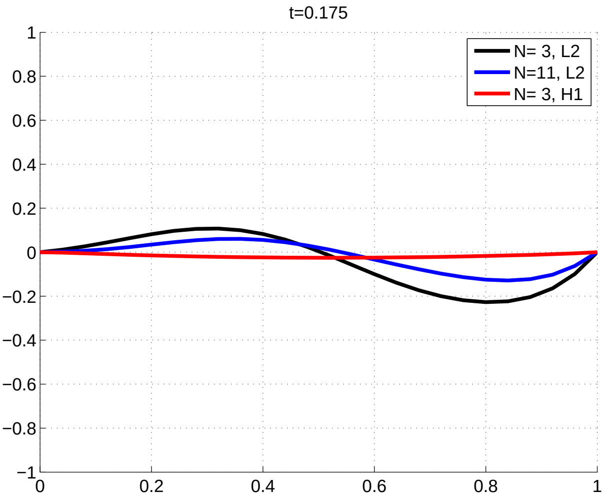
UNIVERSITÄT BAYREUTH

MPC with L_2 vs. H_1 cost



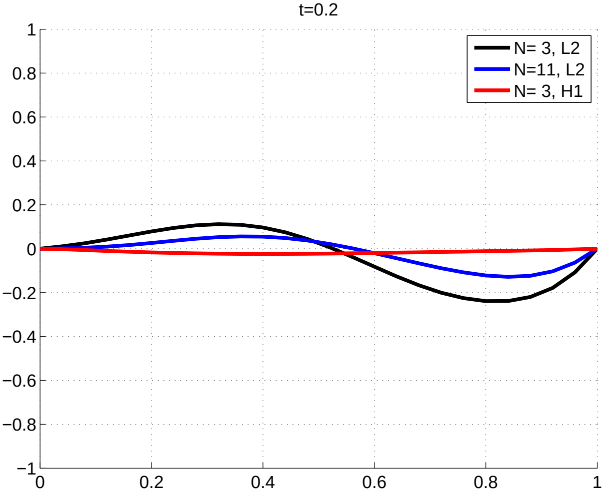
MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



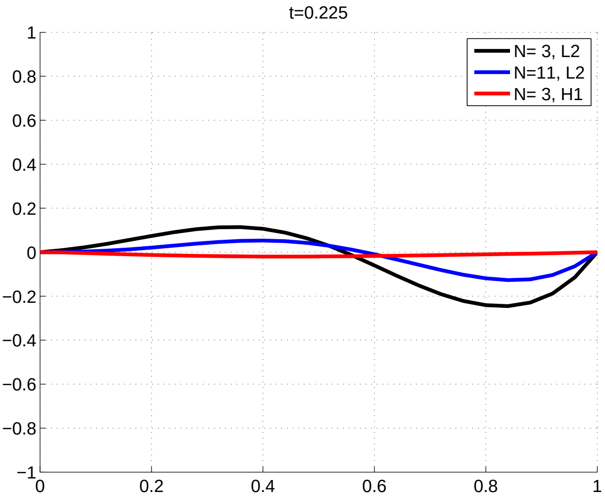
MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



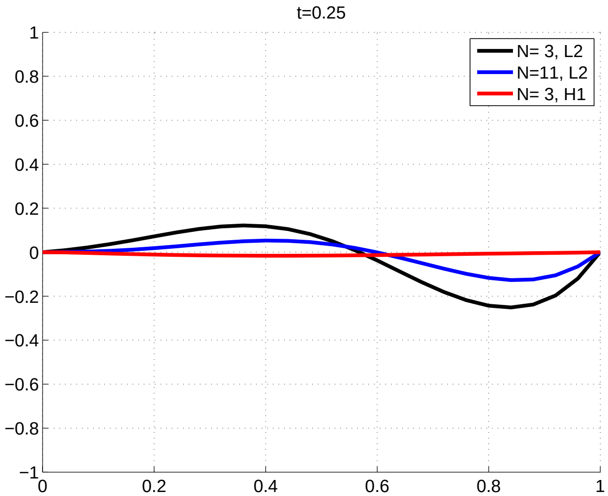
MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

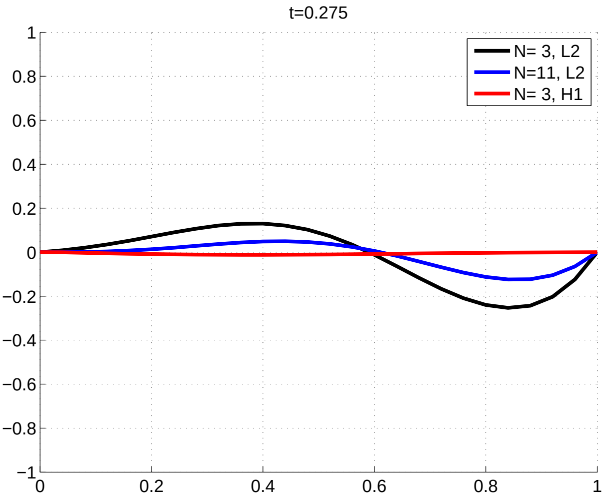
MPC with L_2 vs. H_1 cost



MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

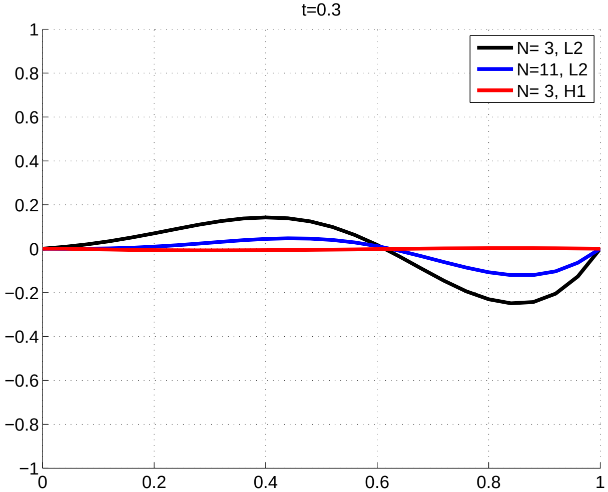
UNIVERSITÄT BAYREUTH

MPC with L_2 vs. H_1 cost



MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

MPC with L_2 vs. H_1 cost



MPC with L_2 and H_1 cost, $\lambda = 0.1$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

Boundary Control

Now we change our PDE from distributed to (Dirichlet-) boundary control, i.e.

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y)$$

with

domain $\Omega = [0,1]$

solution $y = y(t,x)$

boundary conditions $y(t,0) = u_0(t)$, $y(t,1) = u_1(t)$

parameters $\nu = 0.1$ and $\mu = 10$

Boundary Control

Now we change our PDE from distributed to (Dirichlet-) boundary control, i.e.

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y)$$

with

domain $\Omega = [0, 1]$

solution $y = y(t, x)$

boundary conditions $y(t, 0) = u_0(t)$, $y(t, 1) = u_1(t)$

parameters $\nu = 0.1$ and $\mu = 10$

with boundary control, stability can only be achieved via large gradients in the transient phase

Boundary Control

Now we change our PDE from distributed to (Dirichlet-) boundary control, i.e.

$$y_t = y_x + \nu y_{xx} + \mu y(y+1)(1-y)$$

with

domain $\Omega = [0,1]$

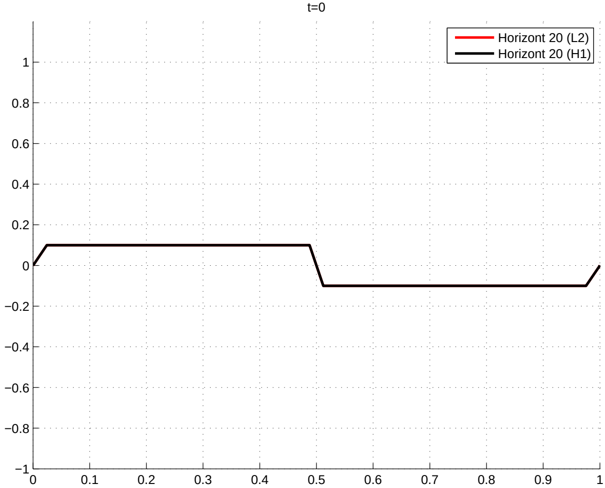
solution $y = y(t,x)$

boundary conditions $y(t,0) = u_0(t)$, $y(t,1) = u_1(t)$

parameters $\nu = 0.1$ and $\mu = 10$

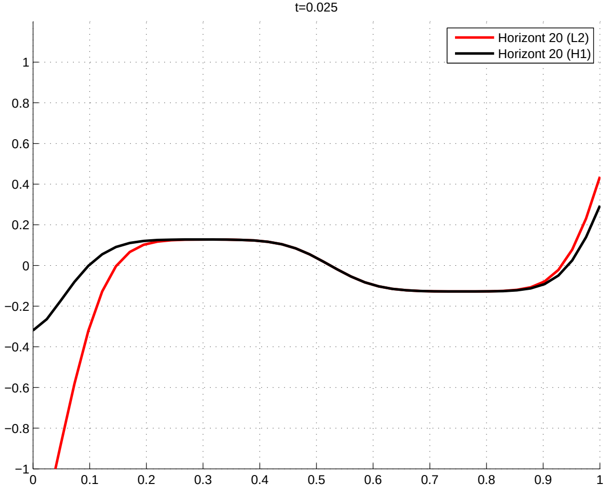
with boundary control, stability can only be achieved via large gradients in the transient phase
$\rightsquigarrow$ L^2 should perform better that H^1

Boundary control, L_2 vs. H_1, $N = 20$



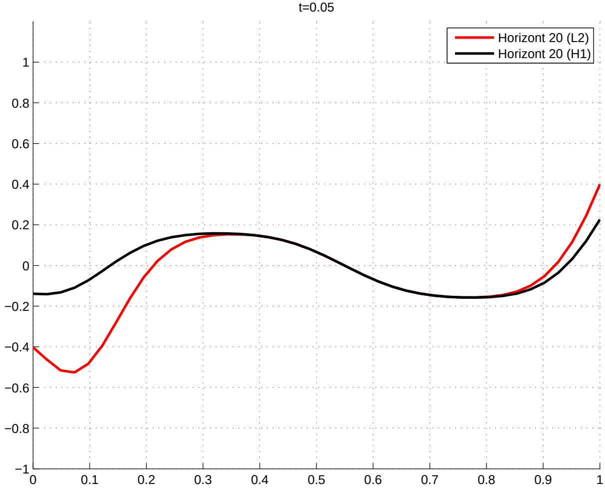
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

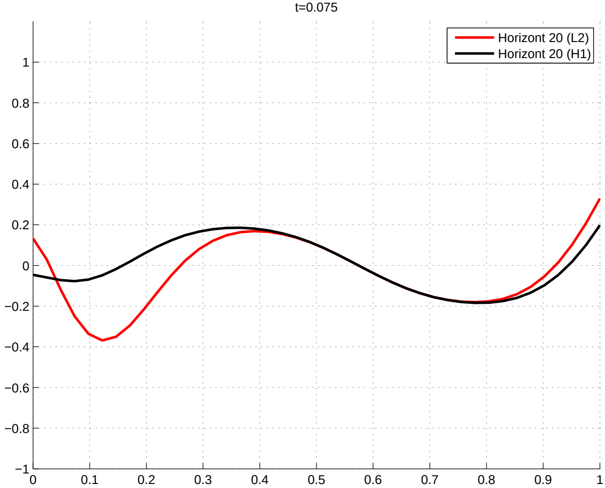
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

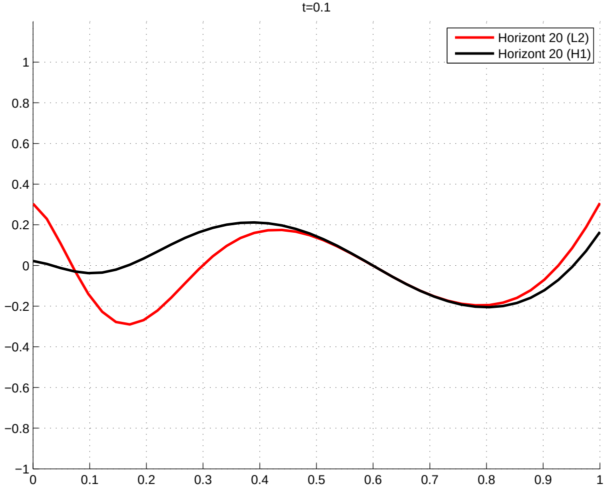
UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



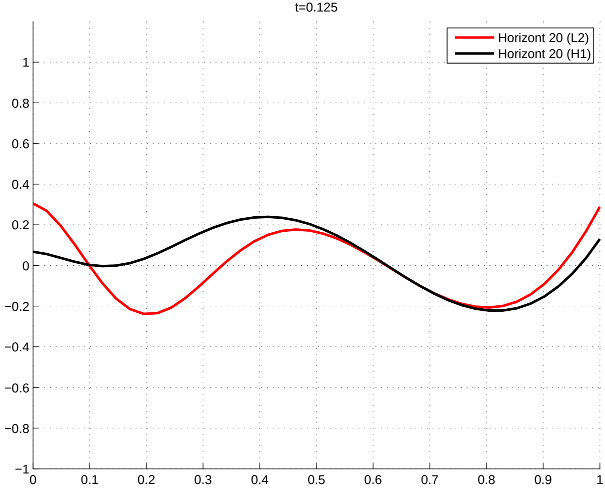
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

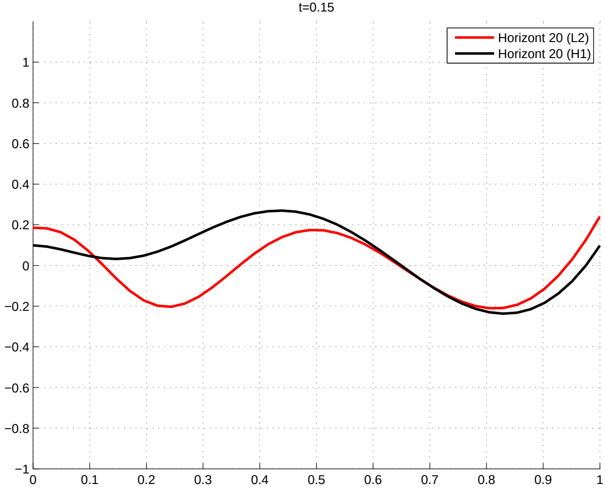
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

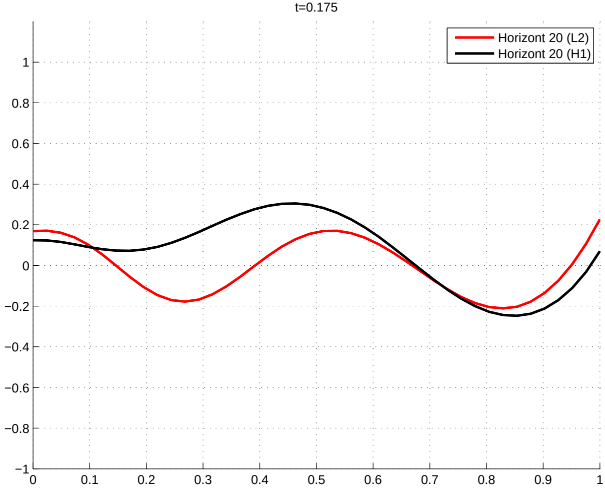
UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



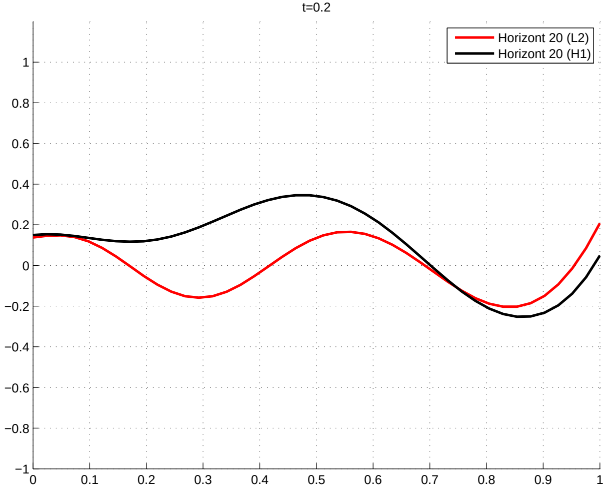
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



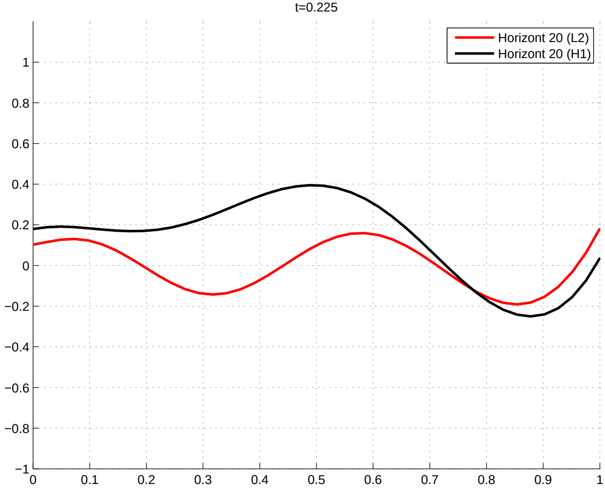
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



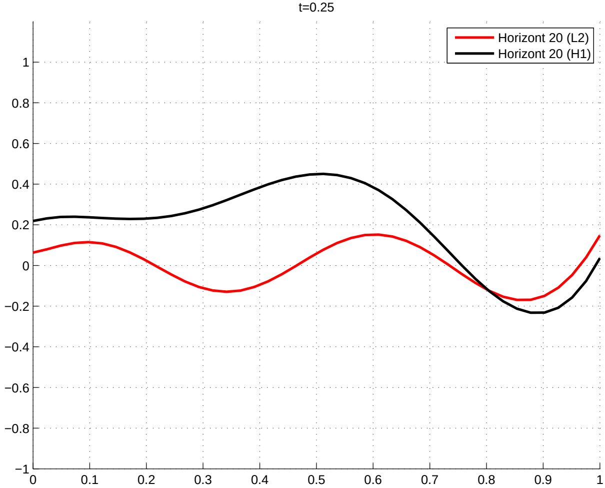
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

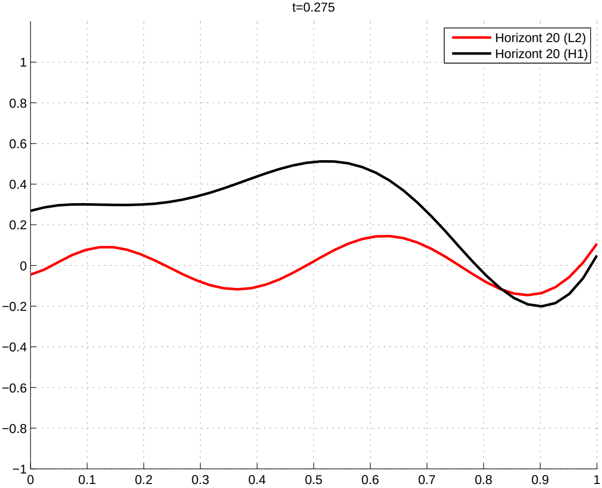
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

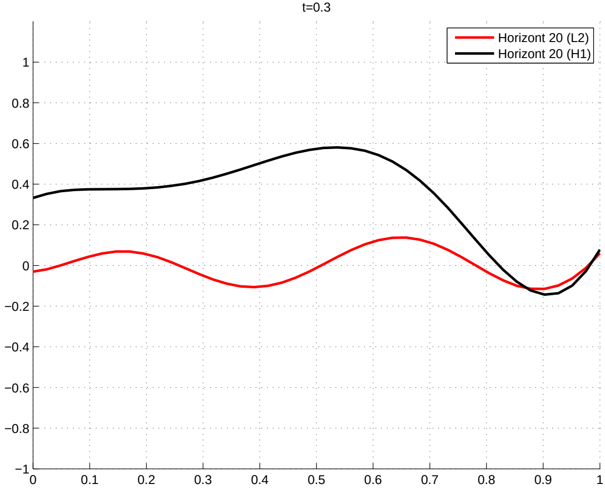
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

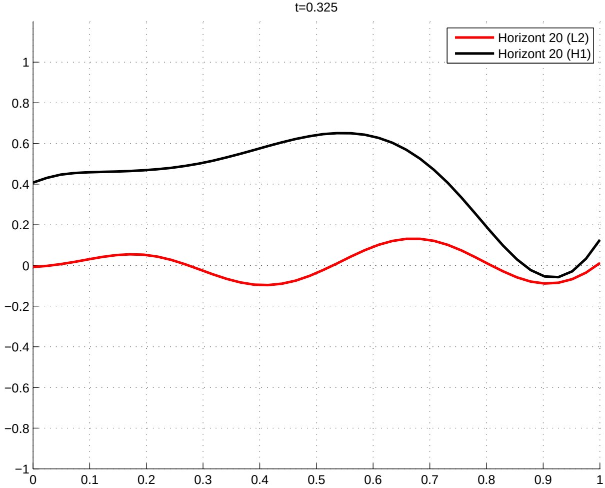
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

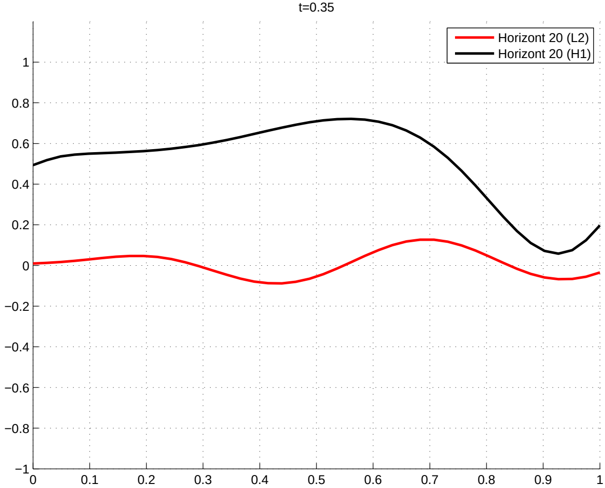
UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

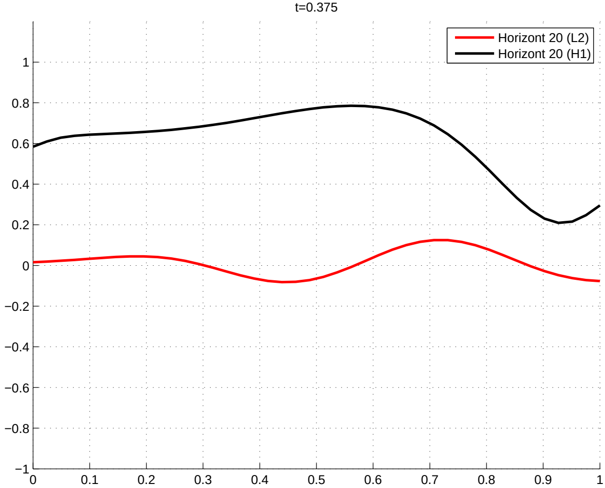
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

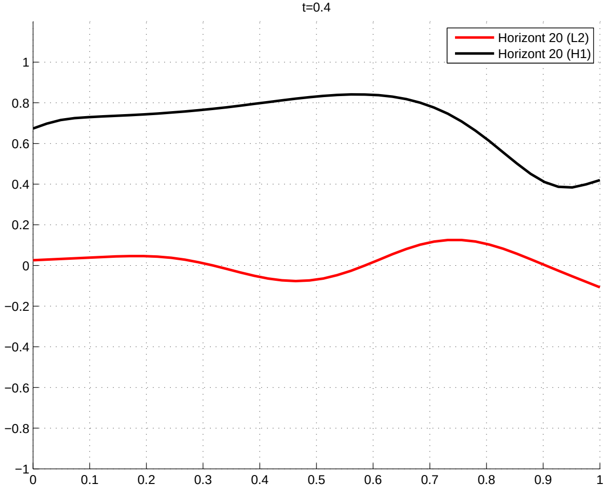
UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

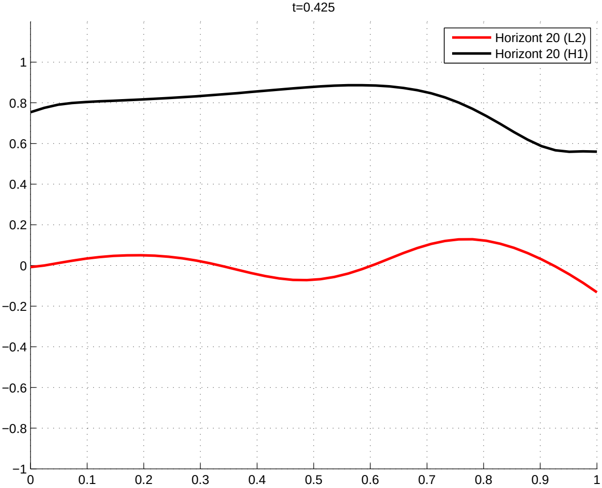
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

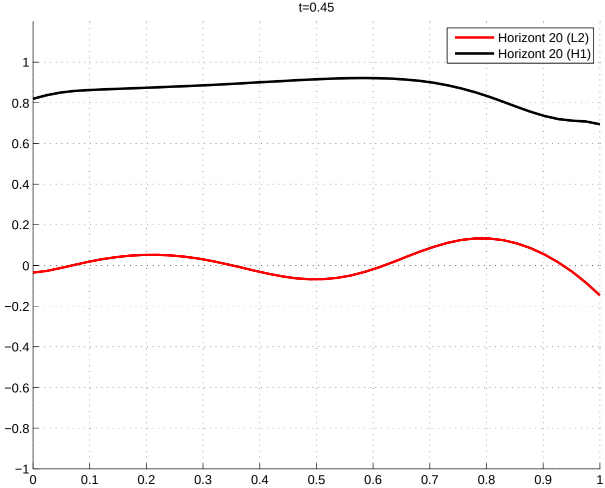
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

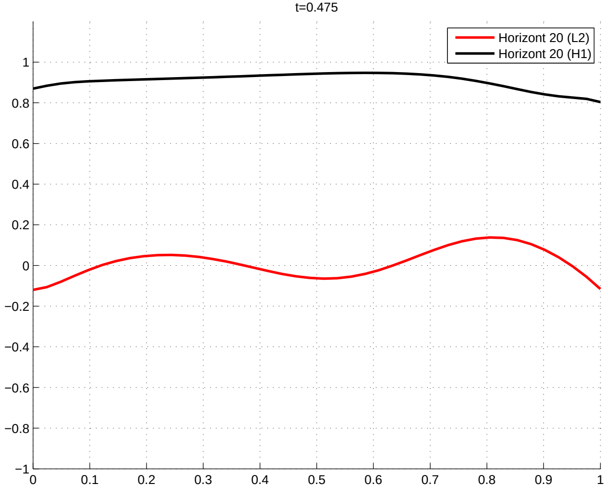
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

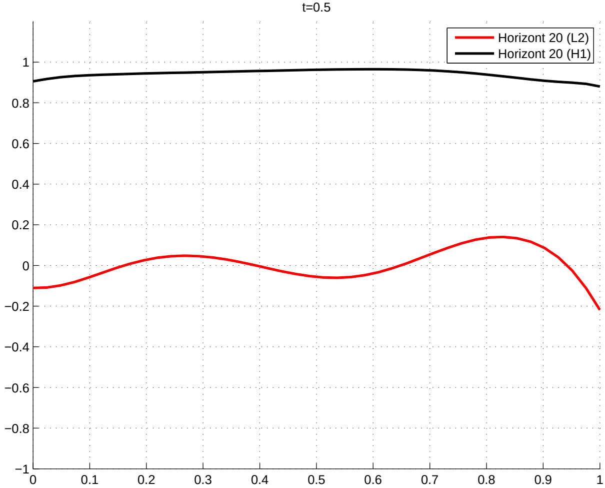
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

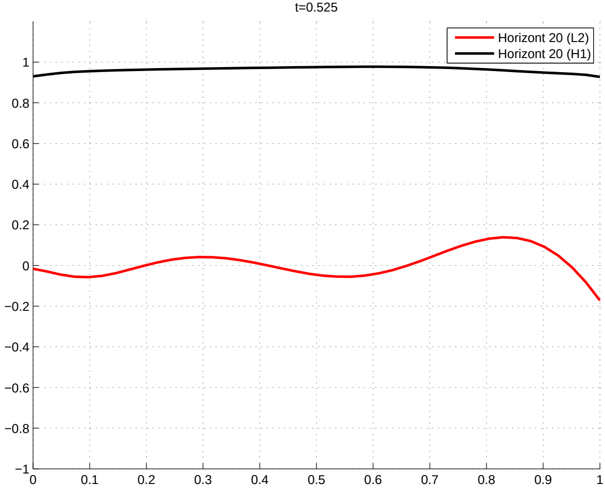
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

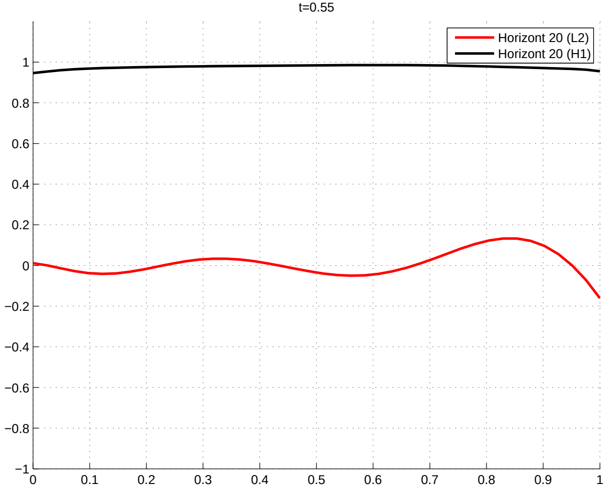
UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

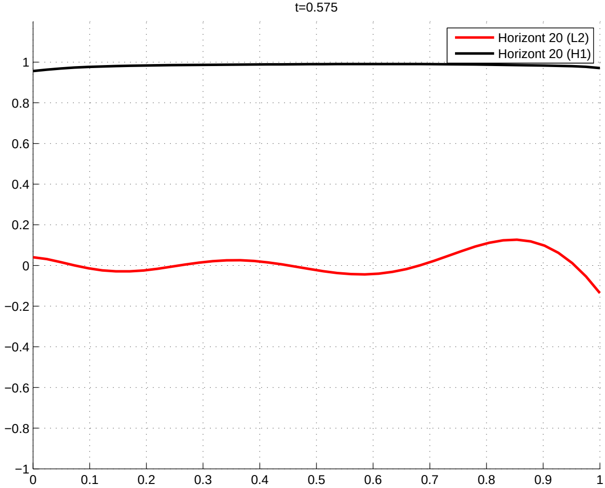
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

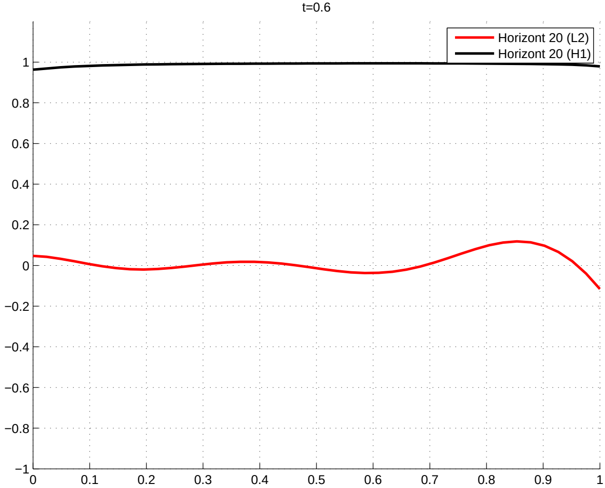
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

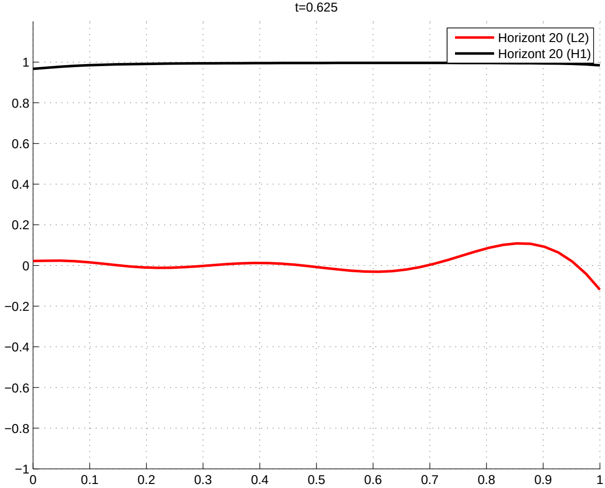
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

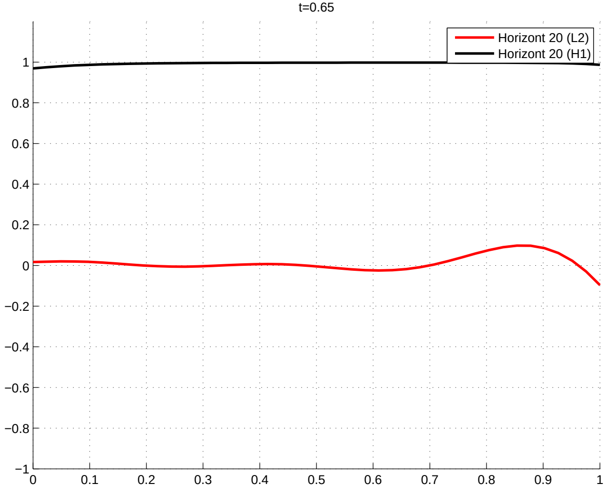
UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



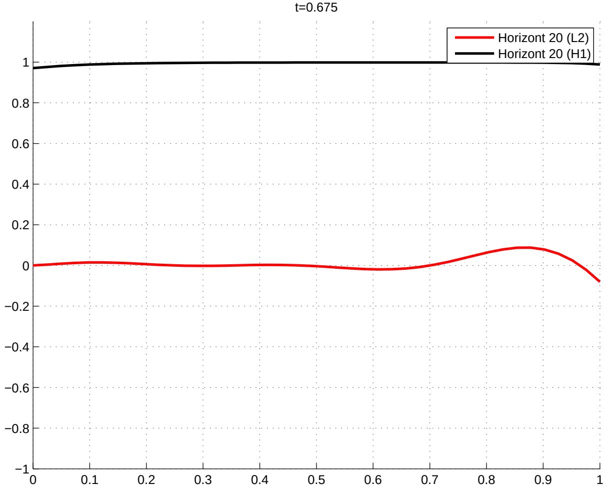
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



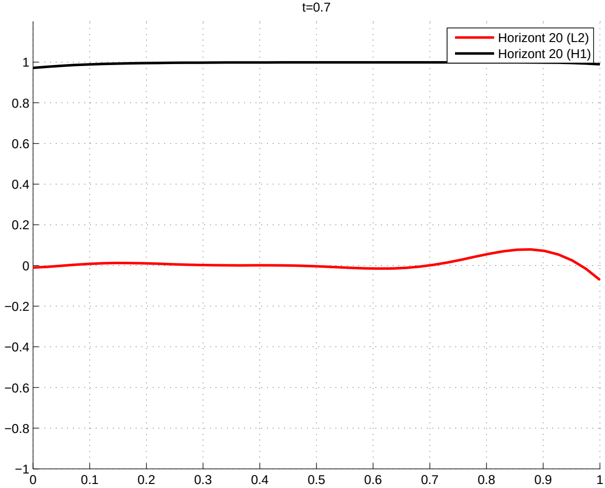
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

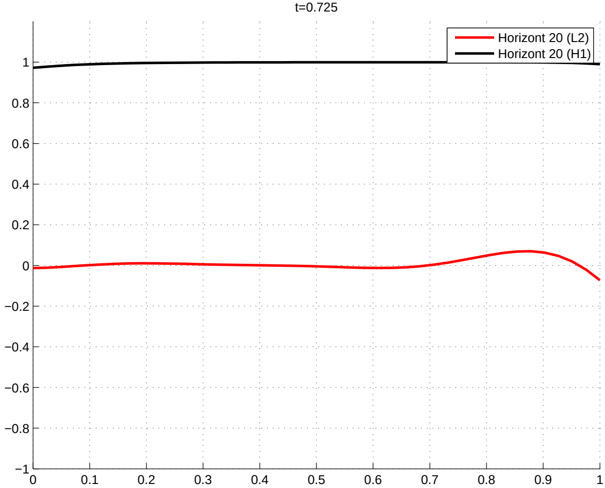
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

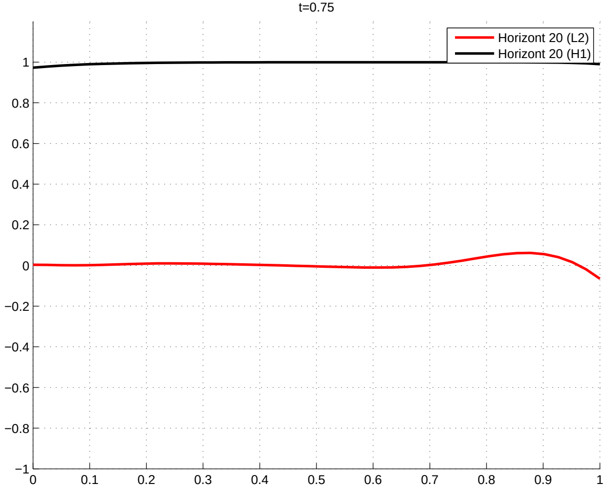
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

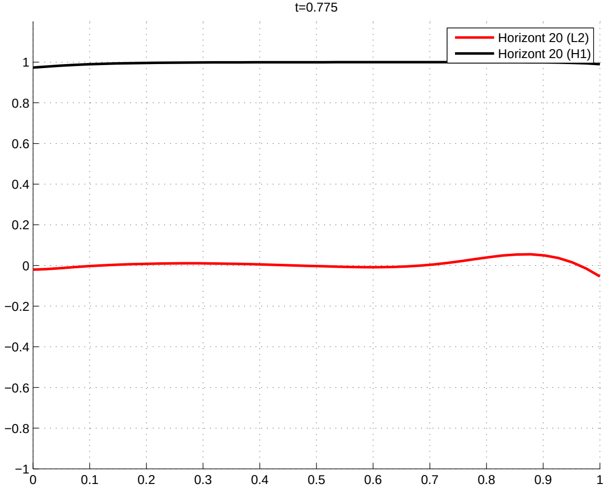
UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



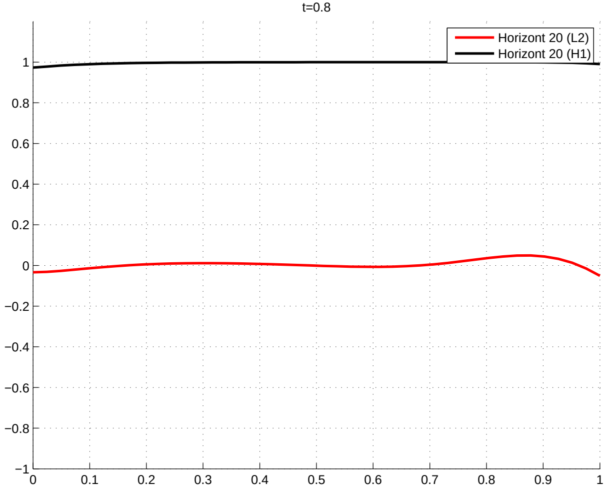
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



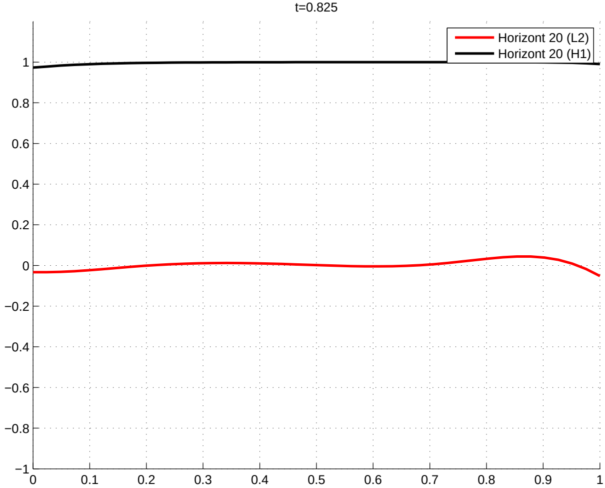
Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

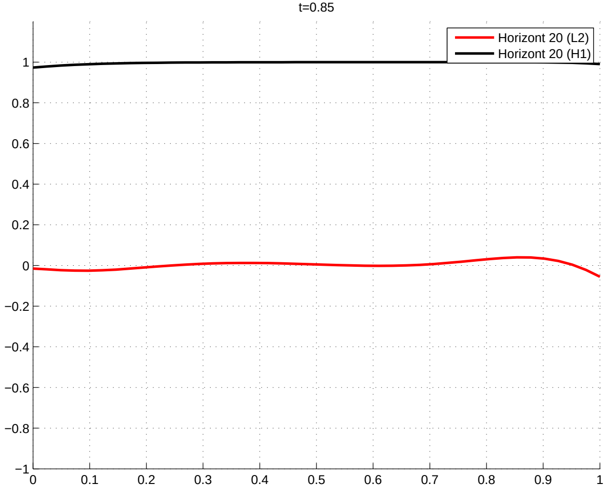
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

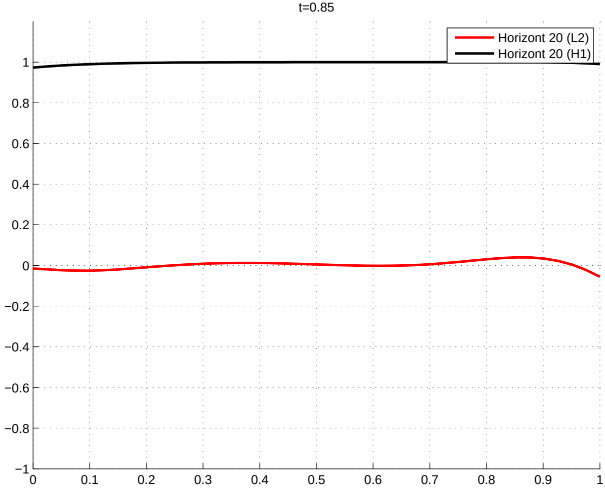
Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

UNIVERSITÄT BAYREUTH

Boundary control, L_2 vs. H_1, $N = 20$



Boundary control, $\lambda = 0.001$, sampling time $T = 0.025$

Can be made rigorous for many PDEs [Altmüller et al. '10ff]

UNIVERSITÄT BAYREUTH

Summary of Section (6)

- Reducing the overshoot constant C by choosing ℓ appropriately can significantly reduce the horizon N needed to obtain stability

Summary of Section (6)

- Reducing the overshoot constant C by choosing ℓ appropriately can significantly reduce the horizon N needed to obtain stability
- Computing tight estimates for C is in general a difficult if not impossible task

Summary of Section (6)

- Reducing the overshoot constant C by choosing ℓ appropriately can significantly reduce the horizon N needed to obtain stability
- Computing tight estimates for C is in general a difficult if not impossible task
- But structural knowledge of the system behavior can be sufficient for choosing a “good” ℓ

UNIVERSITÄT BAYREUTH

(7) Feasibility

Feasibility

Consider the feasible sets

$$\mathcal{F}_N := \{x \in \mathbb{X} \,|\, \text{there exists an admissible } \mathbf{u} \text{ of length } N\}$$

Feasibility

Consider the feasible sets

$$\mathcal{F}_N := \{x \in \mathbb{X} \,|\, \text{there exists an admissible } \mathbf{u} \text{ of length } N\}$$

So far we have assumed

$$V_N(x) \leq \gamma \ell^\star(x) \;\text{ for all }\; x \in \mathbb{X}$$

which implicitly includes the assumption

$$\mathcal{F}_N = \mathbb{X}$$

because $V_N(x) = \infty$ for $x \in \mathbb{X} \setminus \mathcal{F}_N$

Feasibility

Consider the feasible sets

$$\mathcal{F}_N := \{x \in \mathbb{X} \,|\, \text{there exists an admissible } \mathbf{u} \text{ of length } N\}$$

So far we have assumed

$$V_N(x) \le \gamma \ell^\star(x) \text{ for all } x \in \mathbb{X}$$

which implicitly includes the assumption

$$\mathcal{F}_N = \mathbb{X}$$

because $V_N(x) = \infty$ for $x \in \mathbb{X} \setminus \mathcal{F}_N$

What happens if $\mathcal{F}_N \neq \mathbb{X}$ for some $N \in \mathbb{N}$?

The MPC feasibility problem

Even though the open-loop optimal trajectories are forced to satisfy $x^\star(k) \in \mathbb{X}$, the closed loop solutions $x_{\mu_N}(n)$ may violate the state constraints, i.e., $x_{\mu_N}(n) \notin \mathbb{X}$ for some n

The MPC feasibility problem

Even though the open-loop optimal trajectories are forced to satisfy $x^\star(k) \in \mathbb{X}$, the closed loop solutions $x_{\mu_N}(n)$ may violate the state constraints, i.e., $x_{\mu_N}(n) \notin \mathbb{X}$ for some n

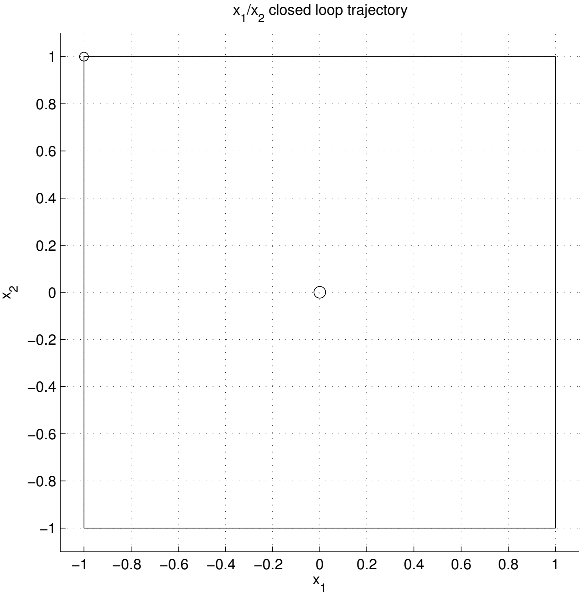
We illustrate this phenomenon by the simple example

$$\begin{pmatrix} x_1^+ \\ x_2^+ \end{pmatrix} = \begin{pmatrix} x_1 + x_2 + u/2 \\ x_2 + u \end{pmatrix}$$

with $\mathbb{X} = [-1,1]^2$ and $\mathbb{U} = [-1/4, 1/4]$. For initial value $x_0 = (-1,1)^T$, the system can be controlled to 0 without leaving $\mathbb{X}$

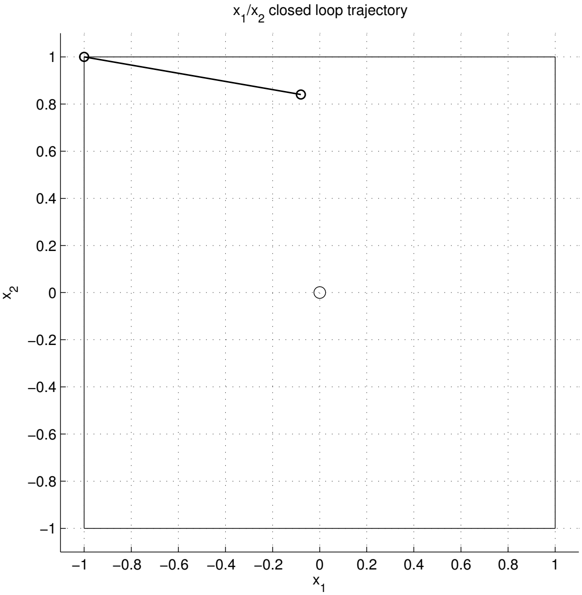
We use MPC with $N = 2$ and $\ell(x,u) = \|x\|^2 + 5u^2$

The MPC feasibility problem: example

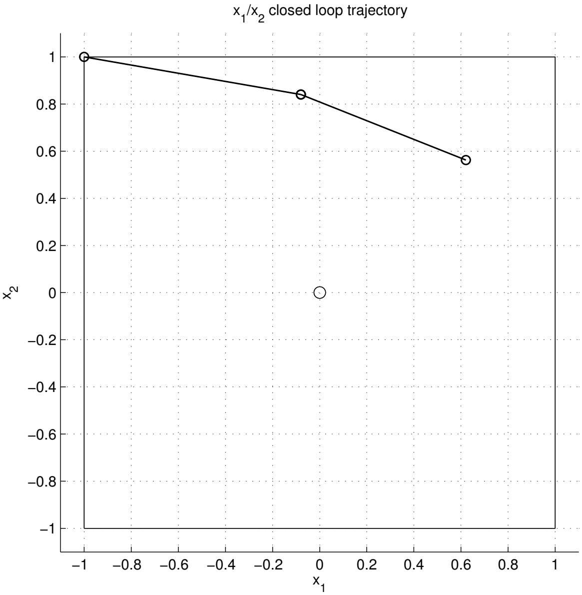


UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example

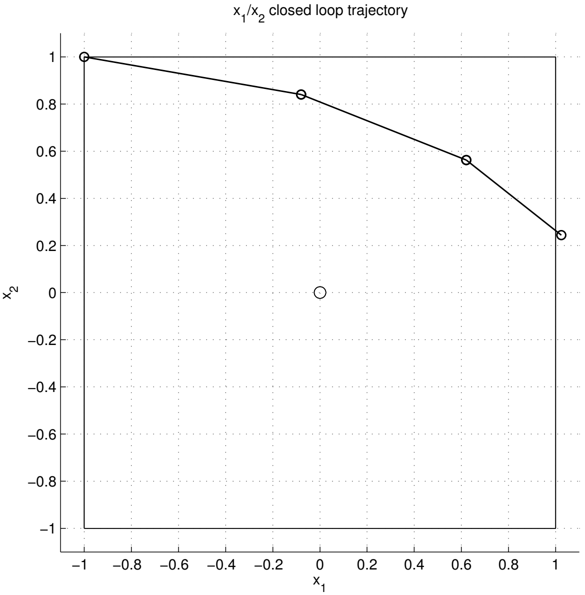


The MPC feasibility problem: example

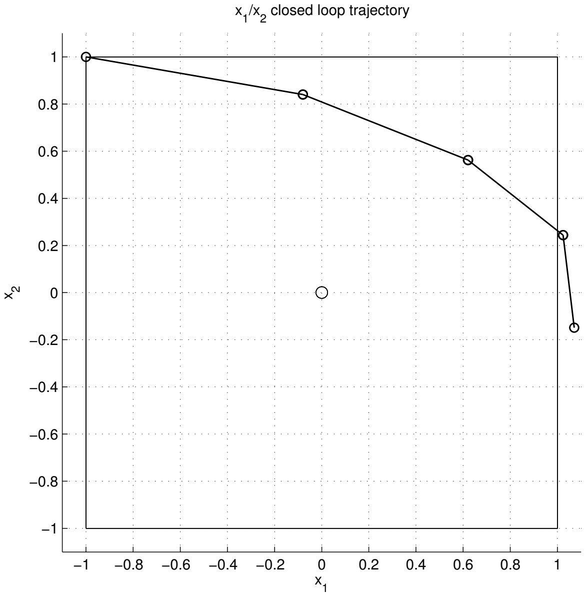


UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example

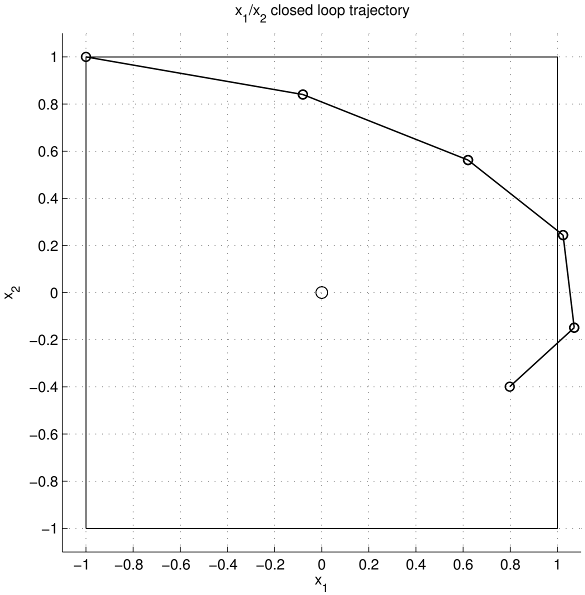


The MPC feasibility problem: example



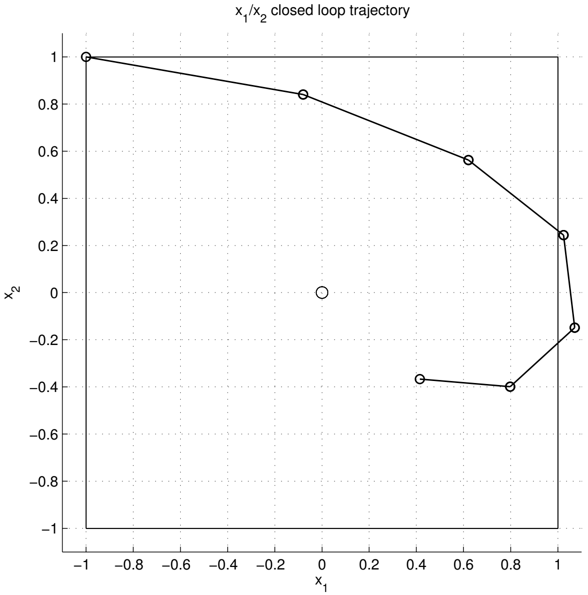
UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example



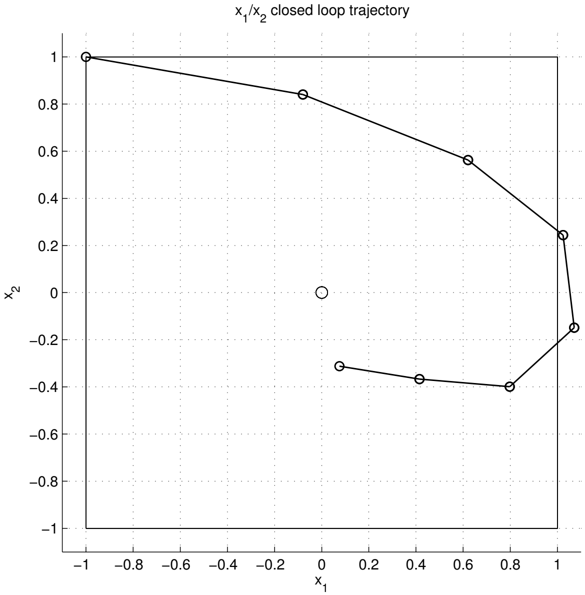
UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example

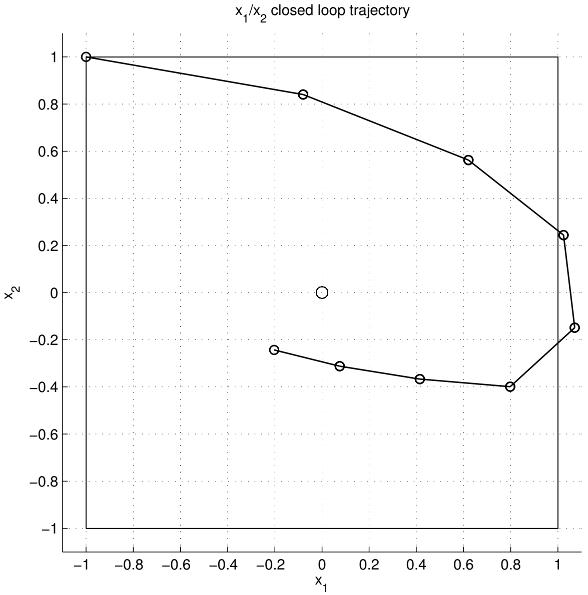


UNIVERSITÄT BAYREUTH

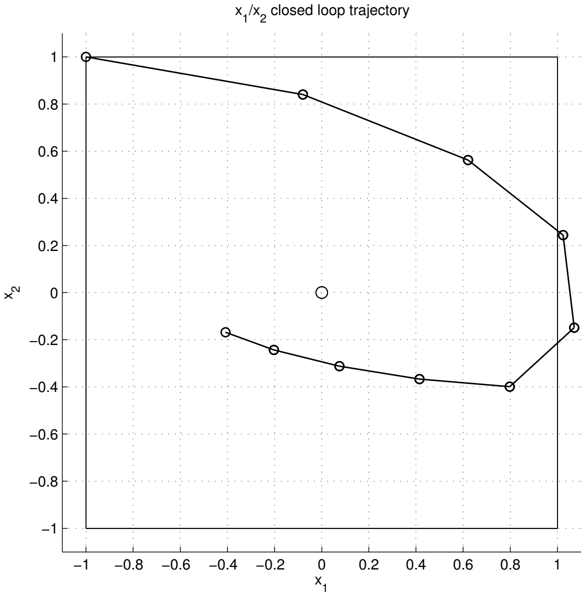
The MPC feasibility problem: example



The MPC feasibility problem: example

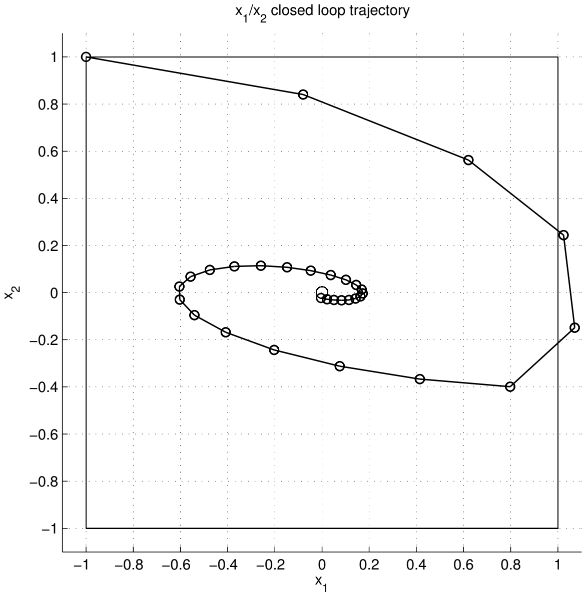


The MPC feasibility problem: example



UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example



UNIVERSITÄT BAYREUTH

The MPC feasibility problem

How can this happen?

The MPC feasibility problem

How can this happen?

Explanation: In this example $\mathcal{F}_N \subsetneq \mathbb{X}$

The MPC feasibility problem

How can this happen?

Explanation: In this example $\mathcal{F}_N \subsetneq \mathbb{X}$

$\rightsquigarrow$ at time n, the finite horizon state constraints guarantee $x^\star(1) \in \mathbb{X}$ but in general not $x^\star(1) \in \mathcal{F}_N$

The MPC feasibility problem

How can this happen?

Explanation: In this example $\mathcal{F}_N \subsetneq \mathbb{X}$

$\rightsquigarrow$ at time n, the finite horizon state constraints guarantee $x^\star(1) \in \mathbb{X}$ but in general not $x^\star(1) \in \mathcal{F}_N$

$\rightsquigarrow$ the optimal control problem at time $n+1$ with initial value $x_{\mu_N}(n+1) = x^\star(1)$ may be infeasible

UNIVERSITÄT BAYREUTH

The MPC feasibility problem

How can this happen?

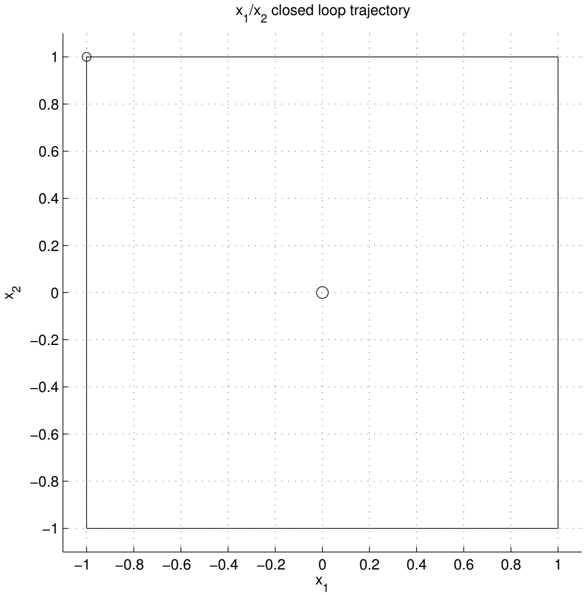
Explanation: In this example $\mathcal{F}_N \subsetneq \mathbb{X}$

$\rightsquigarrow$ at time n, the finite horizon state constraints guarantee $x^\star(1) \in \mathbb{X}$ but in general not $x^\star(1) \in \mathcal{F}_N$

$\rightsquigarrow$ the optimal control problem at time $n+1$ with initial value $x_{\mu_N}(n+1) = x^\star(1)$ may be infeasible

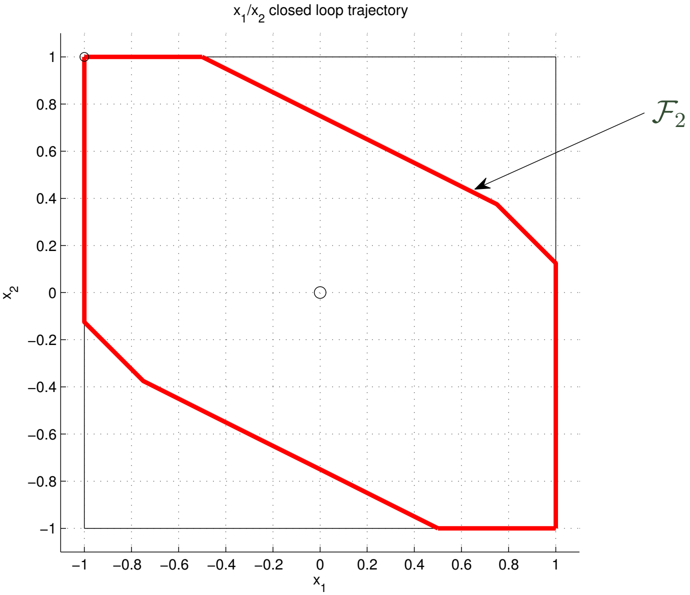
$\rightsquigarrow$ $x_{\mu_N}(n+k) \notin \mathbb{X}$ is inevitable for some $k \geq 2$

The MPC feasibility problem: example again



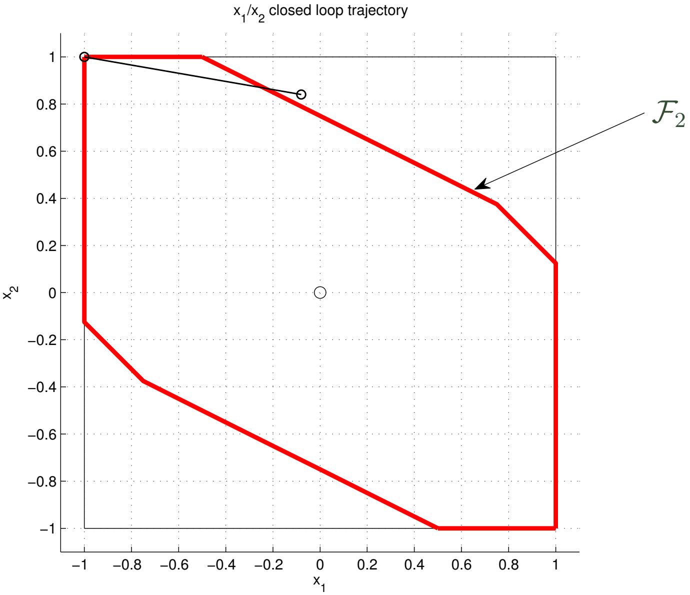
UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example again



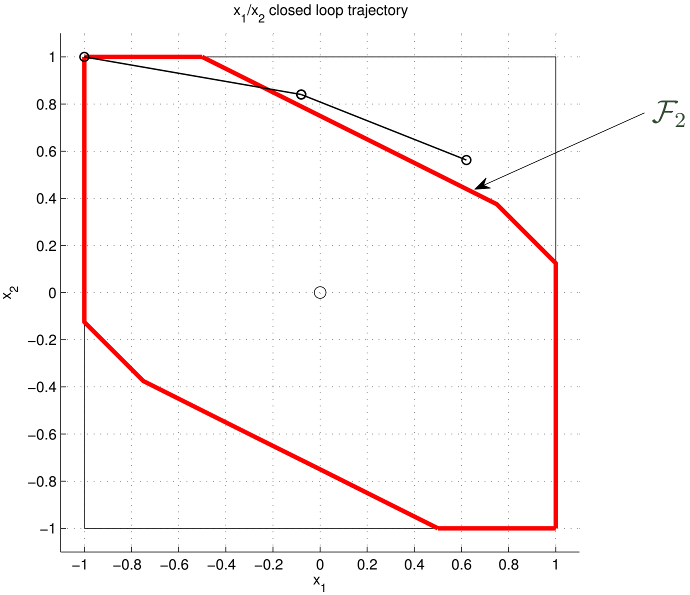
UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example again



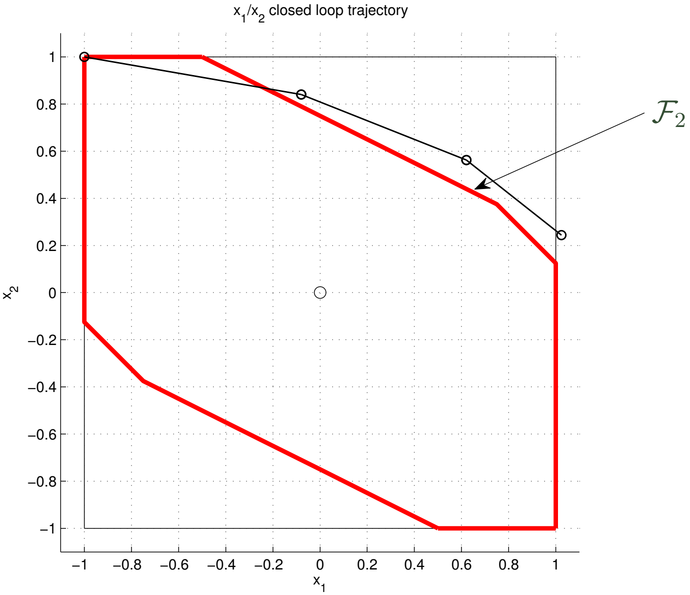
UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example again

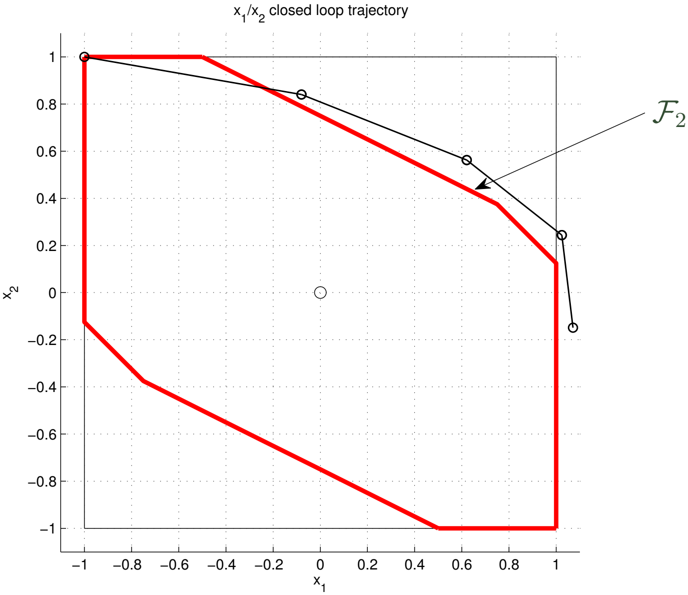


UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example again

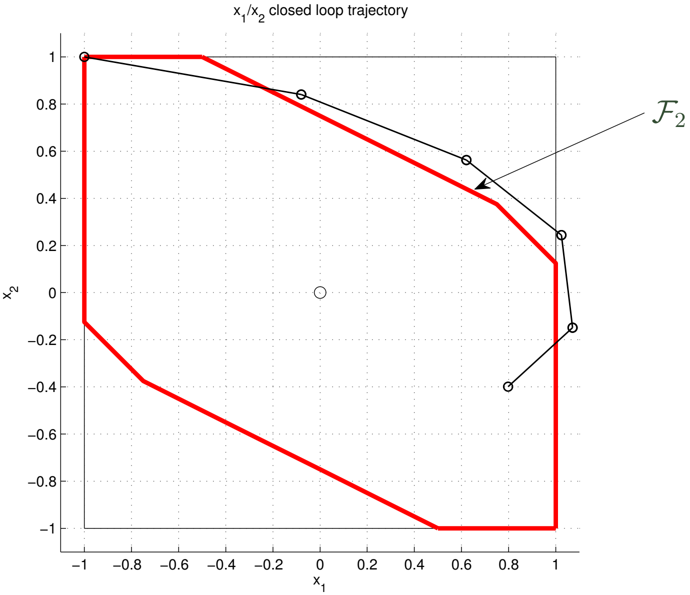


The MPC feasibility problem: example again



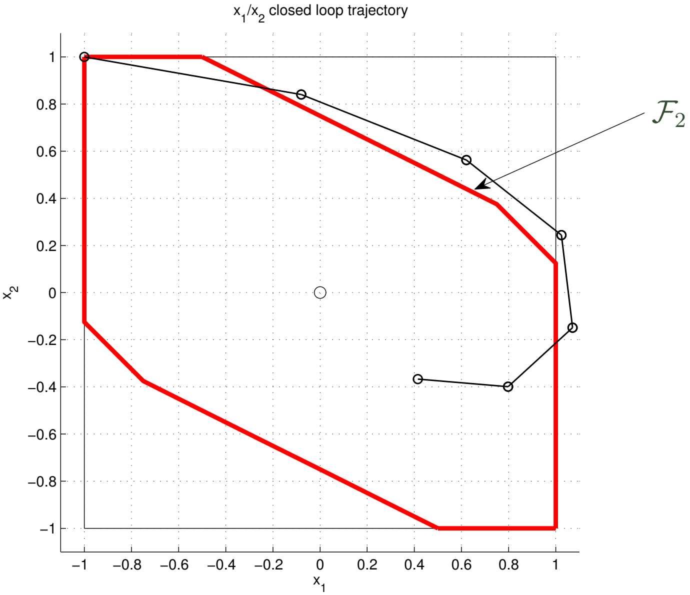
UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example again

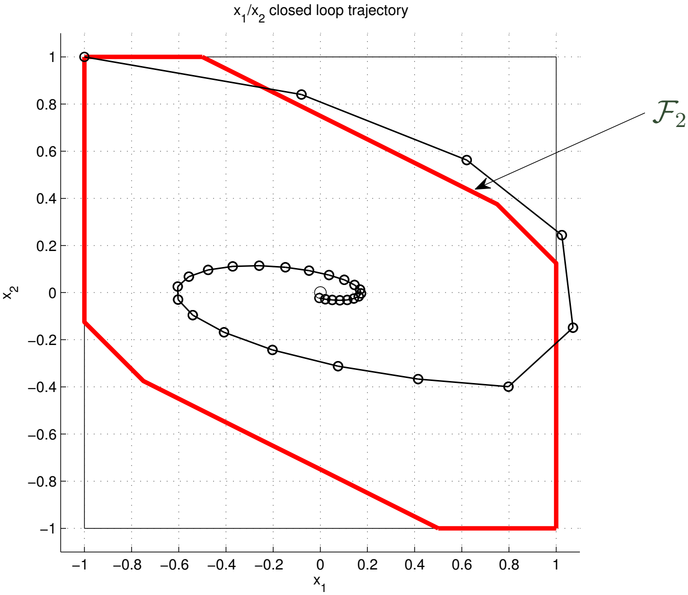


UNIVERSITÄT BAYREUTH

The MPC feasibility problem: example again



The MPC feasibility problem: example again



Recursive feasibility

The MPC scheme with horizon N is well defined on a set $A \subseteq \mathcal{F}_N$ if the following recursive feasibility condition holds:

$$x \in A \quad \Rightarrow \quad f(x, \mu_N(x)) \in A$$

Recursive feasibility

The MPC scheme with horizon N is well defined on a set $A \subseteq \mathcal{F}_N$ if the following recursive feasibility condition holds:

$$x \in A \quad \Rightarrow \quad f(x, \mu_N(x)) \in A$$

In terminal constrained MPC, forward invariance of the terminal constraint set $\mathbb{X}_0$ implies recursive feasibility of the feasible set

$$\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \text{there is an admissible } \mathbf{u} \text{ with } x_{\mathbf{u}}(N, x) \in \mathbb{X}_0\}$$

(this was part of the stability theorem in Section 3)

Recursive feasibility

The MPC scheme with horizon N is well defined on a set $A \subseteq \mathcal{F}_N$ if the following recursive feasibility condition holds:

$$x \in A \quad \Rightarrow \quad f(x, \mu_N(x)) \in A$$

In terminal constrained MPC, forward invariance of the terminal constraint set $\mathbb{X}_0$ implies recursive feasibility of the feasible set

$$\mathbb{X}_N := \{x \in \mathbb{X} \,|\, \text{there is an admissible } \mathbf{u} \text{ with } x_{\mathbf{u}}(N, x) \in \mathbb{X}_0\}$$

(this was part of the stability theorem in Section 3)

Can we find recursively feasible sets for NMPC without terminal constraints?

Recursive feasibility

Theorem: [Kerrigan '00, Gr./Pannek 11] Assume that

$$\mathcal{F}_{N_0} = \mathcal{F}_{N_0-1}$$

holds for some $N_0 \in \mathbb{N}$. Then the set $\mathcal{F}_N$ is recursively feasible for all $N \geq N_0$.

Recursive feasibility

Theorem: [Kerrigan '00, Gr./Pannek 11] Assume that

$$\mathcal{F}_{N_0} = \mathcal{F}_{N_0-1}$$

holds for some $N_0 \in \mathbb{N}$. Then the set $\mathcal{F}_N$ is recursively feasible for all $N \geq N_0$.

Idea of proof:

(1) $\mathcal{F}_{N_0} = \mathcal{F}_{N_0-1}$ implies $\mathcal{F}_N = \mathcal{F}_{N_0-1}$ for all $N \geq N_0 - 1$

UNIVERSITÄT BAYREUTH

Recursive feasibility

Theorem: [Kerrigan '00, Gr./Pannek 11] Assume that

$$\mathcal{F}_{N_0} = \mathcal{F}_{N_0-1}$$

holds for some $N_0 \in \mathbb{N}$. Then the set $\mathcal{F}_N$ is recursively feasible for all $N \geq N_0$.

Idea of proof:

(1) $\mathcal{F}_{N_0} = \mathcal{F}_{N_0-1}$ implies $\mathcal{F}_N = \mathcal{F}_{N_0-1}$ for all $N \geq N_0 - 1$

(2) $x^\star(0) = x \in \mathcal{F}_N$ implies

$$f(x, \mu_N(x)) = x^\star(1) \in \mathcal{F}_{N-1} = \mathcal{F}_{N_0-1} = \mathcal{F}_N$$

Recursive feasibility

Theorem: [Kerrigan '00, Gr./Pannek 11] Assume that

$$\mathcal{F}_{N_0} = \mathcal{F}_{N_0-1}$$

holds for some $N_0 \in \mathbb{N}$. Then the set $\mathcal{F}_N$ is recursively feasible for all $N \geq N_0$.

Idea of proof:

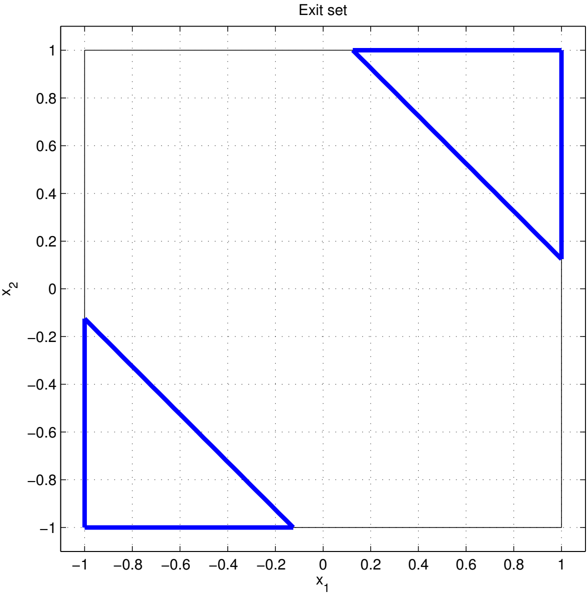
(1) $\mathcal{F}_{N_0} = \mathcal{F}_{N_0-1}$ implies $\mathcal{F}_N = \mathcal{F}_{N_0-1}$ for all $N \geq N_0 - 1$

(2) $x^\star(0) = x \in \mathcal{F}_N$ implies

$$f(x, \mu_N(x)) = x^\star(1) \in \mathcal{F}_{N-1} = \mathcal{F}_{N_0-1} = \mathcal{F}_N$$

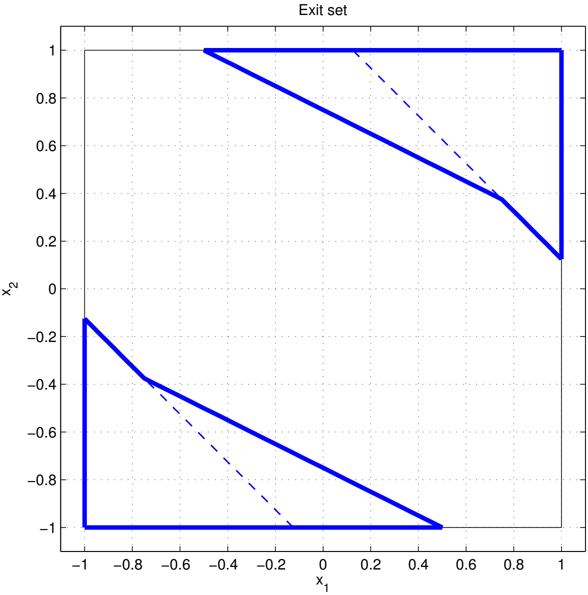
$\Rightarrow$ recursive feasibility of $\mathcal{F}_N$

Feasible sets for our example



$\mathbb{X} \setminus \mathcal{F}_1$

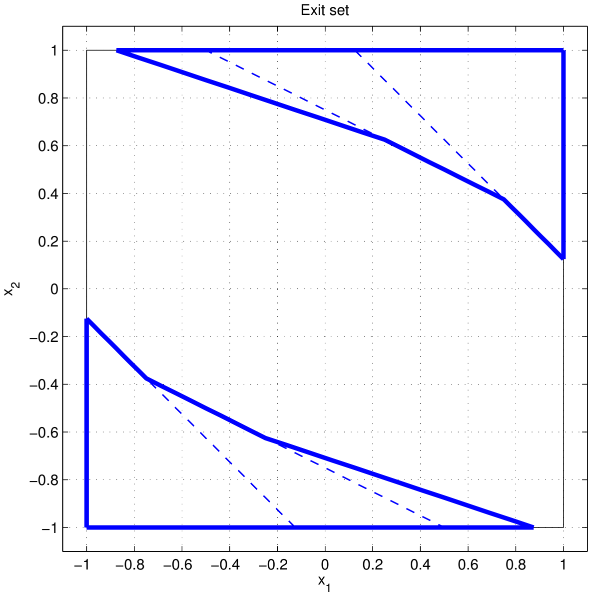
Feasible sets for our example



$\mathbb{X} \setminus \mathcal{F}_2$

UNIVERSITÄT BAYREUTH

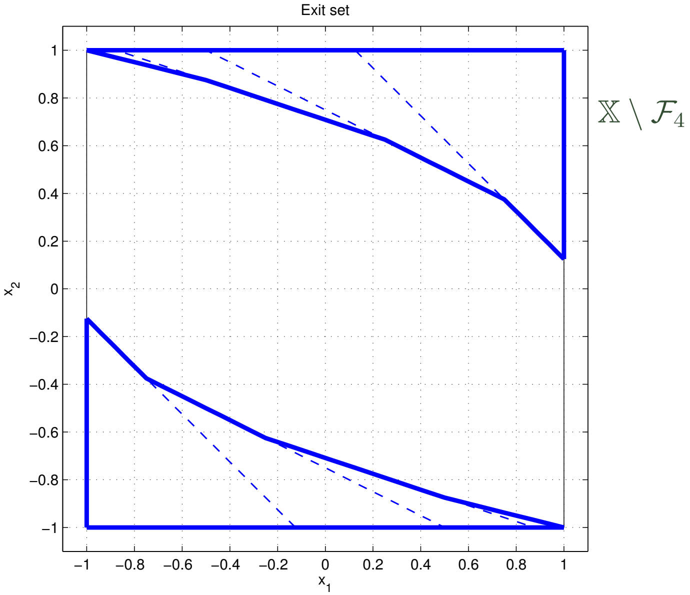
Feasible sets for our example



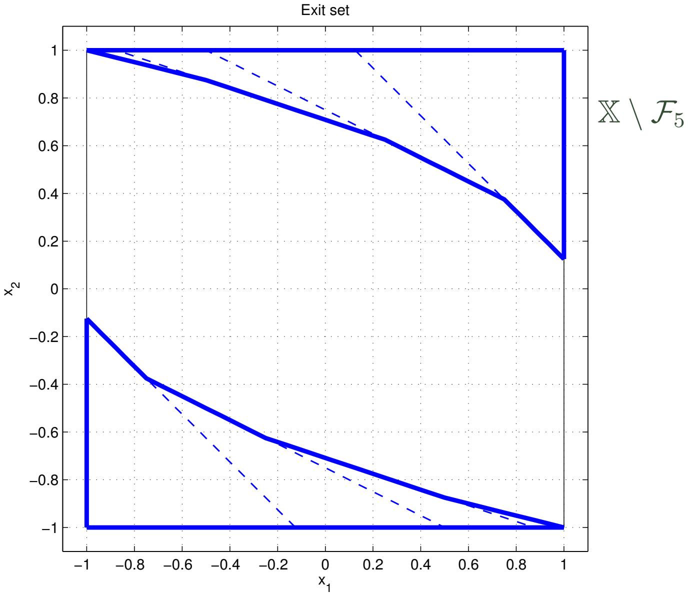
$\mathbb{X} \setminus \mathcal{F}_3$

UNIVERSITÄT BAYREUTH

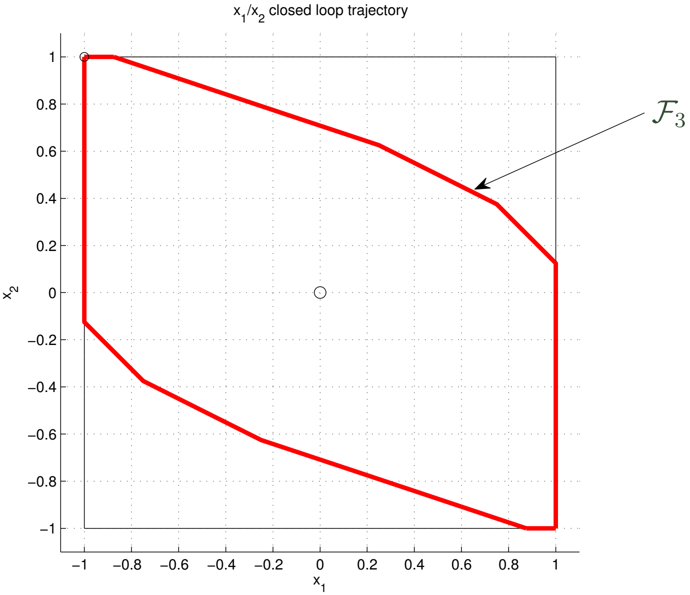
Feasible sets for our example



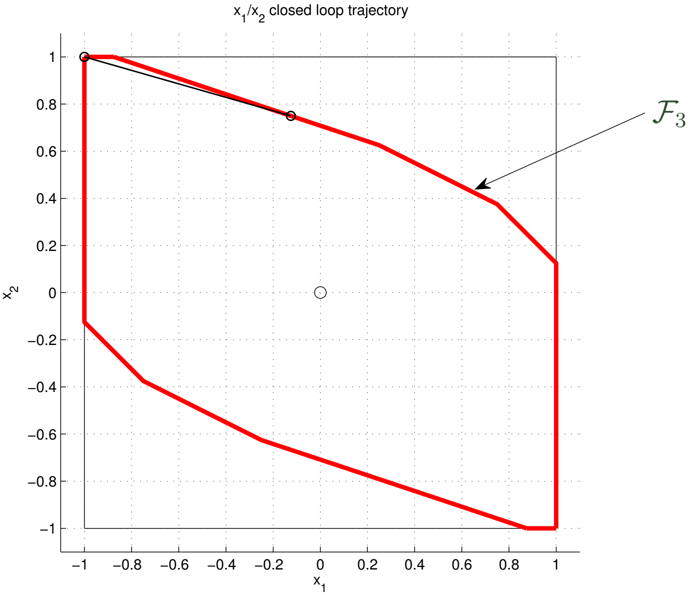
Feasible sets for our example



MPC Closed loop solution for $N = 3$

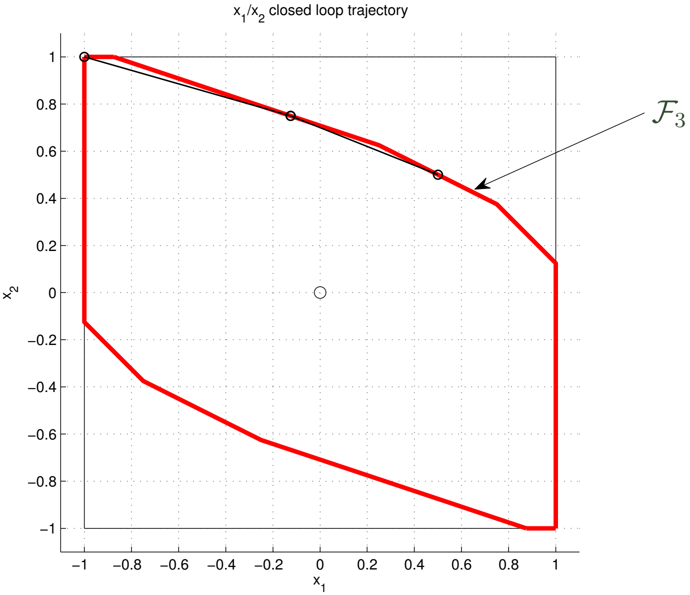


MPC Closed loop solution for $N = 3$

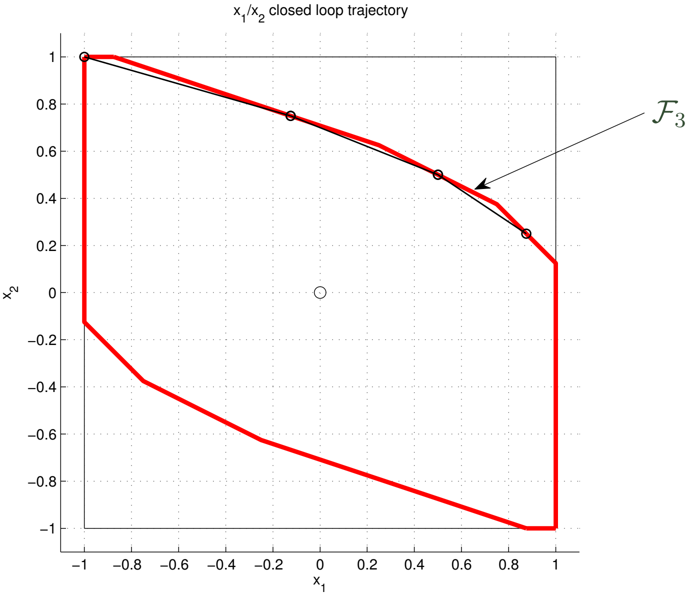


UNIVERSITÄT BAYREUTH

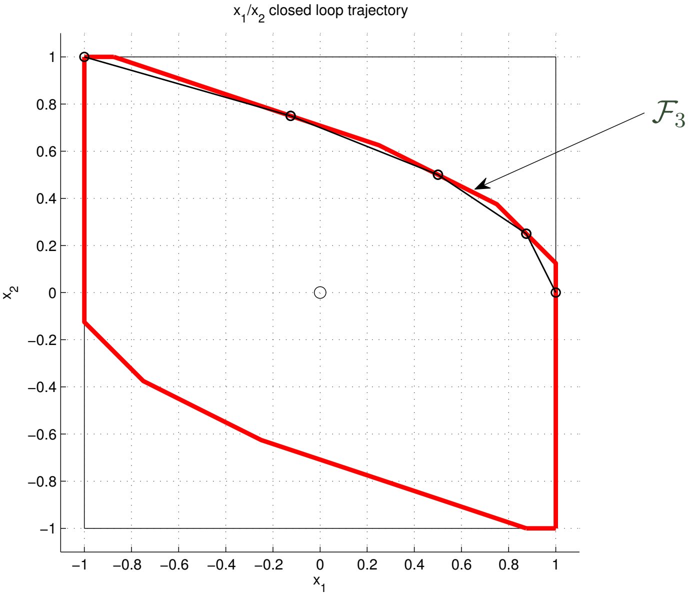
MPC Closed loop solution for $N = 3$



MPC Closed loop solution for $N = 3$

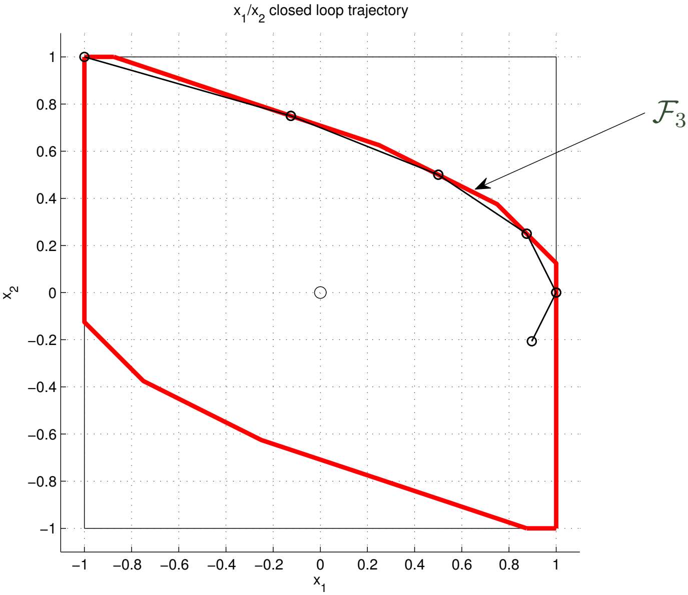


MPC Closed loop solution for $N = 3$



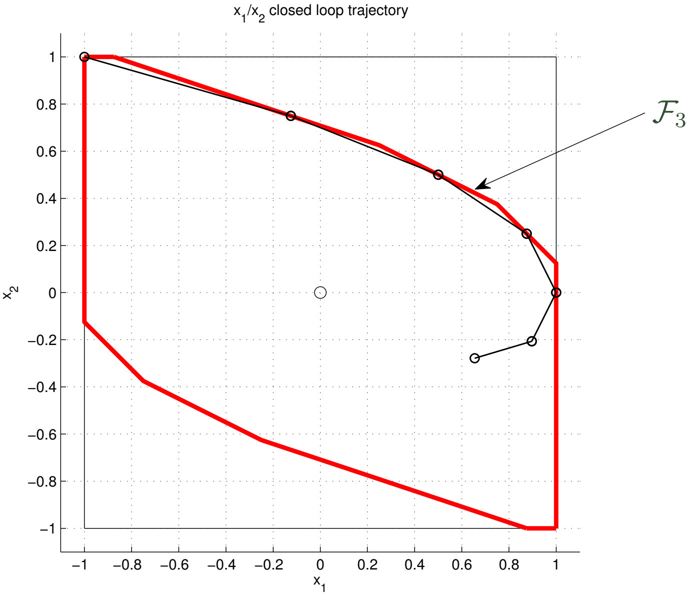
UNIVERSITÄT BAYREUTH

MPC Closed loop solution for $N = 3$

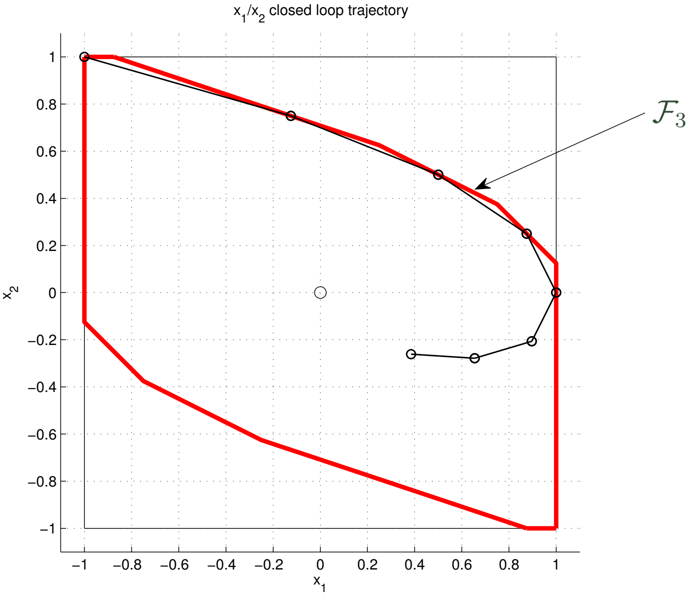


UNIVERSITÄT BAYREUTH

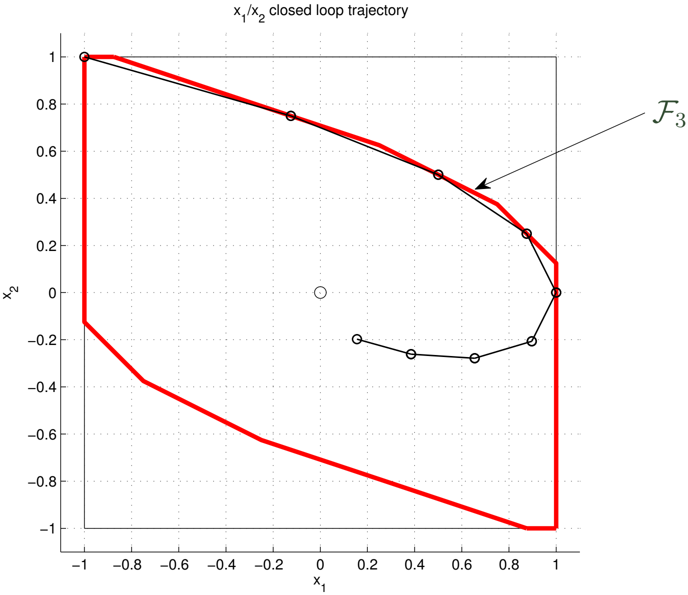
MPC Closed loop solution for $N = 3$



MPC Closed loop solution for $N = 3$

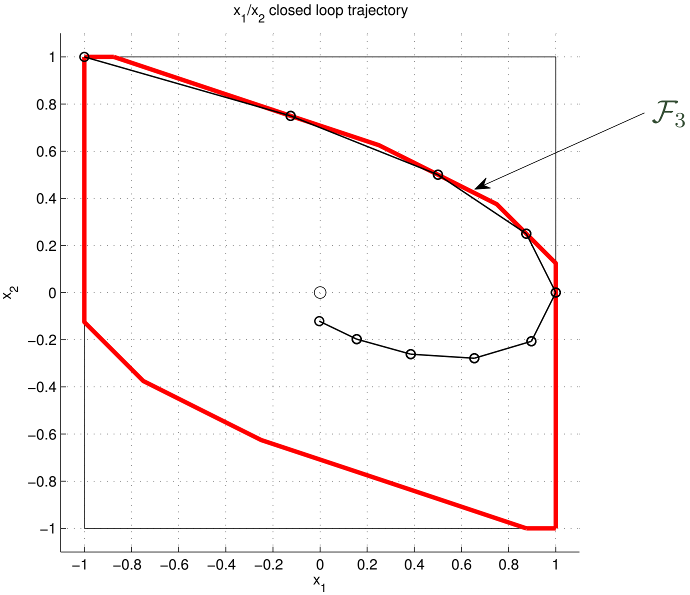


MPC Closed loop solution for $N = 3$

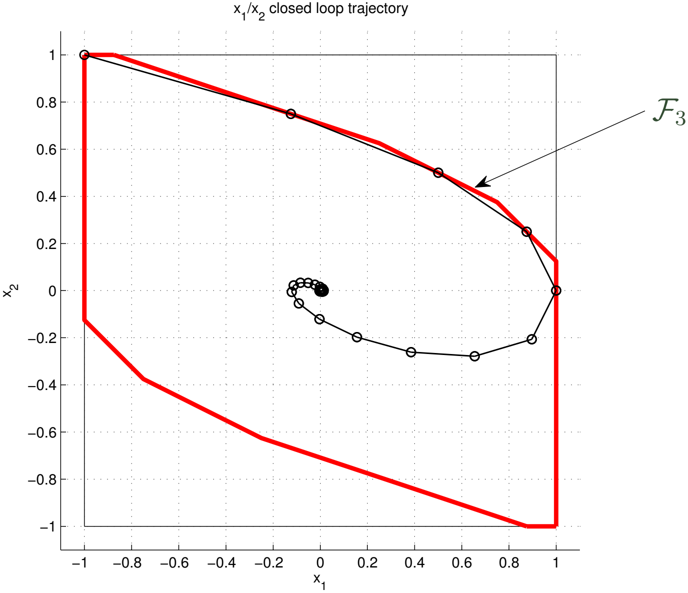


UNIVERSITÄT BAYREUTH

MPC Closed loop solution for $N = 3$



MPC Closed loop solution for $N = 3$



Recursive feasibility

Problem: What if this condition does not hold / cannot be checked?

Recursive feasibility

Problem: What if this condition does not hold / cannot be checked?

Theorem: [Gr./Pannek '11, extending Primbs/Nevistić '00]

Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathcal{F}_N$, $N \in \mathbb{N}$

Assume there exists a forward invariant neighborhood $\mathcal{N}$ of x_*

UNIVERSITÄT BAYREUTH

Recursive feasibility

Problem: What if this condition does not hold / cannot be checked?

Theorem: [Gr./Pannek '11, extending Primbs/Nevistić '00]

Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathcal{F}_N$, $N \in \mathbb{N}$

Assume there exists a forward invariant neighborhood $\mathcal{N}$ of x_*

Then for each $c > 0$ there exists $N_c > 0$ such that for all $N \geq N_c$ the level set

$$A_c := \{x \in \mathcal{F}_N \,|\, V_N(x) \leq c\}$$

is recursively feasible and the MPC closed loop is asymptotically stable with basin of attraction containing A_c

Recursive feasibility

Problem: What if this condition does not hold / cannot be checked?

Theorem: [Gr./Pannek '11, extending Primbs/Nevistić '00]

Assume $V_N(x) \leq \gamma \ell^\star(x)$ for all $x \in \mathcal{F}_N$, $N \in \mathbb{N}$

Assume there exists a forward invariant neighborhood $\mathcal{N}$ of x_*

Then for each $c > 0$ there exists $N_c > 0$ such that for all $N \geq N_c$ the level set

$$A_c := \{x \in \mathcal{F}_N \,|\, V_N(x) \leq c\}$$

is recursively feasible and the MPC closed loop is asymptotically stable with basin of attraction containing A_c

If $\mathbb{X}$ is compact, then $A_c = \mathcal{F}_\infty$ for all sufficiently large N

Idea of proof

$V_N(x) \leq \gamma \ell^\star(x)$ implies exponential decay of $\ell^\star(x^\star(k))$
(as in Variant 2 of the stability proof in Section 5)

Idea of proof

$V_N(x) \leq \gamma \ell^\star(x)$ implies exponential decay of $\ell^\star(x^\star(k))$ (as in Variant 2 of the stability proof in Section 5)

$\Rightarrow \quad x^\star(N-1) \in \mathcal{N}$ for $x \in A_c$ and $N \geq N_c$

Idea of proof

$V_N(x) \le \gamma \ell^\star(x)$ implies exponential decay of $\ell^\star(x^\star(k))$ (as in Variant 2 of the stability proof in Section 5)

$\Rightarrow$ $x^\star(N-1) \in \mathcal{N}$ for $x \in A_c$ and $N \ge N_c$

$\Rightarrow$ forward invariance of $\mathcal{N}$ implies that solution can be extended

Idea of proof

$V_N(x) \leq \gamma \ell^\star(x)$ implies exponential decay of $\ell^\star(x^\star(k))$
(as in Variant 2 of the stability proof in Section 5)

$\Rightarrow$ $x^\star(N-1) \in \mathcal{N}$ for $x \in A_c$ and $N \geq N_c$

$\Rightarrow$ forward invariance of $\mathcal{N}$ implies that solution can be extended

$\Rightarrow$ recursive feasibility

Discussion

Feasibility properties of MPC without terminal constraints

- Advantage: In contrast to $\mathbb{X}_0$ in the terminal constrained setting, $\mathcal{N}$ does not need to be known, mere existence is sufficient

Discussion

Feasibility properties of MPC without terminal constraints

- Advantage: In contrast to $\mathbb{X}_0$ in the terminal constrained setting, $\mathcal{N}$ does not need to be known, mere existence is sufficient
- Drawback: In terminal constrained MPC, feasibility at time $n = 0$ implies recursive feasibility. This property is lost without terminal constraints

Discussion

Feasibility properties of MPC without terminal constraints

- Advantage: In contrast to $\mathbb{X}_0$ in the terminal constrained setting, $\mathcal{N}$ does not need to be known, mere existence is sufficient
- Drawback: In terminal constrained MPC, feasibility at time $n = 0$ implies recursive feasibility. This property is lost without terminal constraints

  If this is desired, a forward invariant terminal constraint $\mathbb{X}_0$ can be used without terminal cost

Discussion

Feasibility properties of MPC without terminal constraints

- Advantage: In contrast to $\mathbb{X}_0$ in the terminal constrained setting, $\mathcal{N}$ does not need to be known, mere existence is sufficient
- Drawback: In terminal constrained MPC, feasibility at time $n = 0$ implies recursive feasibility. This property is lost without terminal constraints

  If this is desired, a forward invariant terminal constraint $\mathbb{X}_0$ can be used without terminal cost — the stability proof without terminal constraints also works for this setting

Final discussion: comparison of stabilizing MPC with and without terminal constraints

Properties of stabilizing MPC without terminal constraints compared to terminal constrained MPC

Final discussion: comparison of stabilizing MPC with and without terminal constraints

Properties of stabilizing MPC without terminal constraints compared to terminal constrained MPC

- $\oplus$ needs fewer a priori information to set up the scheme

Final discussion: comparison of stabilizing MPC with and without terminal constraints

Properties of stabilizing MPC without terminal constraints compared to terminal constrained MPC

- ⊕ needs fewer a priori information to set up the scheme
- ⊖ results are typically less constructive

Final discussion: comparison of stabilizing MPC with and without terminal constraints

Properties of stabilizing MPC without terminal constraints compared to terminal constrained MPC

- ⊕ needs fewer a priori information to set up the scheme
- ⊖ results are typically less constructive
- ⊕ may exhibit larger operating regions

Final discussion: comparison of stabilizing MPC with and without terminal constraints

Properties of stabilizing MPC without terminal constraints compared to terminal constrained MPC

- $\oplus$ needs fewer a priori information to set up the scheme
- $\ominus$ results are typically less constructive
- $\oplus$ may exhibit larger operating regions
- $\ominus$ may need larger N for obtaining stability near x_*

Part B: Economic Model Predictive Control

(8) Economic MPC with terminal constraints

Motivation for economic MPC

Typical approach in practice (e.g., in chemical process control):

Motivation for economic MPC

Typical approach in practice (e.g., in chemical process control):

(1) compute an economically good equilibrium (x_*, u_*)
("good" $=$ high yield, small energy consumption, etc.)

Motivation for economic MPC

Typical approach in practice (e.g., in chemical process control):

(1) compute an economically good equilibrium (x_*, u_*)
("good" $=$ high yield, small energy consumption, etc.)

(2) design a controller stabilizing (x_*, u_*), e.g., by MPC

Motivation for economic MPC

Typical approach in practice (e.g., in chemical process control):

(1) compute an economically good equilibrium (x_*, u_*)
("good" $=$ high yield, small energy consumption, etc.)

(2) design a controller stabilizing (x_*, u_*), e.g., by MPC

This works fine as long as the system state is close to x_*

Motivation for economic MPC

Typical approach in practice (e.g., in chemical process control):

(1) compute an economically good equilibrium (x_*, u_*)
("good" $=$ high yield, small energy consumption, etc.)

(2) design a controller stabilizing (x_*, u_*), e.g., by MPC

This works fine as long as the system state is close to x_* but on the way towards x_* performance in the sense of the chosen criterion may be bad

Motivation for economic MPC

Typical approach in practice (e.g., in chemical process control):

(1) compute an economically good equilibrium (x_*, u_*)
("good" $=$ high yield, small energy consumption, etc.)

(2) design a controller stabilizing (x_*, u_*), e.g., by MPC

This works fine as long as the system state is close to x_* but on the way towards x_* performance in the sense of the chosen criterion may be bad

Idea: Use a stage cost ℓ which does not penalize the distance to some x_* but directly encodes the desired economic criterion

UNIVERSITÄT BAYREUTH

Mathematical difference of stabilizing and economic MPC

In stabilizing MPC, the stage cost $\ell(x,u)$ penalizes the distance to some equilibrium $(x_*,u_*) \in \mathbb{X} \times \mathbb{U}$. In particular, we required

$$\ell(x,u) > \ell(x_*,u_*) \quad \text{for all } (x,u) \in \mathbb{X} \times \mathbb{U}$$

Mathematical difference of stabilizing and economic MPC

In stabilizing MPC, the stage cost $\ell(x,u)$ penalizes the distance to some equilibrium $(x_*,u_*) \in \mathbb{X}\times\mathbb{U}$. In particular, we required

$$\ell(x,u) > \ell(x_*,u_*) \quad \text{for all } (x,u)\in\mathbb{X}\times\mathbb{U}$$

In economic MPC, we remove this requirement. We use the same algorithm as in stabilizing MPC, but allow for more general ℓ to have more freedom to model economic objectives

Mathematical difference of stabilizing and economic MPC

In stabilizing MPC, the stage cost $\ell(x,u)$ penalizes the distance to some equilibrium $(x_*, u_*) \in \mathbb{X} \times \mathbb{U}$. In particular, we required

$$\ell(x,u) > \ell(x_*,u_*) \quad \text{for all } (x,u) \in \mathbb{X} \times \mathbb{U}$$

In economic MPC, we remove this requirement. We use the same algorithm as in stabilizing MPC, but allow for more general ℓ to have more freedom to model economic objectives

We still consider equilibria, but they are now implicitly defined via the optimization criterion. In order to distinguish them from (x_*, u_*) in stabilizing MPC, they are denoted by (x^e, u^e)

Example 1: mimimum energy control

Example 1: Keep the state of the system inside an admissible set $\mathbb{X}$ minimizing the quadratic control effort

$$\ell(x,u) = u^2$$

with dynamics

$$x(n+1) = 2x(n) + \mathbf{u}(n)$$

and constraints $\mathbb{X} = [-2,2]$, $\mathbb{U} = [-3,3]$

Example 1: mimimum energy control

Example 1: Keep the state of the system inside an admissible set $\mathbb{X}$ minimizing the quadratic control effort

$$\ell(x,u) = u^2$$

with dynamics

$$x(n+1) = 2x(n) + \mathbf{u}(n)$$

and constraints $\mathbb{X} = [-2,2]$, $\mathbb{U} = [-3,3]$

For this example, it is optimal to control the system to $x^e = 0$ and keep it there with $u^e = 0 \quad \rightsquigarrow \quad \ell(x^e,u^e) = 0$

Example 2: a macroeconomic problem

Example 2: a (very simple) macroeconomic example

[Brock/Mirman '72]

Example 2: a macroeconomic problem

Example 2: a (very simple) macroeconomic example

[Brock/Mirman '72]

Minimize the (negative) performance

$$\ell(x,u) = -\ln(Ax^\alpha - u), \quad A = 5,\ \alpha = 0.34$$

for dynamics $x(n+1) = \mathbf{u}(n)$

and constraints $\mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

Example 2: a macroeconomic problem

Example 2: a (very simple) macroeconomic example
[Brock/Mirman '72]

Minimize the (negative) performance

$$\ell(x, u) = -\ln(Ax^\alpha - u), \quad A = 5,\ \alpha = 0.34$$

for dynamics $x(n+1) = \mathbf{u}(n)$

and constraints $\mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

For this example, the optimal control policy is less obvious

Questions for Economic MPC

Questions:

- In which sense can we expect performance estimates for economic MPC?

Questions for Economic MPC

Questions:

- In which sense can we expect performance estimates for economic MPC?
- How should terminal constraints be chosen in order to be useful?

Questions for Economic MPC

Questions:

- In which sense can we expect performance estimates for economic MPC?
- How should terminal constraints be chosen in order to be useful?
- Can we expect asymptotic stability properties?

Questions for Economic MPC

Questions:

- In which sense can we expect performance estimates for economic MPC?
- How should terminal constraints be chosen in order to be useful?
- Can we expect asymptotic stability properties?

For answering these questions, we restrict ourselves to an equilibrium analysis

Questions for Economic MPC

Questions:

- In which sense can we expect performance estimates for economic MPC?
- How should terminal constraints be chosen in order to be useful?
- Can we expect asymptotic stability properties?

For answering these questions, we restrict ourselves to an equilibrium analysis (a generalization to periodic orbits is possible)

Questions for Economic MPC

Questions:

- In which sense can we expect performance estimates for economic MPC?
- How should terminal constraints be chosen in order to be useful?
- Can we expect asymptotic stability properties?

For answering these questions, we restrict ourselves to an equilibrium analysis (a generalization to periodic orbits is possible)

To this end, recall that $(x^e, u^e) \in \mathbb{X} \times \mathbb{U}$ is an equilibrium, if

$$f(x^e, u^e) = x^e$$

Economic MPC with terminal constraints

Theorem: [Angeli/Amrit/Rawlings '09] Consider an economic MPC problem with bounded optimal value function V_N which the optimal control problem

$$\underset{\mathbf{u}\text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n), \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \;\; x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

with terminal constraint $x_{\mathbf{u}}(N) = x^e$ is used to generate the MPC feedback law μ_N.

UNIVERSITÄT BAYREUTH

Economic MPC with terminal constraints

Theorem: [Angeli/Amrit/Rawlings '09] Consider an economic MPC problem with bounded optimal value function V_N which the optimal control problem

$$\underset{\mathbf{u} \text{ admissible}}{\text{minimize}} \quad J_N(x_{\mu_N}(n), \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x_{\mathbf{u}}(k), \mathbf{u}(k)), \quad x_{\mathbf{u}}(0) = x_{\mu_N}(n)$$

with terminal constraint $x_{\mathbf{u}}(N) = x^e$ is used to generate the MPC feedback law μ_N. Then the inequality

$$\overline{J}^{cl}_{\infty}(x, \mu_N) \leq \ell(x^e, u^e)$$

holds for the averaged closed loop functional

$$\overline{J}^{cl}_{\infty}(x, \mu_N) := \limsup_{K \to \infty} \frac{1}{K} \sum_{k=0}^{K-1} \ell(x_{\mu_N}(k, x), \mu(x_{\mu_N}(k, x)))$$

Sketch of proof

Prolonging an optimal control $\mathbf{u}^\star$ with length $N-1$ at the end by the control value u^e yields a control $\mathbf{u}$ satisfying

$$J_N(x,\mathbf{u}) - V_{N-1}(x) \le \ell(x^e, u^e)$$

UNIVERSITÄT BAYREUTH

Sketch of proof

Prolonging an optimal control $\mathbf{u}^\star$ with length $N-1$ at the end by the control value u^e yields a control $\mathbf{u}$ satisfying

$$J_N(x, \mathbf{u}) - V_{N-1}(x) \le \ell(x^e, u^e)$$

This implies

$$V_N(x) - V_{N-1}(x) \le \ell(x^e, u^e)$$

Sketch of proof

Prolonging an optimal control $\mathbf{u}^\star$ with length $N-1$ at the end by the control value u^e yields a control $\mathbf{u}$ satisfying

$$J_N(x,\mathbf{u}) - V_{N-1}(x) \leq \ell(x^e,u^e)$$

This implies

$$V_N(x) - V_{N-1}(x) \leq \ell(x^e,u^e)$$

which together with the dynamic programming principle yields

$$\ell(x,\mu_N(x)) \leq \ell(x^e,u^e) + V_N(x) - V_N(f(x,\mu_N(x)))$$

Sketch of proof

Prolonging an optimal control $\mathbf{u}^\star$ with length $N-1$ at the end by the control value u^e yields a control $\mathbf{u}$ satisfying

$$J_N(x,\mathbf{u}) - V_{N-1}(x) \le \ell(x^e,u^e)$$

This implies

$$V_N(x) - V_{N-1}(x) \le \ell(x^e,u^e)$$

which together with the dynamic programming principle yields

$$\ell(x,\mu_N(x)) \le \ell(x^e,u^e) + V_N(x) - V_N(f(x,\mu_N(x)))$$

Summing and averaging then implies

$$\overline{J}_K^{cl}(x,\mu_N) \le \ell(x^e,u^e) + \frac{1}{K}\Big(V_N(x) - V_N(x_{\mu_N}(K))\Big)$$

which shows the assertion for $K\to\infty$, since V_N is bounded

Optimality of this estimate

Can we ensure that this estimate is optimal?

UNIVERSITÄT BAYREUTH

Optimality of this estimate

Can we ensure that this estimate is optimal?

Yes, if the system exhibits an infinite horizon averaged optimal equilibrium

Optimality of this estimate

Can we ensure that this estimate is optimal?

Yes, if the system exhibits an infinite horizon averaged optimal equilibrium, i.e., if there exists an equilibrium (x^e, u^e) with

$$\overline{J}_\infty(x, \mathbf{u}) \geq \ell(x^e, u^e)$$

for all $x \in \mathbb{X}$ and all admissible $\mathbf{u}$

Optimality of this estimate

Can we ensure that this estimate is optimal?

Yes, if the system exhibits an infinite horizon averaged optimal equilibrium, i.e., if there exists an equilibrium (x^e, u^e) with

$$\overline{J}_\infty(x, \mathbf{u}) \geq \ell(x^e, u^e)$$

for all $x \in \mathbb{X}$ and all admissible $\mathbf{u}$

This conclusion is obvious, since

$$\overline{J}^{cl}_\infty(x, \mu_N) \geq \inf_{\mathbf{u} \text{ admissible}} \overline{J}_\infty(x, \mathbf{u})$$

UNIVERSITÄT BAYREUTH

Optimality of this estimate

Can we ensure that this estimate is optimal?

Yes, if the system exhibits an infinite horizon averaged optimal equilibrium, i.e., if there exists an equilibrium (x^e, u^e) with

$$\overline{J}_\infty(x, \mathbf{u}) \geq \ell(x^e, u^e)$$

for all $x \in \mathbb{X}$ and all admissible $\mathbf{u}$

This conclusion is obvious, since

$$\overline{J}^{cl}_\infty(x, \mu_N) \geq \inf_{\mathbf{u} \text{ admissible}} \overline{J}_\infty(x, \mathbf{u})$$

Can we give an easily checkable sufficient condition for the existence of such an equilibrium?

UNIVERSITÄT BAYREUTH

Dissipativity

Given an equilibrium (x^e, u^e), we use the following

Definition: [Willems '72] The optimal control problem is called strictly dissipative if there exists $\lambda : \mathbb{X} \to \mathbb{R}$ and $\alpha \in \mathcal{K}_\infty$ such that

(D) $$\ell(x, u) + \lambda(x) - \lambda(f(x, u)) - \ell(x^e, u^e) \geq \alpha(\|x - x^e\|)$$

holds for all $x \in \mathbb{X}$ and $u \in \mathbb{U}$ and some $\alpha \in \mathcal{K}_\infty$

UNIVERSITÄT BAYREUTH

Dissipativity

Given an equilibrium (x^e, u^e), we use the following

Definition: [Willems '72] The optimal control problem is called strictly dissipative if there exists $\lambda : \mathbb{X} \to \mathbb{R}$ and $\alpha \in \mathcal{K}_\infty$ such that

(D) $$\ell(x,u) + \lambda(x) - \lambda(f(x,u)) - \ell(x^e,u^e) \geq \alpha(\|x - x^e\|)$$

holds for all $x \in \mathbb{X}$ and $u \in \mathbb{U}$ and some $\alpha \in \mathcal{K}_\infty$

physical interpretation of (D):

$\lambda(x)$ = energy stored in the system

UNIVERSITÄT BAYREUTH

Dissipativity

Given an equilibrium (x^e, u^e), we use the following

Definition: [Willems '72] The optimal control problem is called strictly dissipative if there exists $\lambda : \mathbb{X} \to \mathbb{R}$ and $\alpha \in \mathcal{K}_\infty$ such that

$$\text{(D)} \qquad \ell(x,u) + \lambda(x) - \lambda(f(x,u)) - \ell(x^e,u^e) \geq \alpha(\|x - x^e\|)$$

holds for all $x \in \mathbb{X}$ and $u \in \mathbb{U}$ and some $\alpha \in \mathcal{K}_\infty$

physical interpretation of (D):

$\lambda(x)$ = energy stored in the system

$\ell(x,u) - \ell(x^e,u^e)$ = energy supplied to the system

Dissipativity

Given an equilibrium (x^e, u^e), we use the following

Definition: [Willems '72] The optimal control problem is called strictly dissipative if there exists $\lambda : \mathbb{X} \to \mathbb{R}$ and $\alpha \in \mathcal{K}_\infty$ such that

(D) $$\ell(x,u) + \lambda(x) - \lambda(f(x,u)) - \ell(x^e,u^e) \geq \alpha(\|x - x^e\|)$$

holds for all $x \in \mathbb{X}$ and $u \in \mathbb{U}$ and some $\alpha \in \mathcal{K}_\infty$

physical interpretation of (D):

$\lambda(x)$ = energy stored in the system

$\ell(x,u) - \ell(x^e,u^e)$ = energy supplied to the system

strict dissipativity: some amount of energy is dissipated (=lost)

Strict dissipativity

(D) $\ell(x,u) + \lambda(x) - \lambda(f(x,u)) - \ell(x^e,u^e) \geq \alpha(\|x - x^e\|)$

Strict dissipativity (D) is

- satisfied for affine linear f and linear quadratic ℓ under mild regularity conditions on f, ℓ, $\mathbb{X}$ and $\mathbb{U}$ [Damm/Gr./Stieler/Worthmann '12]

UNIVERSITÄT BAYREUTH

Strict dissipativity

(D) $\ell(x,u) + \lambda(x) - \lambda(f(x,u)) - \ell(x^e,u^e) \geq \alpha(\|x - x^e\|)$

Strict dissipativity (D) is

- satisfied for affine linear f and linear quadratic ℓ under mild regularity conditions on f, ℓ, $\mathbb{X}$ and $\mathbb{U}$ [Damm/Gr./Stieler/Worthmann '12]
- more restrictive for nonlinear dynamics, see, e.g., the bilinear example in [Müller/Allgöwer '12]

Strict dissipativity

(D) $\ell(x,u) + \lambda(x) - \lambda(f(x,u)) - \ell(x^e,u^e) \geq \alpha(\|x - x^e\|)$

Strict dissipativity (D) is

- satisfied for affine linear f and linear quadratic ℓ under mild regularity conditions on f, ℓ, $\mathbb{X}$ and $\mathbb{U}$ [Damm/Gr./Stieler/Worthmann '12]
- more restrictive for nonlinear dynamics, see, e.g., the bilinear example in [Müller/Allgöwer '12]
- sufficient and "close to necessary" for the existence of an infinite horizon averaged optimal equilibrium [Müller/Angeli/Allgöwer '13]

Example 1: mimimum energy control

Example 1:

$$x(n+1) = 2x(n) + \mathbf{u}(n), \qquad \ell(x,u) = u^2$$

with constraints $\mathbb{X} = [-2, 2]$, $\mathbb{U} = [-3, 3]$

Example 1: mimimum energy control

Example 1:

$$x(n+1) = 2x(n) + \mathbf{u}(n), \qquad \ell(x,u) = u^2$$

with constraints $\mathbb{X} = [-2, 2]$, $\mathbb{U} = [-3, 3]$

The system has an optimal equilibrium at $(x^e, u^e) = (0, 0)$ and is strictly dissipative with $\lambda(x) = -x^2/2$

Example 1: mimimum energy control

Example 1:

$$x(n+1) = 2x(n) + \mathbf{u}(n), \qquad \ell(x,u) = u^2$$

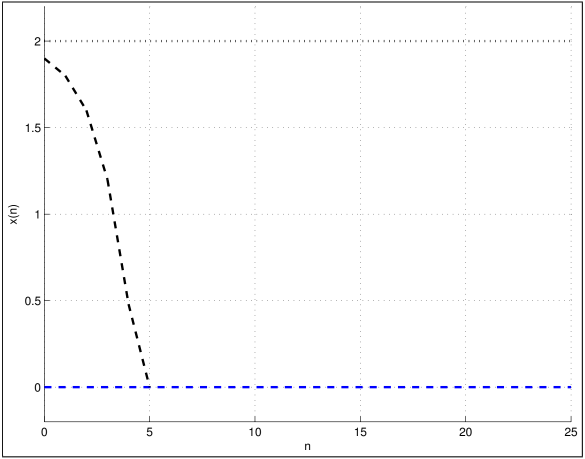
with constraints $\mathbb{X} = [-2,2]$, $\mathbb{U} = [-3,3]$

The system has an optimal equilibrium at $(x^e, u^e) = (0,0)$ and is strictly dissipative with $\lambda(x) = -x^2/2$

Using the terminal constraint $x_{\mathbf{u}}(N) = 0$, we will see that the closed loop trajectories converge to 0 (and the averaged functional equals 0)

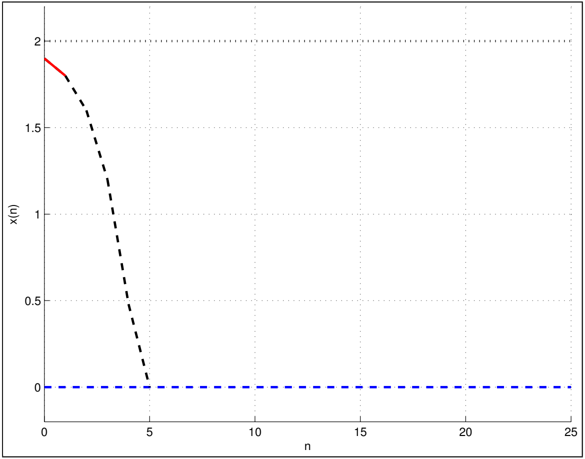
UNIVERSITÄT BAYREUTH

Example 1: trajectories



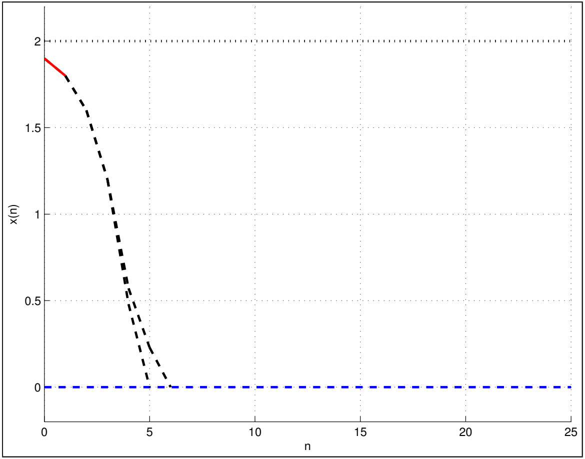
$N = 5$

Example 1: trajectories



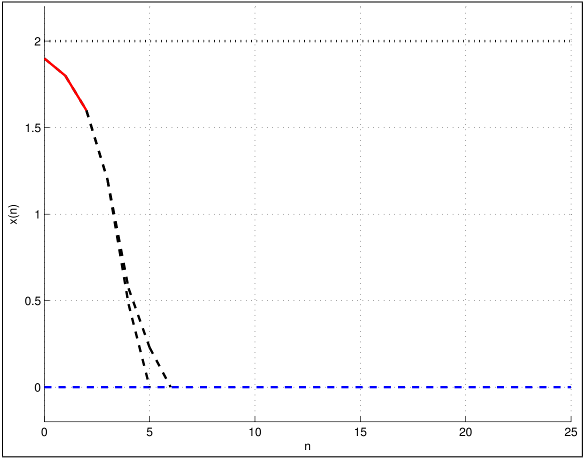
$N = 5$

Example 1: trajectories



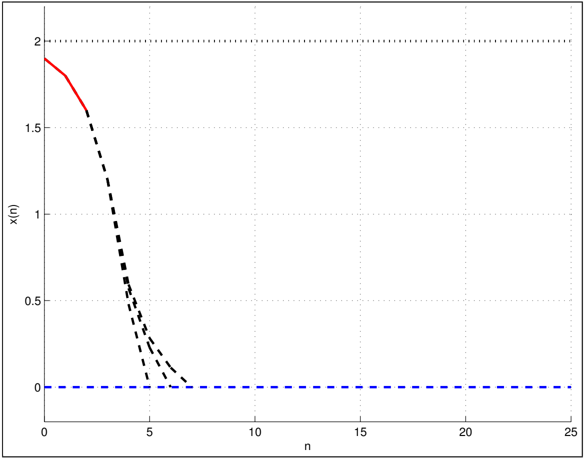
$N = 5$

Example 1: trajectories



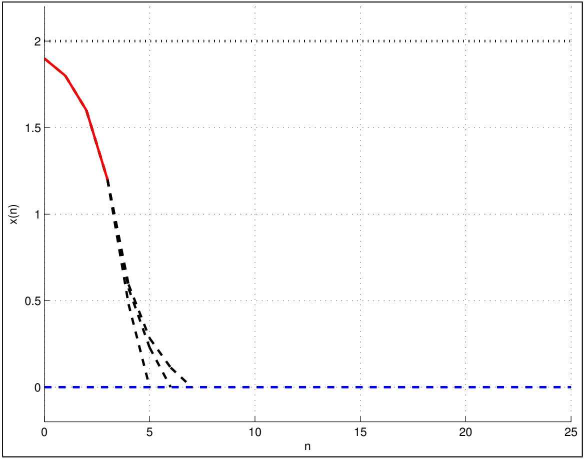
$N = 5$

Example 1: trajectories



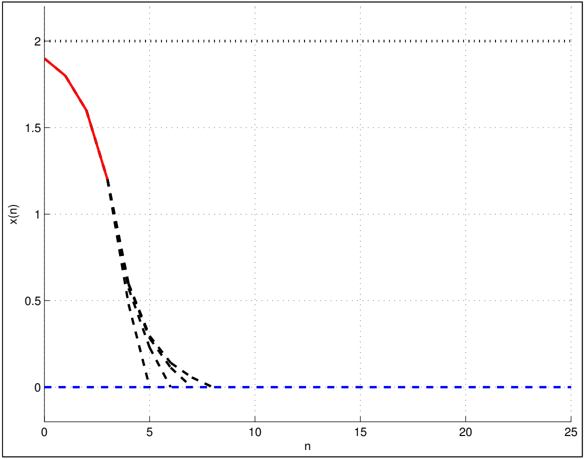
$N = 5$

Example 1: trajectories



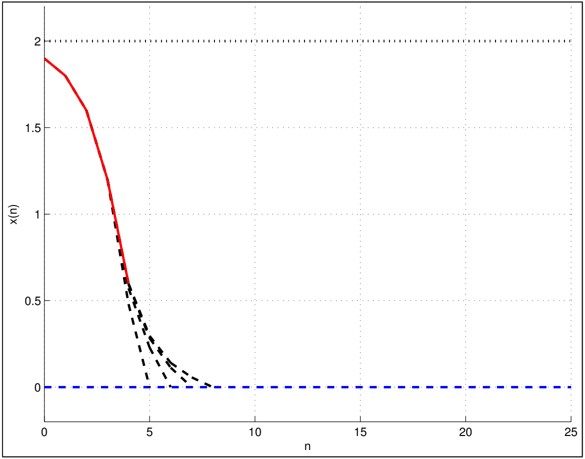
$N = 5$

Example 1: trajectories



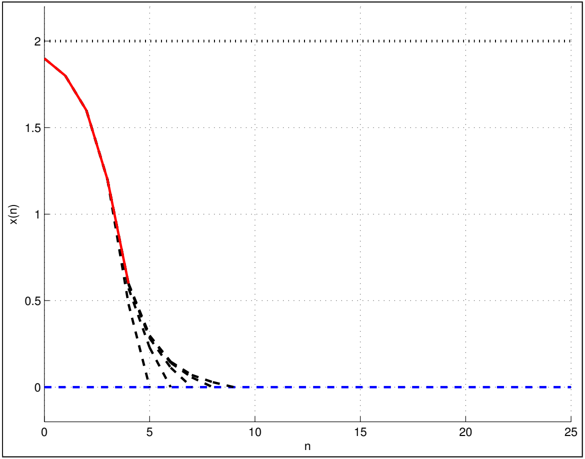
$N = 5$

Example 1: trajectories



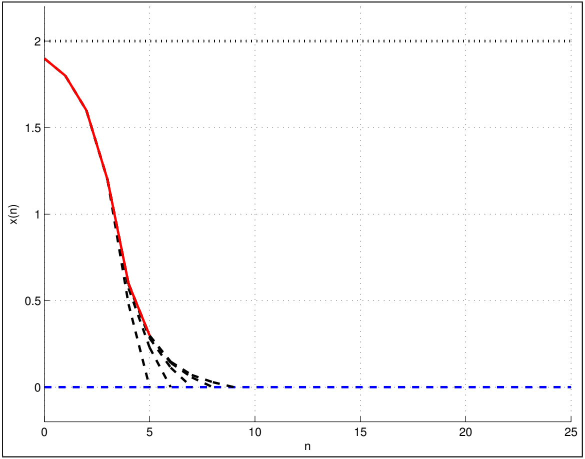
$N = 5$

Example 1: trajectories



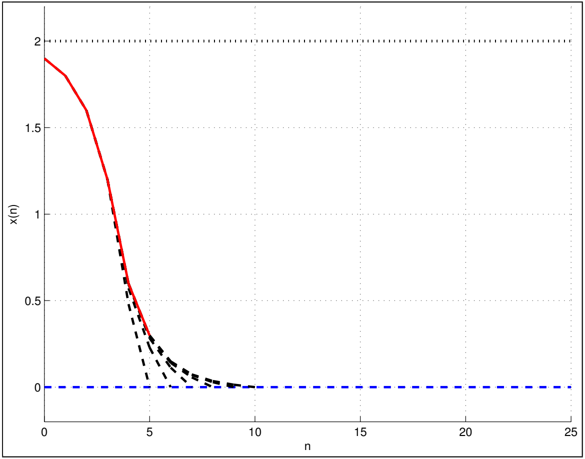
$N = 5$

Example 1: trajectories



$N = 5$

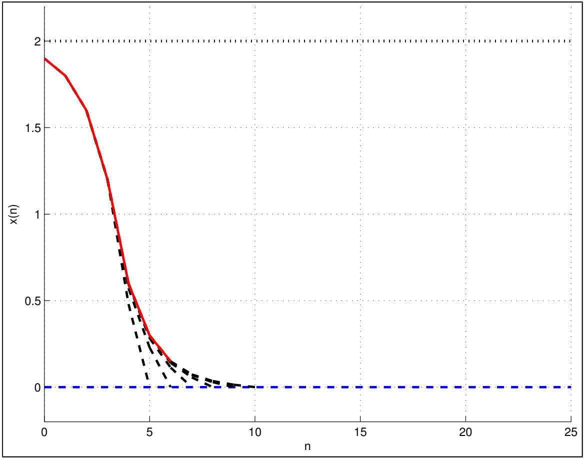
Example 1: trajectories



$N = 5$

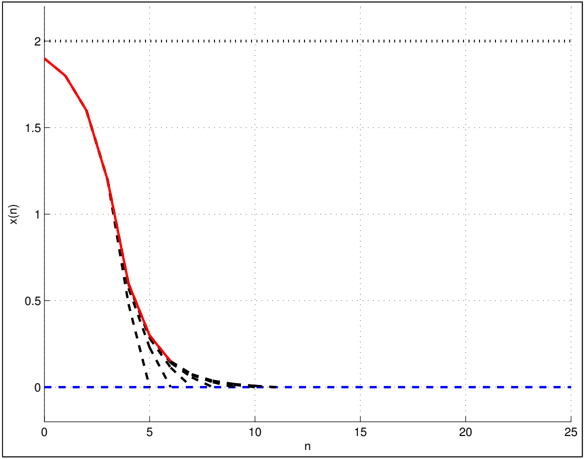
UNIVERSITÄT BAYREUTH

Example 1: trajectories



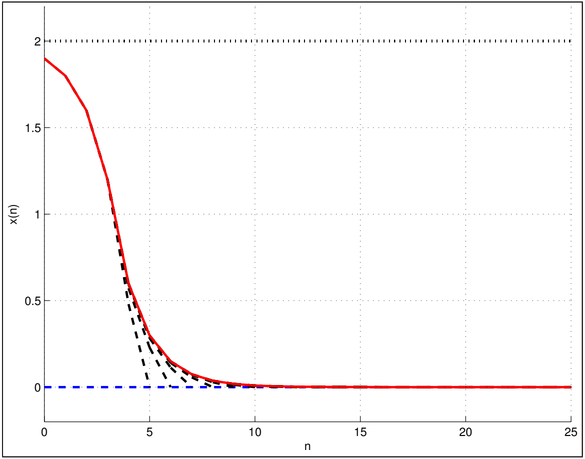
$N = 5$

Example 1: trajectories



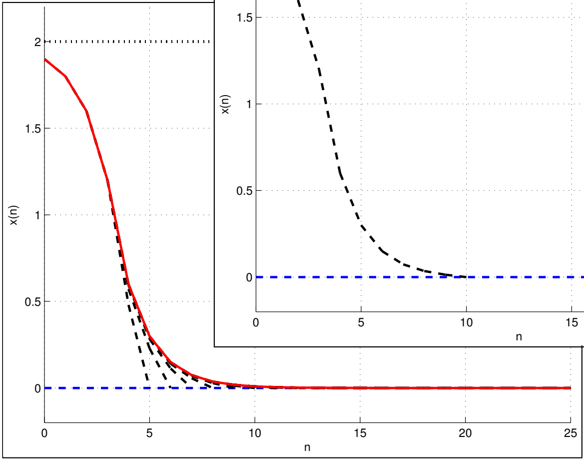
$N = 5$

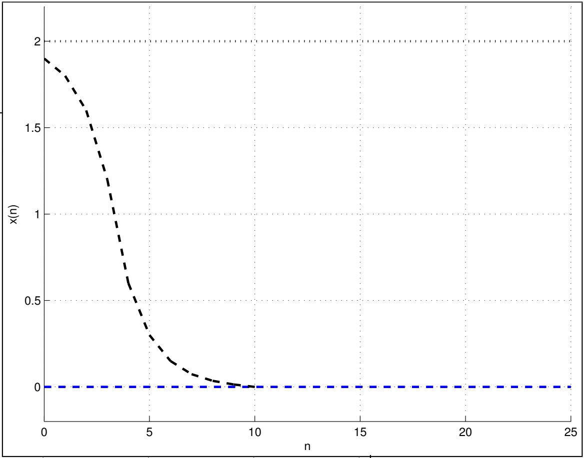
Example 1: trajectories



$N = 5$

Example 1: trajectories

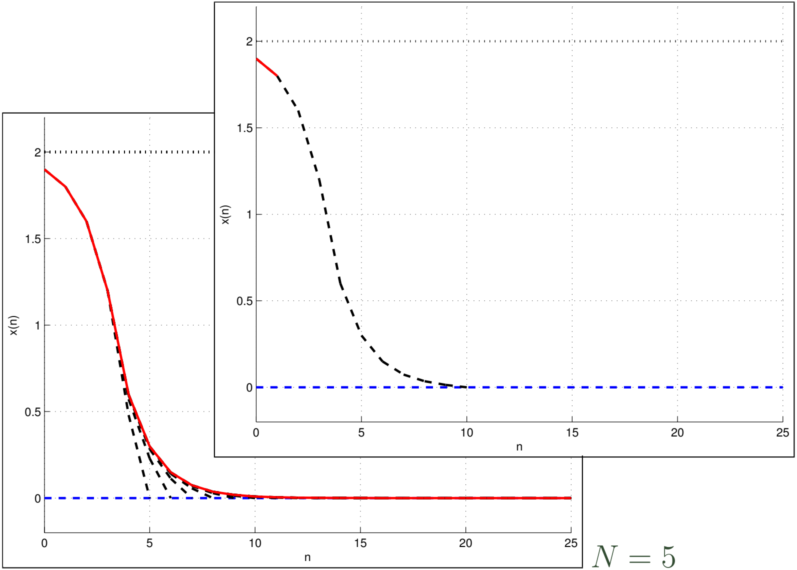




$N = 10$

$N = 5$

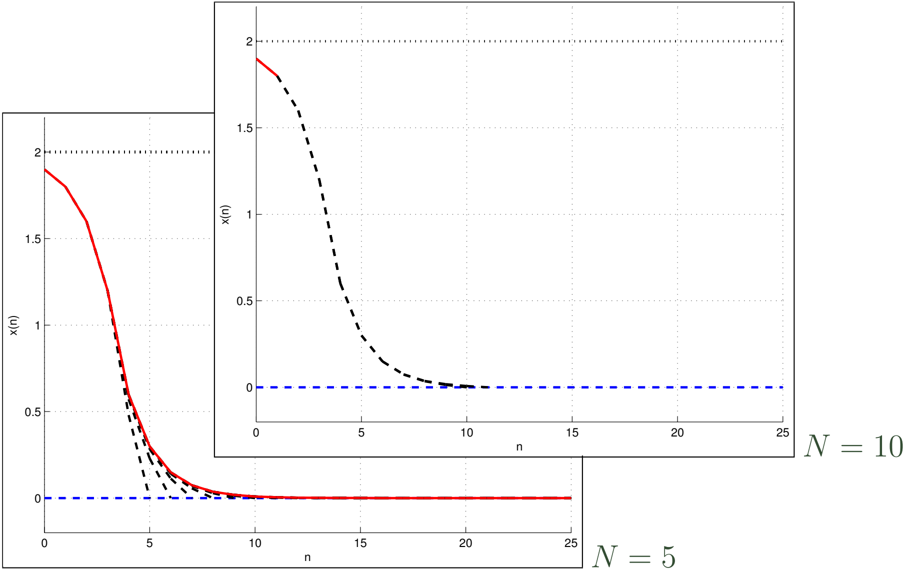
Example 1: trajectories



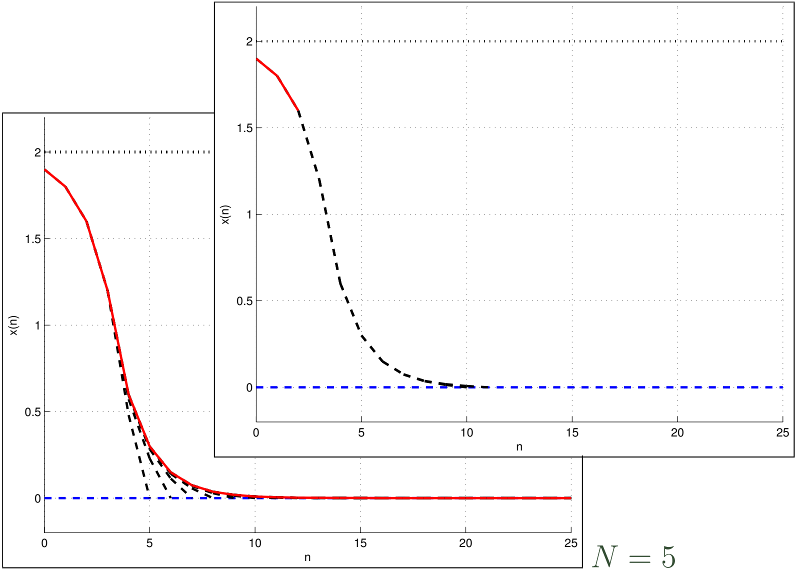
$N = 10$

$N = 5$

Example 1: trajectories



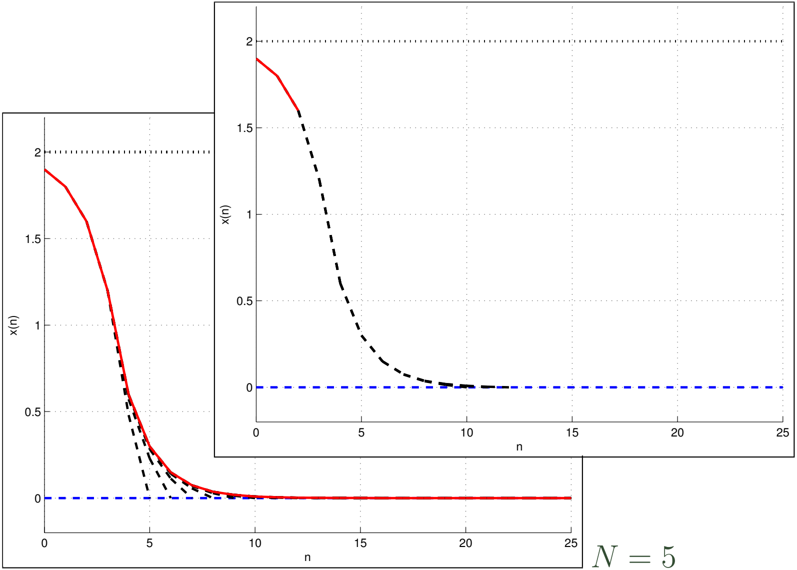
Example 1: trajectories



$N = 10$

$N = 5$

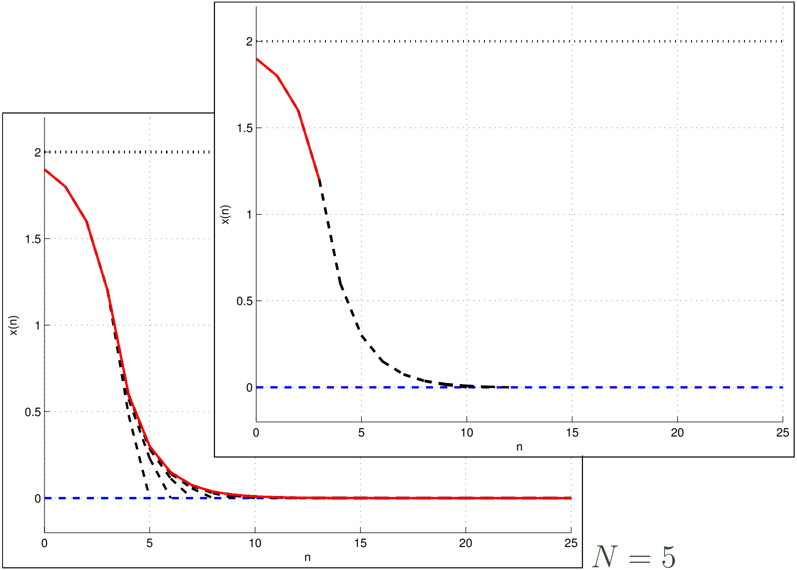
Example 1: trajectories



$N = 10$

$N = 5$

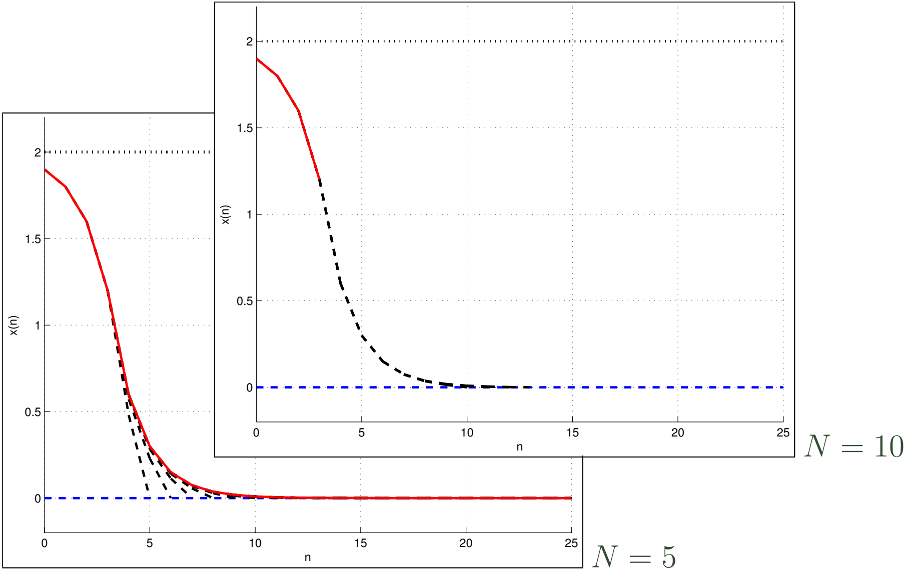
Example 1: trajectories



$N = 10$

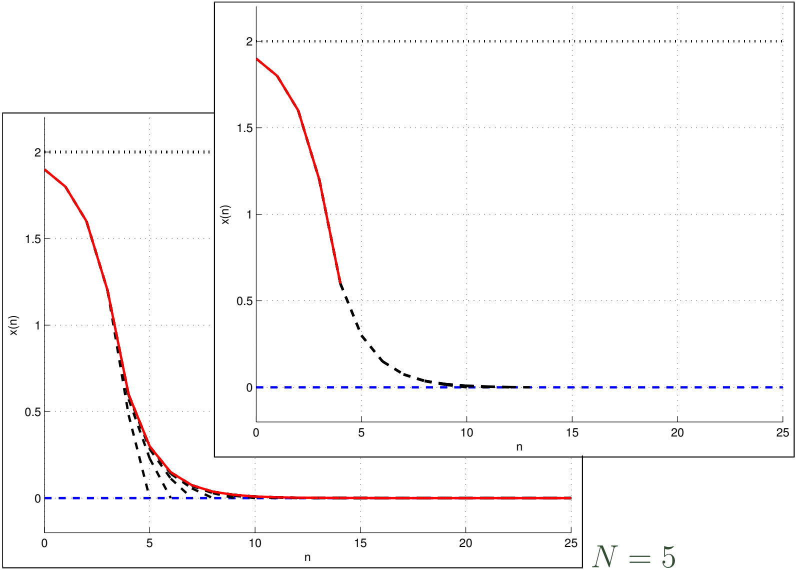
$N = 5$

Example 1: trajectories



UNIVERSITÄT BAYREUTH

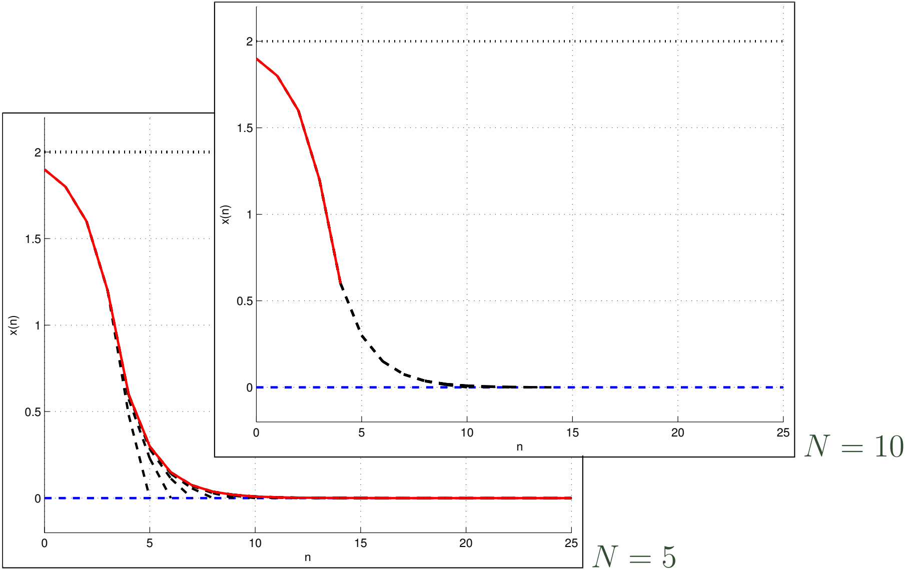
Example 1: trajectories



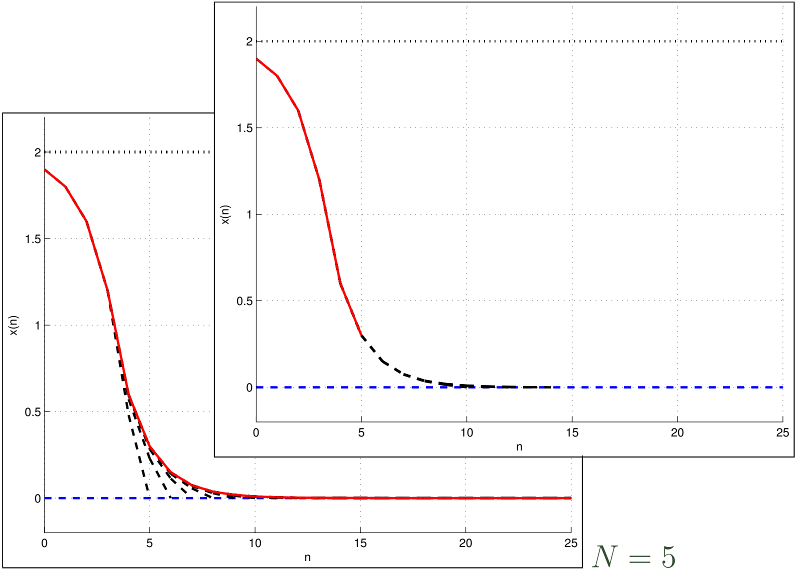
$N = 10$

$N = 5$

Example 1: trajectories



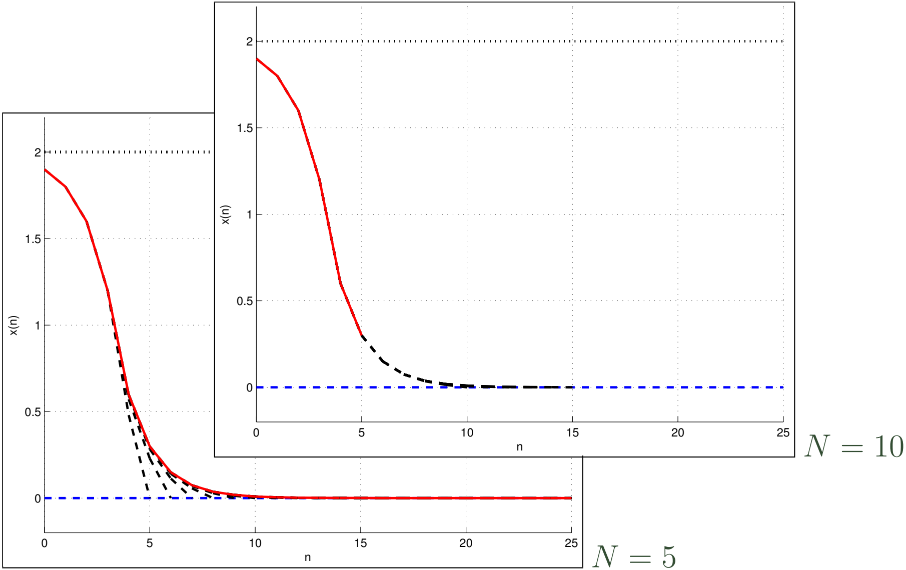
Example 1: trajectories



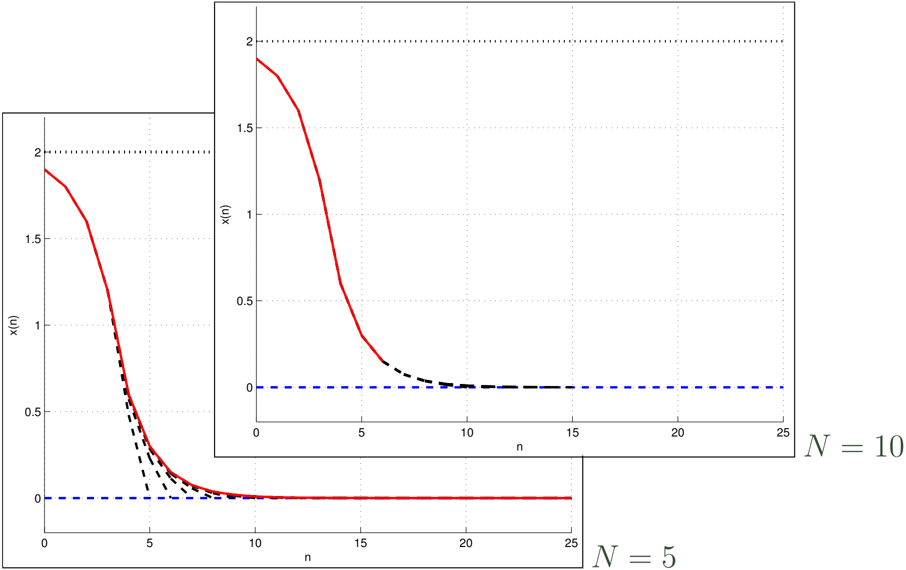
$N = 10$

$N = 5$

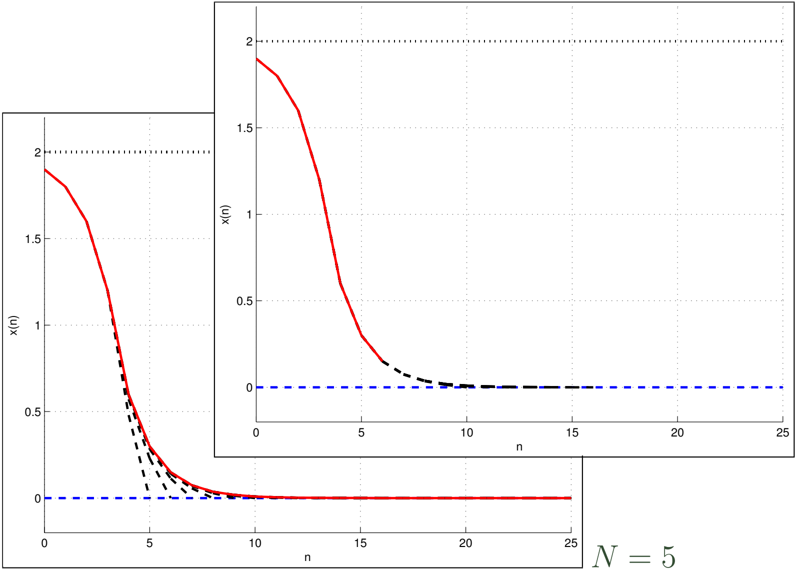
Example 1: trajectories



Example 1: trajectories



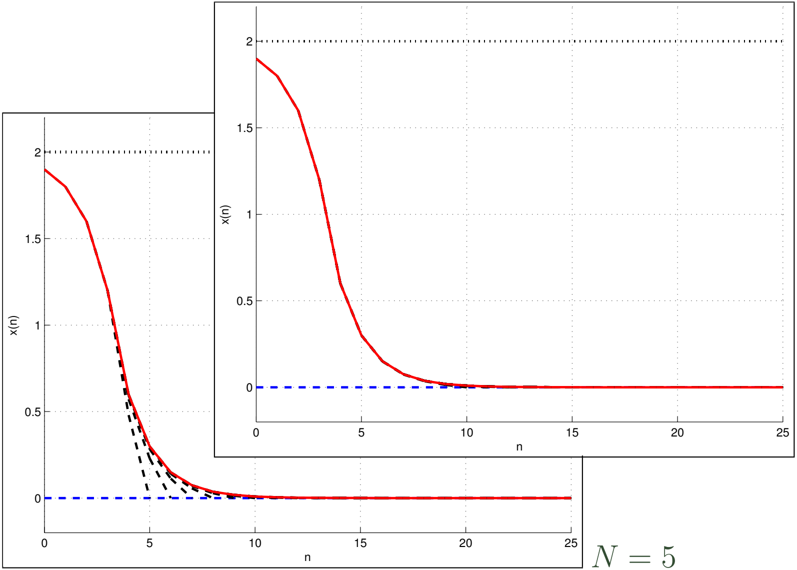
Example 1: trajectories



$N = 10$

$N = 5$

Example 1: trajectories



$N = 10$

$N = 5$

Example 2: Macroeconomic model

[Brock/Mirman '72]

Minimize the average performance with

$$x(n+1) = \mathbf{u}(n), \quad \ell(x,u) = -\ln(Ax^\alpha - u)$$

with $A = 5, \alpha = 0.34$ and constraints $\mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

Example 2: Macroeconomic model

[Brock/Mirman '72]

Minimize the average performance with

$$x(n+1) = \mathbf{u}(n), \quad \ell(x,u) = -\ln(Ax^\alpha - u)$$

with $A = 5, \alpha = 0.34$ and constraints $\mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

This problem exhibits the optimal equilibrium

$$x^e \approx 2.2344 \quad \text{with } \ell(x^e, u^e) \approx 1.4673$$

and is strictly dissipative with $\lambda(x) \approx 0.2306x$

Example 2: Macroeconomic model

[Brock/Mirman '72]

Minimize the average performance with

$$x(n+1) = \mathbf{u}(n), \quad \ell(x,u) = -\ln(Ax^\alpha - u)$$

with $A = 5, \alpha = 0.34$ and constraints $\mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

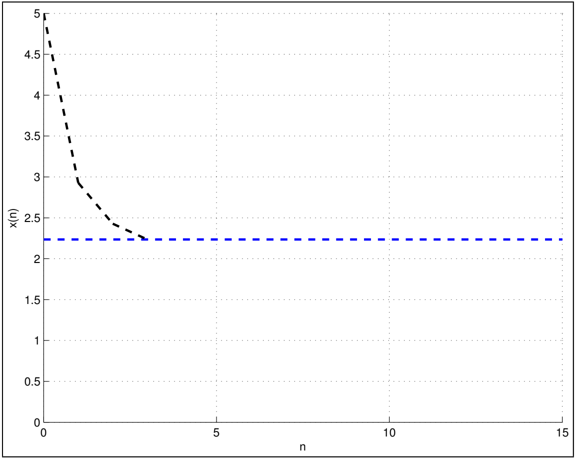
This problem exhibits the optimal equilibrium

$$x^e \approx 2.2344 \quad \text{with } \ell(x^e, u^e) \approx 1.4673$$

and is strictly dissipative with $\lambda(x) \approx 0.2306x$

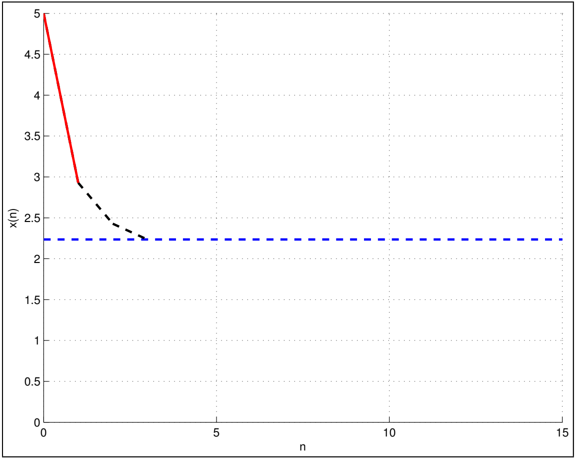
Again, with the terminal constraint $x_{\mathbf{u}}(N) = x^e$ the closed loop trajectories converge to x^e (and the averaged functional equals $\ell(x^e, u^e)$)

Example 2: trajectories



$N = 3$

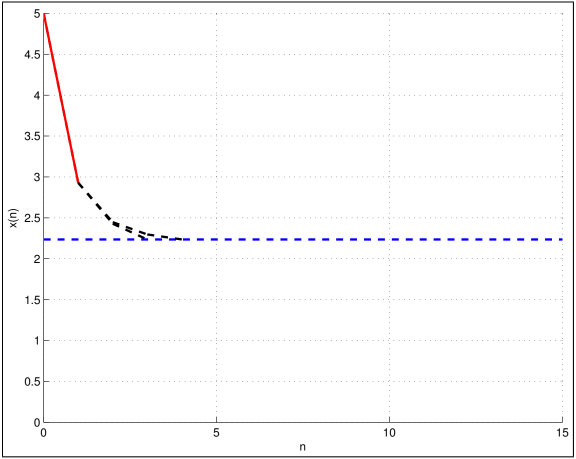
Example 2: trajectories



$N = 3$

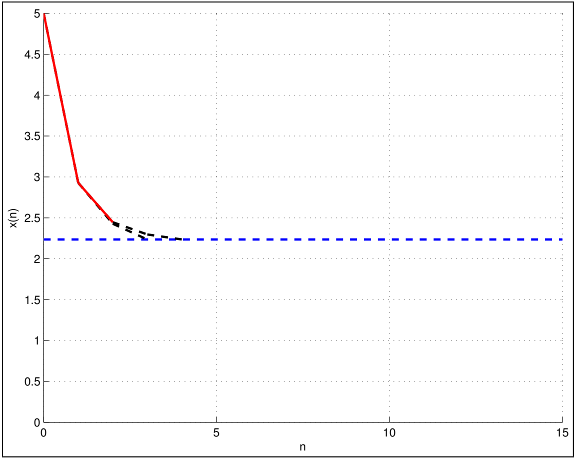
UNIVERSITÄT BAYREUTH

Example 2: trajectories



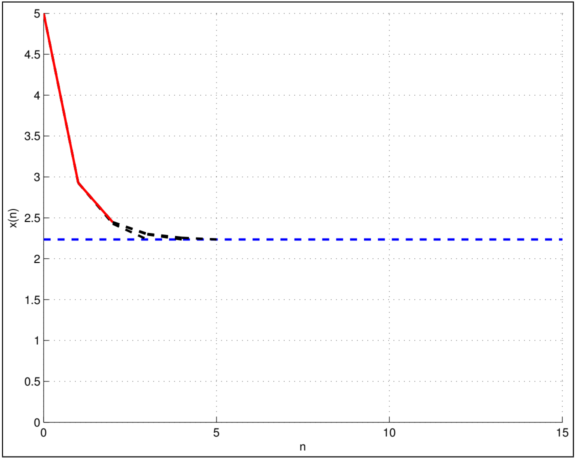
$N = 3$

Example 2: trajectories



$N = 3$

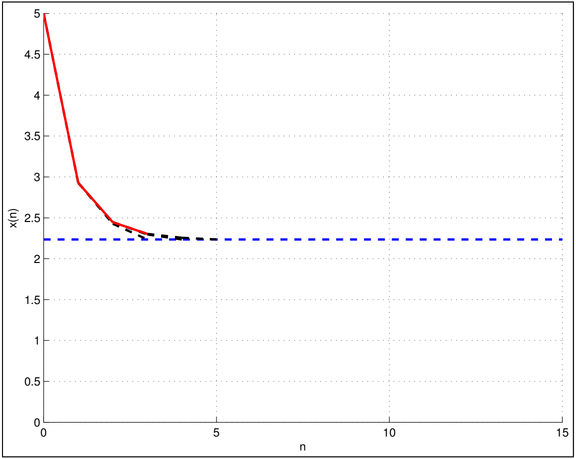
Example 2: trajectories



$N = 3$

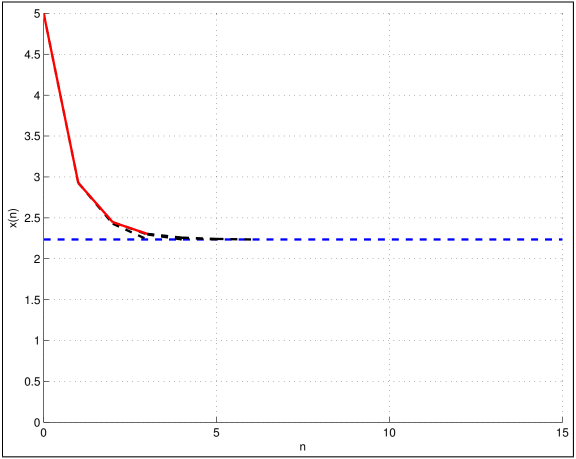
UNIVERSITÄT BAYREUTH

Example 2: trajectories



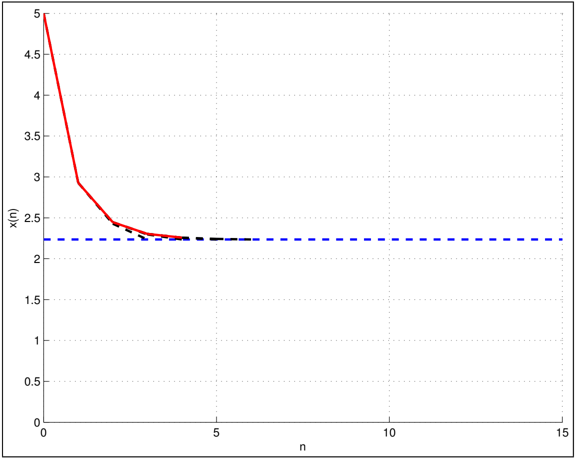
$N = 3$

Example 2: trajectories



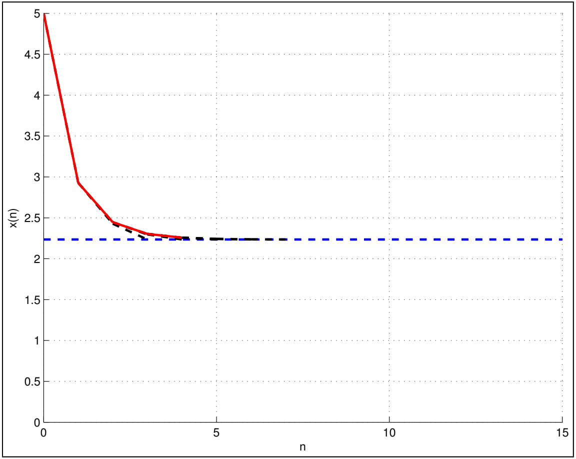
$N = 3$

Example 2: trajectories



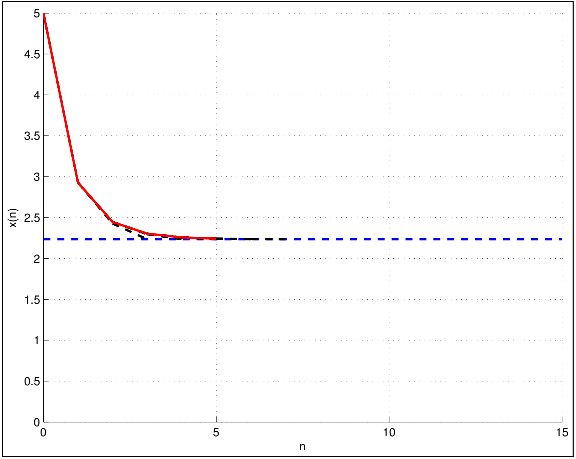
$N = 3$

Example 2: trajectories



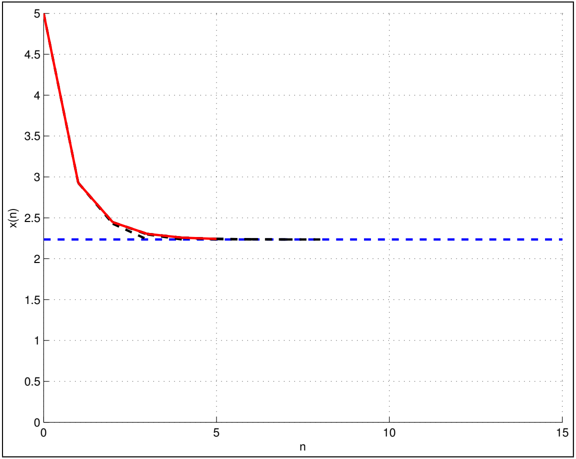
$N = 3$

Example 2: trajectories



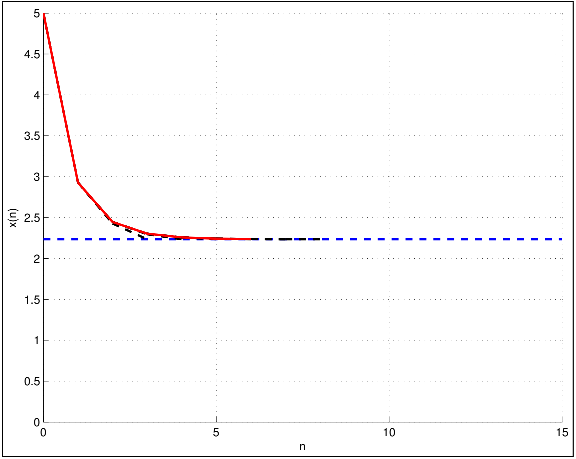
$N = 3$

Example 2: trajectories



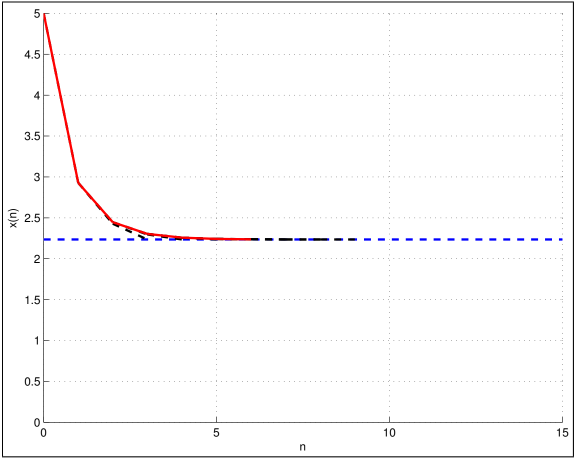
$N = 3$

Example 2: trajectories



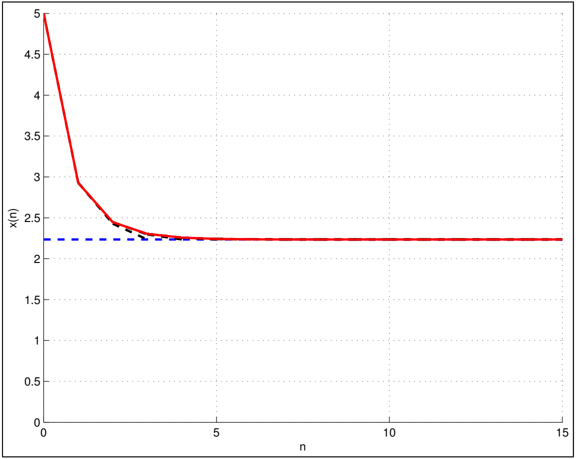
$N = 3$

Example 2: trajectories



$N = 3$

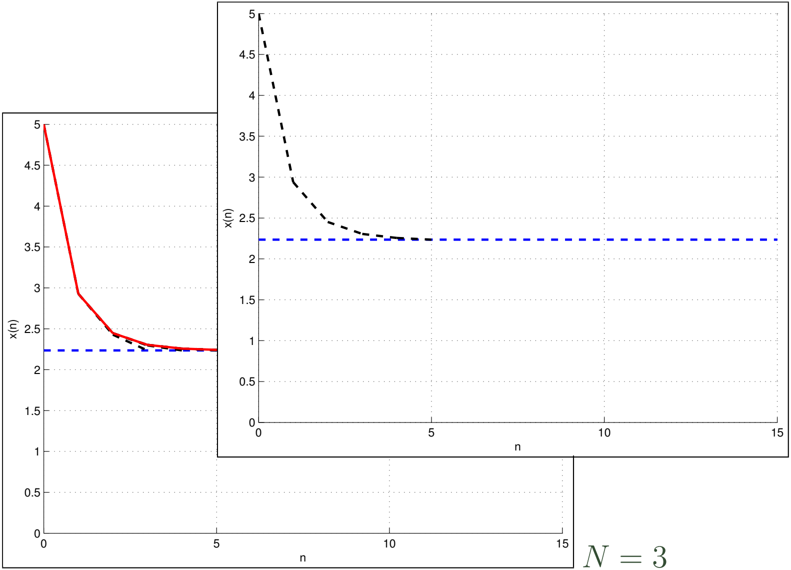
Example 2: trajectories



$N = 3$

UNIVERSITÄT BAYREUTH

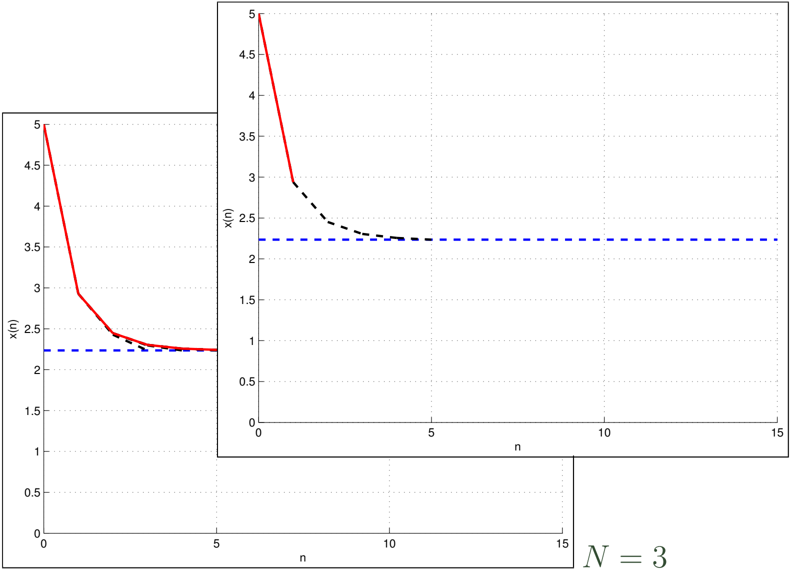
Example 2: trajectories



$N = 5$

$N = 3$

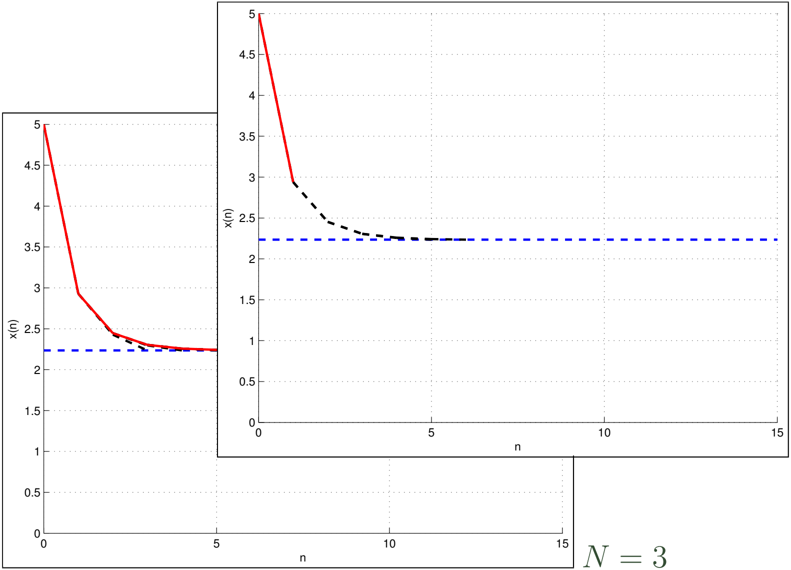
Example 2: trajectories



$N = 5$

$N = 3$

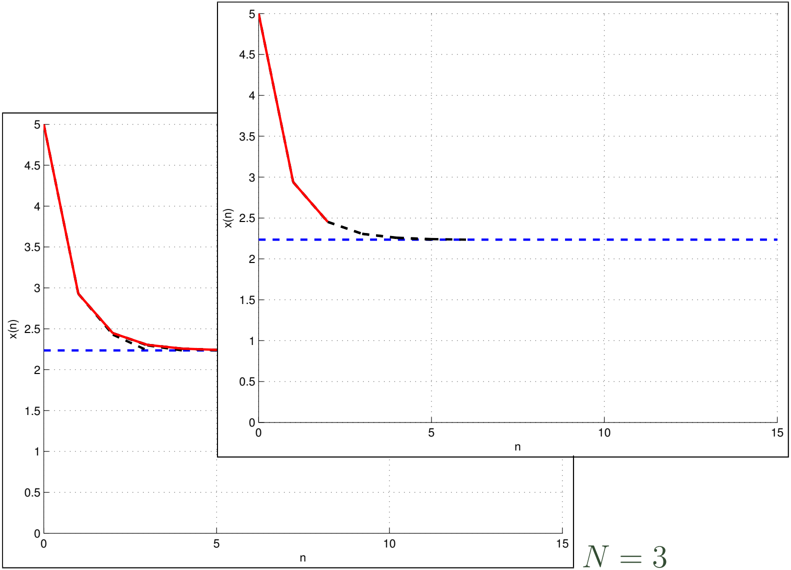
Example 2: trajectories



$N = 5$

$N = 3$

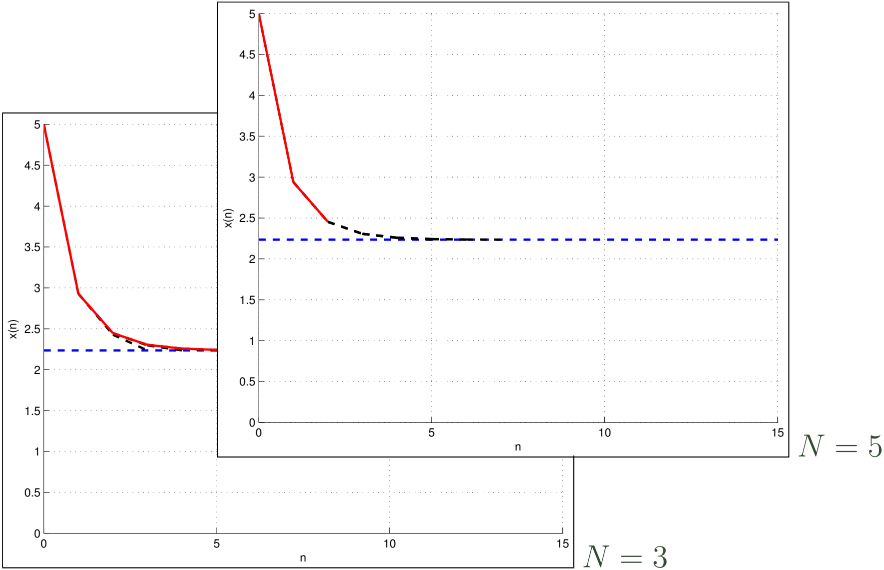
Example 2: trajectories



$N = 5$

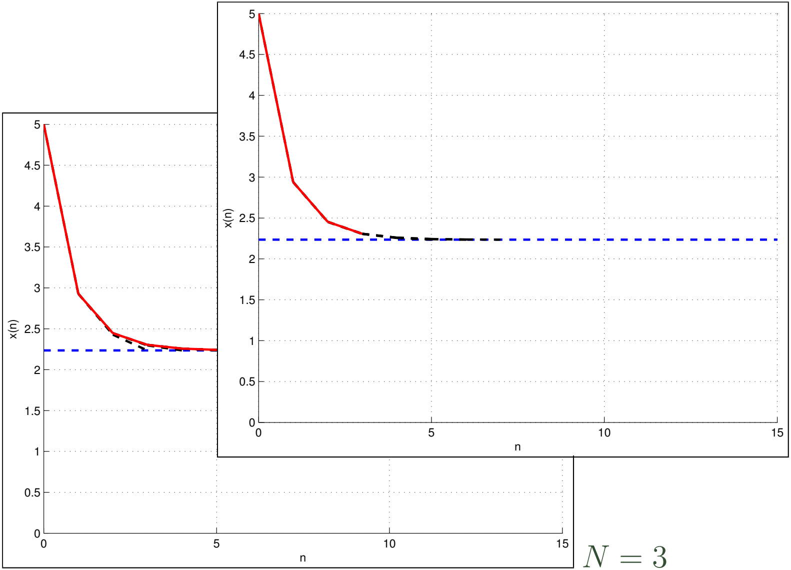
$N = 3$

Example 2: trajectories



UNIVERSITÄT BAYREUTH

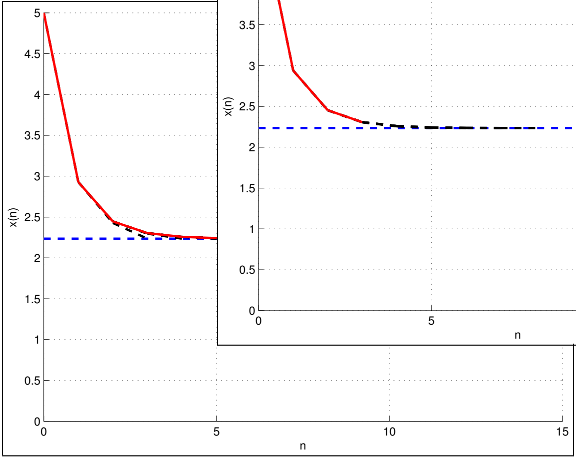
Example 2: trajectories



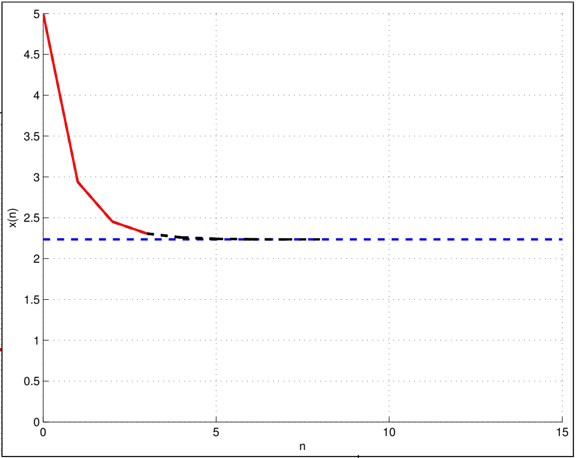
$N = 5$

$N = 3$

Example 2: trajectories

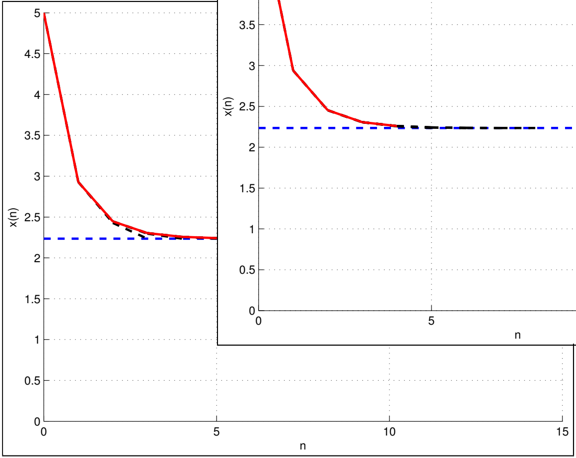


$N = 3$

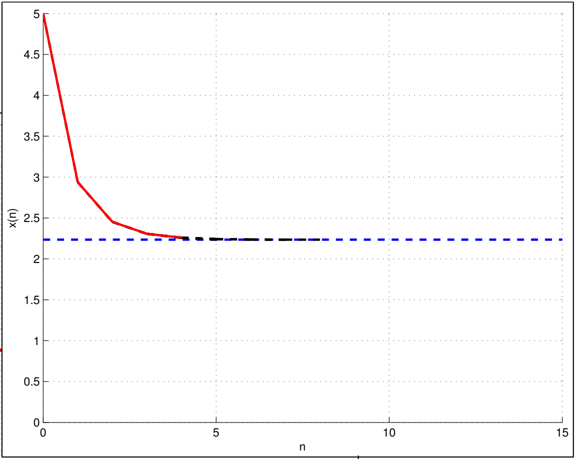


$N = 5$

Example 2: trajectories

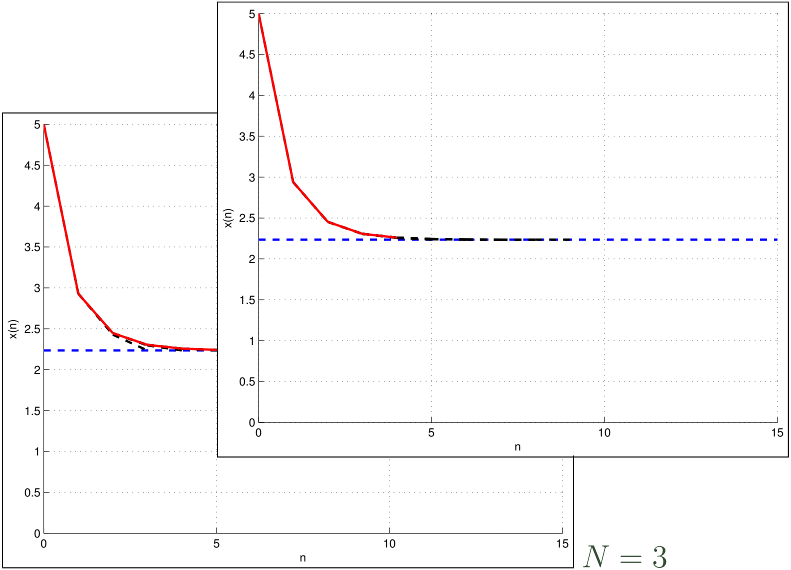


$N = 3$



$N = 5$

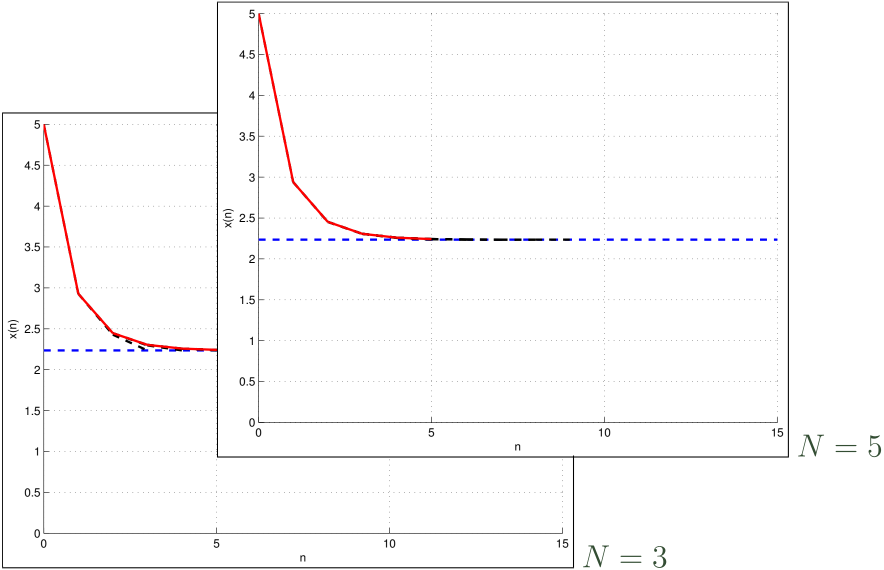
Example 2: trajectories



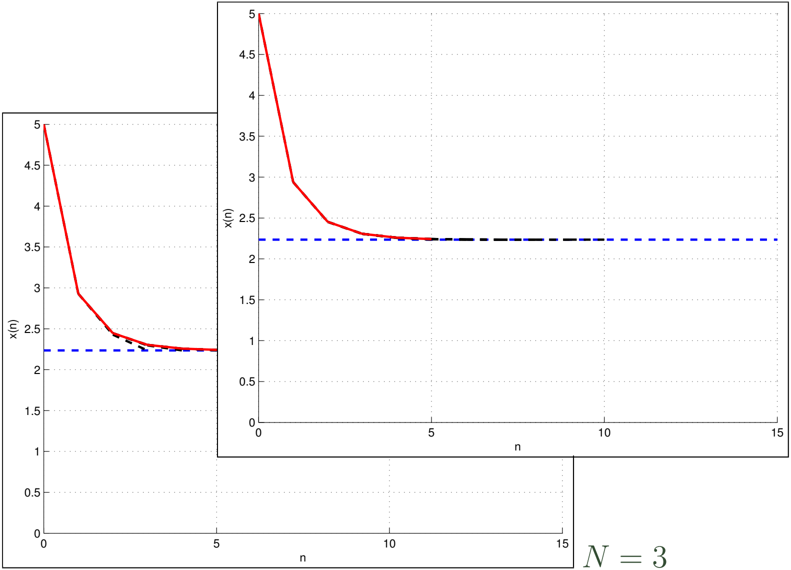
$N = 5$

$N = 3$

Example 2: trajectories



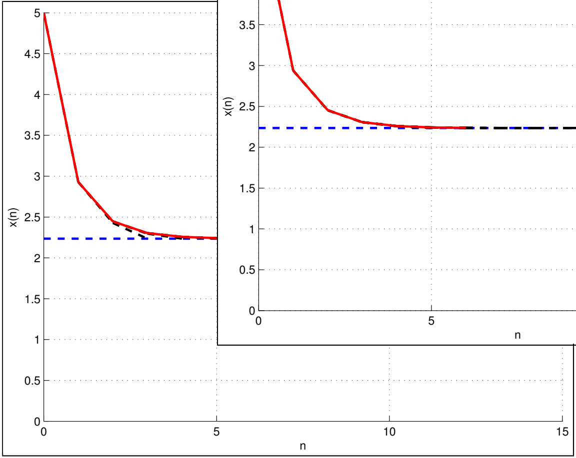
Example 2: trajectories



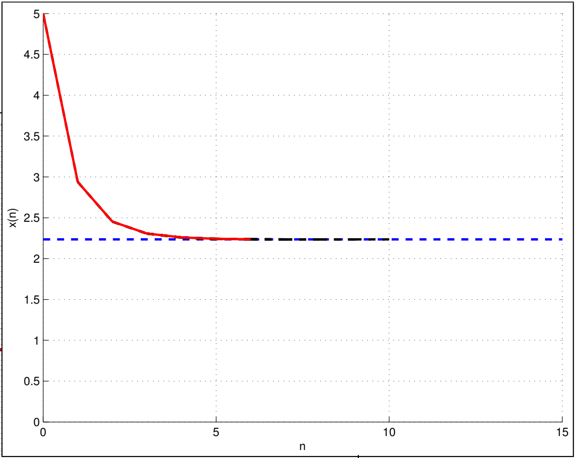
$N = 5$

$N = 3$

Example 2: trajectories



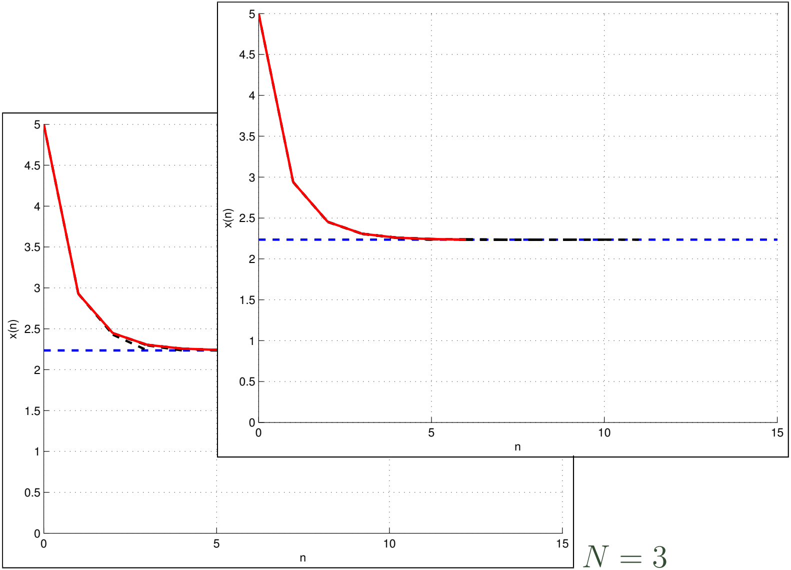
$N = 3$



$N = 5$

UNIVERSITÄT BAYREUTH

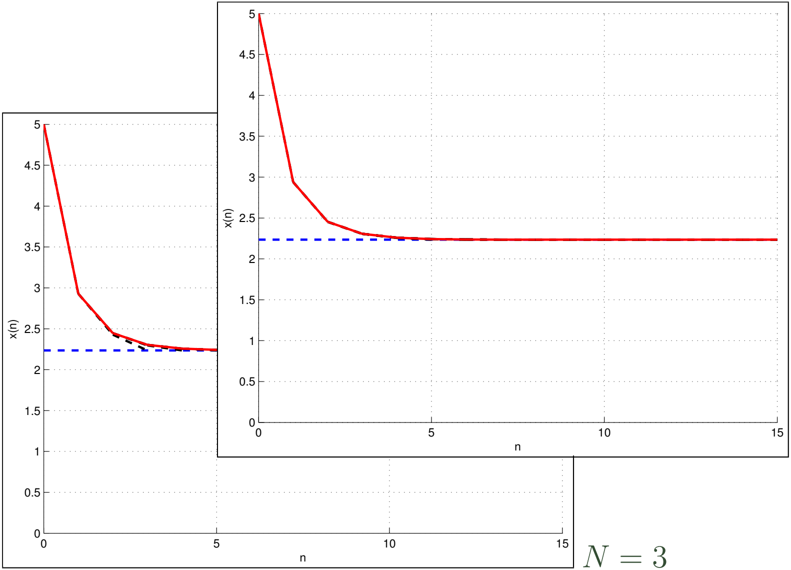
Example 2: trajectories



$N = 5$

$N = 3$

Example 2: trajectories



$N = 5$

$N = 3$

UNIVERSITÄT BAYREUTH

Discussion

- Averaged optimality is a rather weak concept:

Discussion

- Averaged optimality is a rather weak concept:

  Trajectories can do arbitrary detours as long as in the end $\ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \to \ell(x^e, u^e)$ holds

Discussion

- Averaged optimality is a rather weak concept:

  Trajectories can do arbitrary detours as long as in the end $\ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \to \ell(x^e, u^e)$ holds

- Estimates for their behavior on finite time intervals — also called "transient behaviour" — have been recently obtained by our group; a paper for CDC2015 is in preparation

Discussion

- Averaged optimality is a rather weak concept:

  Trajectories can do arbitrary detours as long as in the end $\ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \to \ell(x^e, u^e)$ holds

- Estimates for their behavior on finite time intervals — also called "transient behaviour" — have been recently obtained by our group; a paper for CDC2015 is in preparation

- The concept of good transient behaviour will be explained in the next section

Discussion

- Averaged optimality is a rather weak concept:

  Trajectories can do arbitrary detours as long as in the end $\ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \to \ell(x^e, u^e)$ holds

- Estimates for their behavior on finite time intervals — also called "transient behaviour" — have been recently obtained by our group; a paper for CDC2015 is in preparation

- The concept of good transient behaviour will be explained in the next section

Extensions: instead of equilibria, the terminal constraints can be formulated for periodic solutions [Angeli/Amrit/Rawlings '09]

Discussion

- Averaged optimality is a rather weak concept:

  Trajectories can do arbitrary detours as long as in the end $\ell(x_{\mu_N}(k), \mu_N(x_{\mu_N}(k))) \to \ell(x^e, u^e)$ holds

- Estimates for their behavior on finite time intervals — also called "transient behaviour" — have been recently obtained by our group; a paper for CDC2015 is in preparation

- The concept of good transient behaviour will be explained in the next section

Extensions: instead of equilibria, the terminal constraints can be formulated for periodic solutions [Angeli/Amrit/Rawlings '09]

Regional terminal constraints and Lyapunov-like terminal costs are also possible, but their construction is difficult

Asymptotic stability

Assuming an optimal equilibrium exists, what about its asymptotic stability for the MPC closed loop?

Asymptotic stability

Assuming an optimal equilibrium exists, what about its asymptotic stability for the MPC closed loop? Apparently, this property holds for the two numerical examples

Asymptotic stability

Assuming an optimal equilibrium exists, what about its asymptotic stability for the MPC closed loop? Apparently, this property holds for the two numerical examples

This is not by chance, since strict dissipativity (D) ensures asymptotic stability:

Asymptotic stability

Assuming an optimal equilibrium exists, what about its asymptotic stability for the MPC closed loop? Apparently, this property holds for the two numerical examples

This is not by chance, since strict dissipativity (D) ensures asymptotic stability:

Theorem: [Diehl/Amrit/Rawlings '11, Angeli/Amrit/Rawlings '12] Assume that the optimal control problem is strictly dissipative for the equilibrium (x^e, u^e). Then the MPC closed loop for the scheme with terminal constraint $x_{\mathbf{u}}(N) = x^e$ is asymptotically stable at x^e.

UNIVERSITÄT BAYREUTH

Sketch of proof

(D) $$\ell(x,u) - \ell(x^e,u^e) + \lambda(x) - \lambda(f(x,u)) \geq \alpha(\|x - x^e\|)$$

Sketch of proof

(D) $$\underbrace{\ell(x,u) - \ell(x^e,u^e) + \lambda(x) - \lambda(f(x,u))}_{=:\,\tilde{\ell}(x,u)} \geq \alpha(\|x - x^e\|)$$

UNIVERSITÄT BAYREUTH

Sketch of proof

(D) $$\underbrace{\ell(x,u)-\ell(x^e,u^e)+\lambda(x)-\lambda(f(x,u))}_{=:\,\tilde{\ell}(x,u)} \geq \alpha(\|x-x^e\|)$$

Due to the terminal constraints the functionals J_N (using ℓ) and $\widetilde{J}_N$ (using $\tilde{\ell}$) differ only by a constant independent of $\mathbf{u}$

Sketch of proof

(D) $$\underbrace{\ell(x,u) - \ell(x^e,u^e) + \lambda(x) - \lambda(f(x,u))}_{=:\,\tilde{\ell}(x,u)} \ge \alpha(\|x - x^e\|)$$

Due to the terminal constraints the functionals J_N (using ℓ) and $\widetilde{J}_N$ (using $\tilde{\ell}$) differ only by a constant independent of $\mathbf{u}$

$\rightsquigarrow$ optimal trajectories coincide

Sketch of proof

(D) $$\underbrace{\ell(x,u) - \ell(x^e,u^e) + \lambda(x) - \lambda(f(x,u))}_{=:\, \tilde{\ell}(x,u)} \geq \alpha(\|x - x^e\|)$$

Due to the terminal constraints the functionals J_N (using ℓ) and $\widetilde{J}_N$ (using $\tilde{\ell}$) differ only by a constant independent of $\mathbf{u}$

$\rightsquigarrow$ optimal trajectories coincide

The optimal control problem with $\tilde{\ell}$ instead of ℓ satisfies all properties for stability of stabilizing MPC (with the corresponding optimal value function $\widetilde{V}_N$ as Lyapunov function)

Sketch of proof

(D) $$\underbrace{\ell(x,u) - \ell(x^e,u^e) + \lambda(x) - \lambda(f(x,u))}_{=: \tilde{\ell}(x,u)} \geq \alpha(\|x - x^e\|)$$

Due to the terminal constraints the functionals J_N (using ℓ) and $\widetilde{J}_N$ (using $\tilde{\ell}$) differ only by a constant independent of $\mathbf{u}$

$\rightsquigarrow$ optimal trajectories coincide

The optimal control problem with $\tilde{\ell}$ instead of ℓ satisfies all properties for stability of stabilizing MPC (with the corresponding optimal value function $\widetilde{V}_N$ as Lyapunov function) $\rightsquigarrow$ asymptotic stability for the modified problem

Sketch of proof

(D) $$\underbrace{\ell(x,u) - \ell(x^e,u^e) + \lambda(x) - \lambda(f(x,u))}_{=:\,\tilde{\ell}(x,u)} \geq \alpha(\|x - x^e\|)$$

Due to the terminal constraints the functionals J_N (using ℓ) and $\widetilde{J}_N$ (using $\tilde{\ell}$) differ only by a constant independent of $\mathbf{u}$

$\rightsquigarrow$ optimal trajectories coincide

The optimal control problem with $\tilde{\ell}$ instead of ℓ satisfies all properties for stability of stabilizing MPC (with the corresponding optimal value function $\widetilde{V}_N$ as Lyapunov function) $\rightsquigarrow$ asymptotic stability for the modified problem

Since the optimal trajectories coincide, the MPC closed loops coincide

Sketch of proof

(D) $$\underbrace{\ell(x,u)-\ell(x^e,u^e)+\lambda(x)-\lambda(f(x,u))}_{=:\,\tilde\ell(x,u)} \ge \alpha(\|x-x^e\|)$$

Due to the terminal constraints the functionals J_N (using ℓ) and $\widetilde{J}_N$ (using $\tilde\ell$) differ only by a constant independent of $\mathbf{u}$

$\rightsquigarrow$ optimal trajectories coincide

The optimal control problem with $\tilde\ell$ instead of ℓ satisfies all properties for stability of stabilizing MPC (with the corresponding optimal value function $\widetilde{V}_N$ as Lyapunov function) $\rightsquigarrow$ asymptotic stability for the modified problem

Since the optimal trajectories coincide, the MPC closed loops coincide $\rightsquigarrow$ asymptotic stability for the original problem

Summary of Section (8)

- Economic MPC means that the cost function is not a-priori related to an equilibrium

Summary of Section (8)

- Economic MPC means that the cost function is not a-priori related to an equilibrium
- However, the results become particularly nice if an optimal equilibrium (x^e, u^e) exist

Summary of Section (8)

- Economic MPC means that the cost function is not a-priori related to an equilibrium
- However, the results become particularly nice if an optimal equilibrium (x^e, u^e) exist
- In contrast to stabilizing MPC, this equilibrium need not be the (unique) minimizer of ℓ over $\mathbb{X} \times \mathbb{U}$

Summary of Section (8)

- Economic MPC means that the cost function is not a-priori related to an equilibrium
- However, the results become particularly nice if an optimal equilibrium (x^e, u^e) exist
- In contrast to stabilizing MPC, this equilibrium need not be the (unique) minimizer of ℓ over $\mathbb{X} \times \mathbb{U}$
- The optimal equilibrium can be used as terminal constraint

Summary of Section (8)

- Economic MPC means that the cost function is not a-priori related to an equilibrium
- However, the results become particularly nice if an optimal equilibrium (x^e, u^e) exist
- In contrast to stabilizing MPC, this equilibrium need not be the (unique) minimizer of ℓ over $\mathbb{X} \times \mathbb{U}$
- The optimal equilibrium can be used as terminal constraint
- Optimality can be proven in a (rather weak) averaged sense, though simulations suggest better optimality properties

Summary of Section (8)

- Economic MPC means that the cost function is not a-priori related to an equilibrium
- However, the results become particularly nice if an optimal equilibrium (x^e, u^e) exist
- In contrast to stabilizing MPC, this equilibrium need not be the (unique) minimizer of ℓ over $\mathbb{X} \times \mathbb{U}$
- The optimal equilibrium can be used as terminal constraint
- Optimality can be proven in a (rather weak) averaged sense, though simulations suggest better optimality properties
- Strict dissipativity ensures both the existence of an optimal equilibrium and asymptotic stability of the closed loop

(9) Economic MPC without terminal constraints

Economic MPC without terminal constraints

What happens without terminal constraints?

Economic MPC without terminal constraints

What happens without terminal constraints? We investigate this for the examples from the last section:

Example 1: Keep the state of the system inside an admissible set $\mathbb{X}$ minimizing the quadratic control effort

$$\ell(x,u) = u^2$$

with dynamics

$$x(n+1) = 2x(n) + \mathbf{u}(n)$$

and constraints $\mathbb{X} = [-2, 2]$, $\mathbb{U} = [-3, 3]$

Economic MPC without terminal constraints

What happens without terminal constraints? We investigate this for the examples from the last section:

Example 1: Keep the state of the system inside an admissible set $\mathbb{X}$ minimizing the quadratic control effort

$$\ell(x, u) = u^2$$

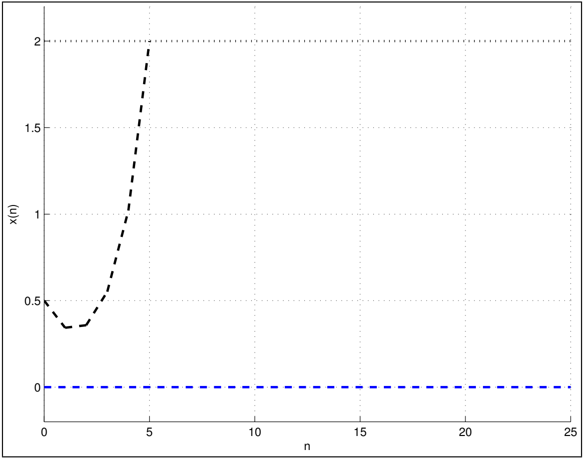
with dynamics

$$x(n+1) = 2x(n) + \mathbf{u}(n)$$

and constraints $\mathbb{X} = [-2, 2]$, $\mathbb{U} = [-3, 3]$

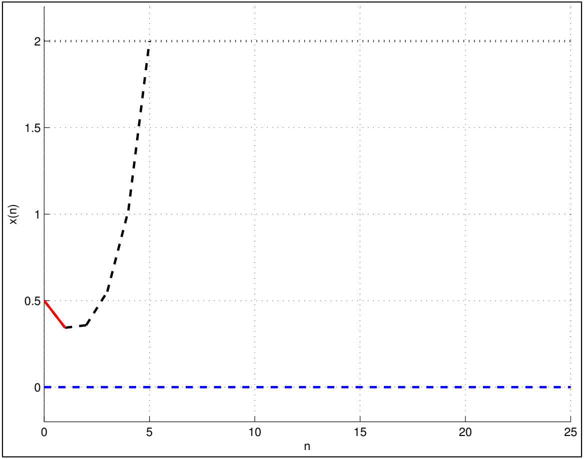
For this example, it is optimal to control the system to $x^e = 0$ and keep it there with $u^e = 0$ $\quad \rightsquigarrow \quad \inf_{\mathbf{u}} J_\infty(x, \mathbf{u}) = 0$

Example 1: trajectories



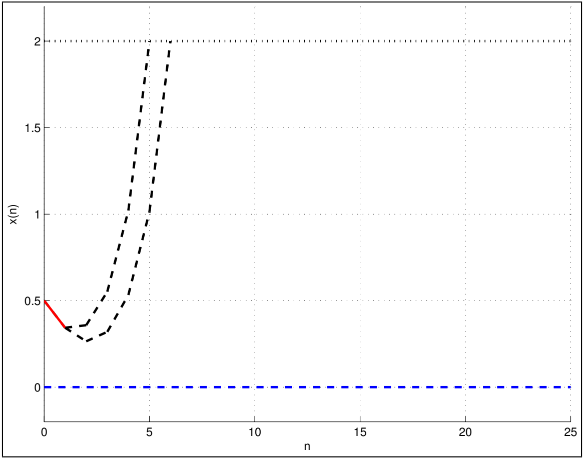
$N = 5$

Example 1: trajectories



$N = 5$

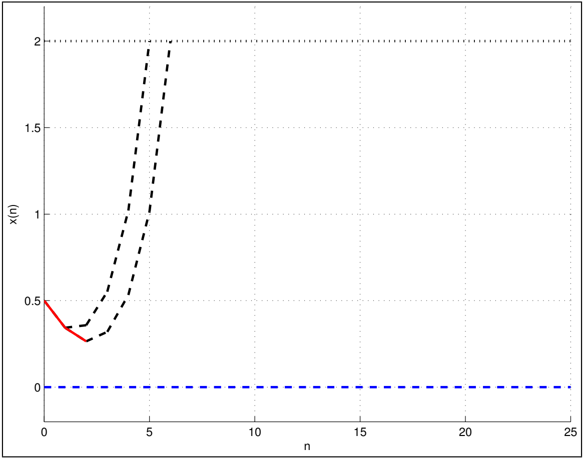
Example 1: trajectories



$N = 5$

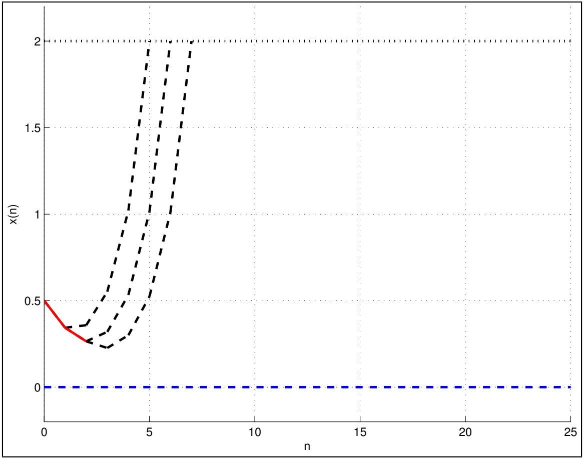
UNIVERSITÄT BAYREUTH

Example 1: trajectories



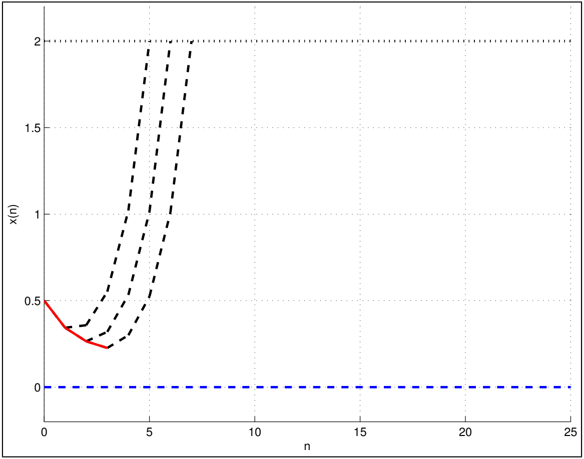
$N = 5$

Example 1: trajectories



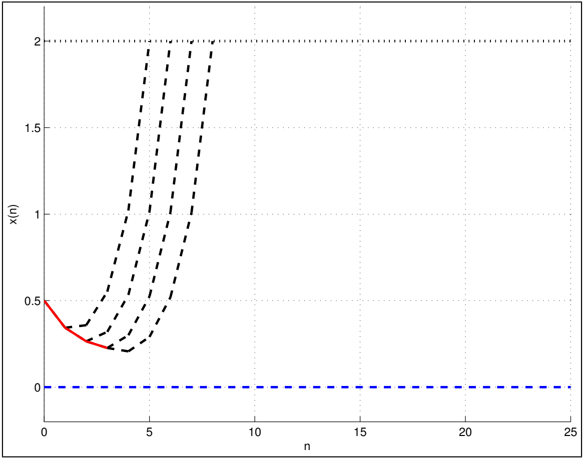
$N = 5$

Example 1: trajectories



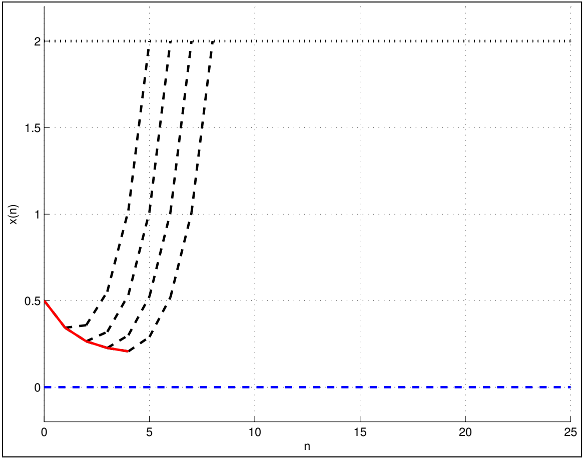
$N = 5$

Example 1: trajectories



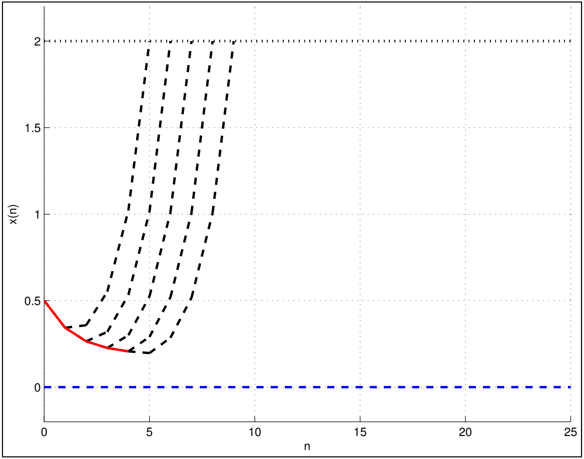
$N = 5$

Example 1: trajectories



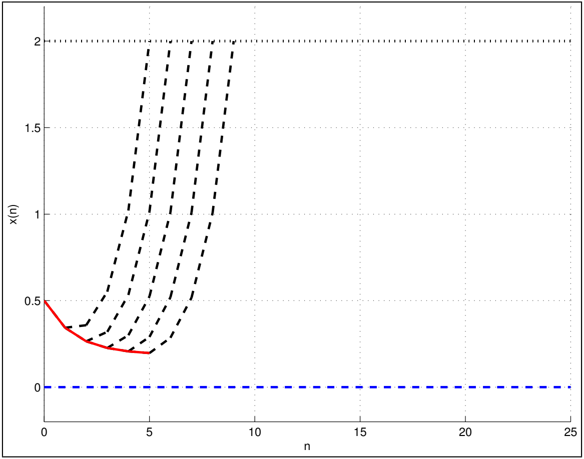
$N = 5$

Example 1: trajectories



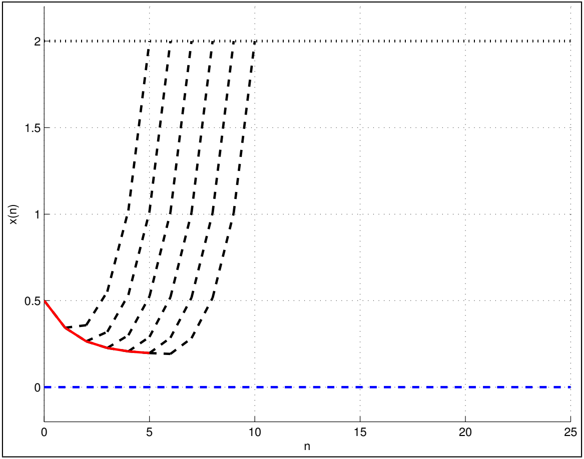
$N = 5$

Example 1: trajectories



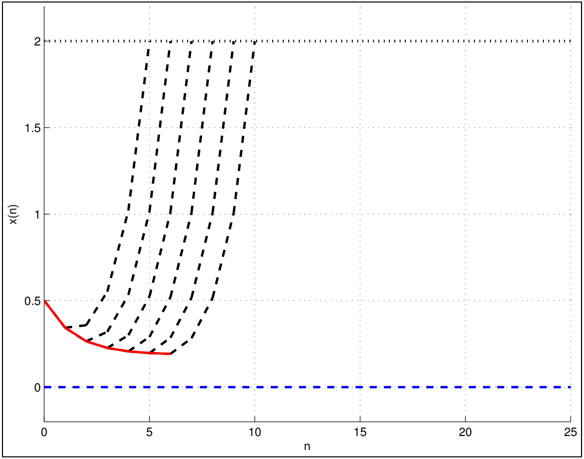
$N = 5$

Example 1: trajectories



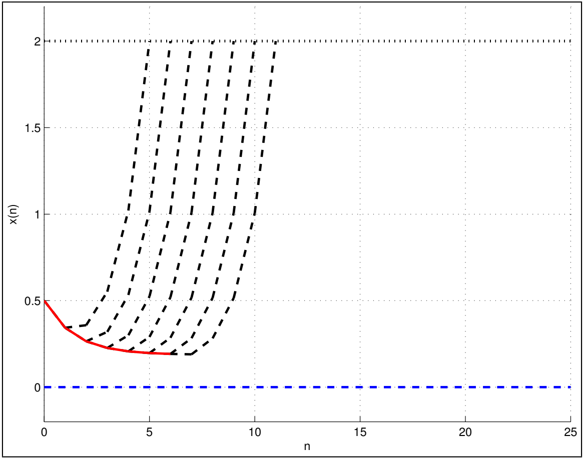
$N = 5$

Example 1: trajectories



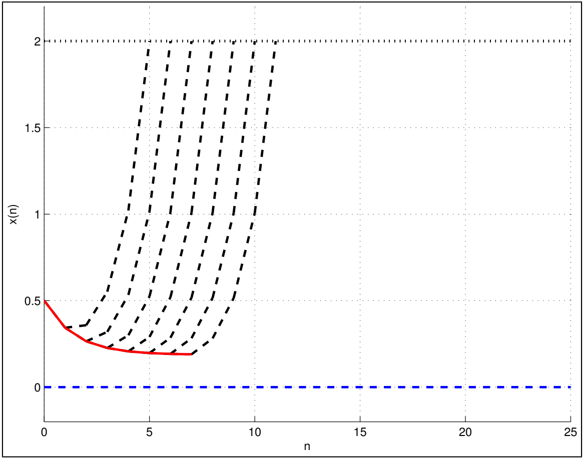
$N = 5$

Example 1: trajectories



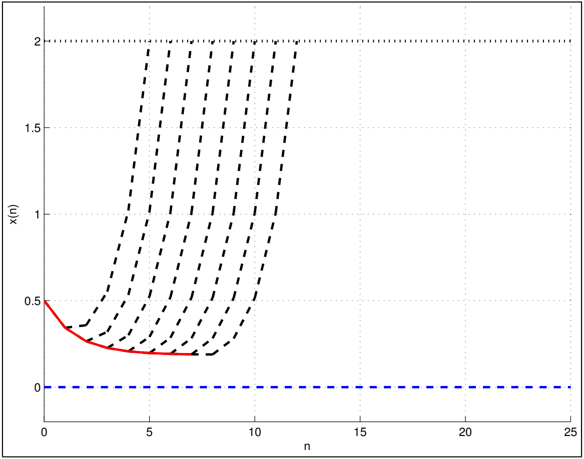
$N = 5$

Example 1: trajectories



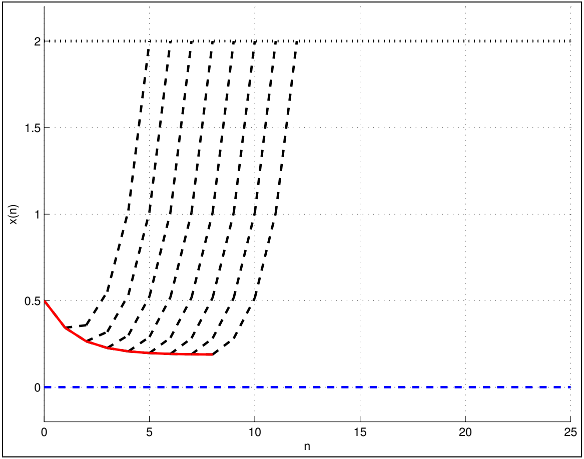
$N = 5$

Example 1: trajectories



$N = 5$

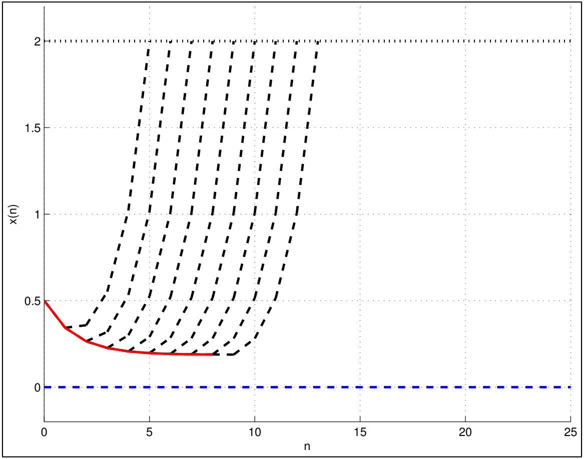
Example 1: trajectories



$N = 5$

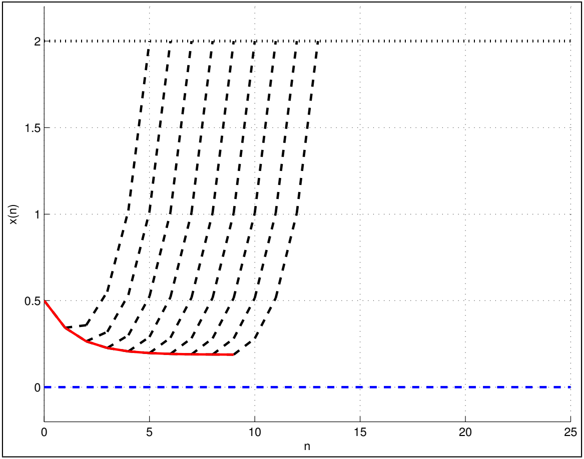
UNIVERSITÄT BAYREUTH

Example 1: trajectories



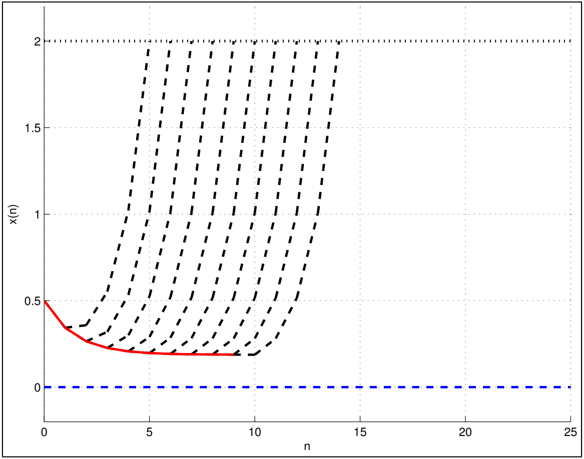
$N = 5$

Example 1: trajectories



$N = 5$

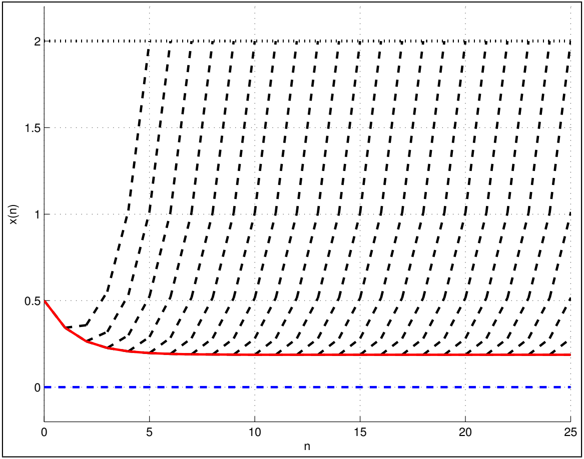
Example 1: trajectories



$N = 5$

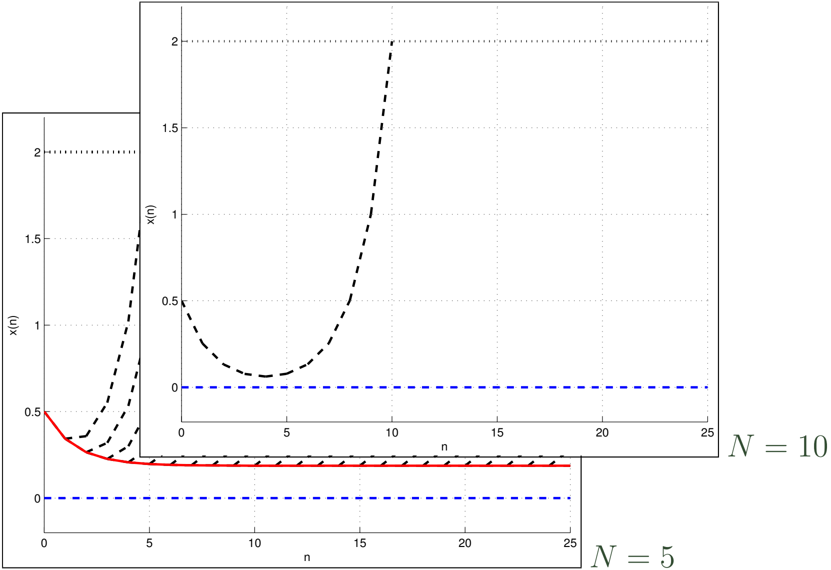
UNIVERSITÄT BAYREUTH

Example 1: trajectories

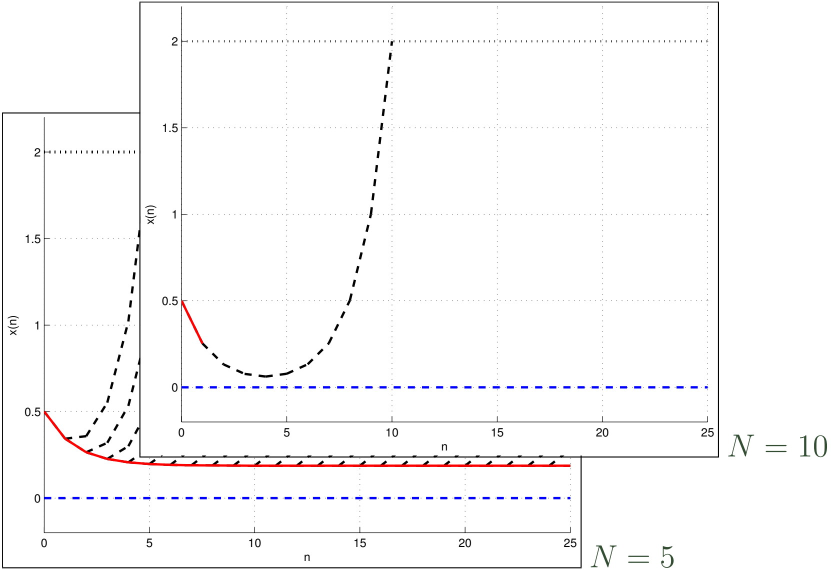


$N = 5$

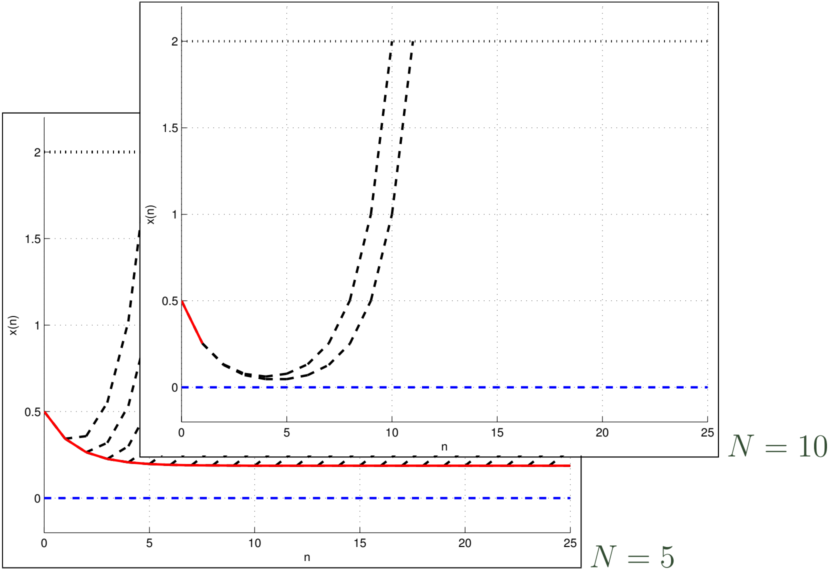
Example 1: trajectories



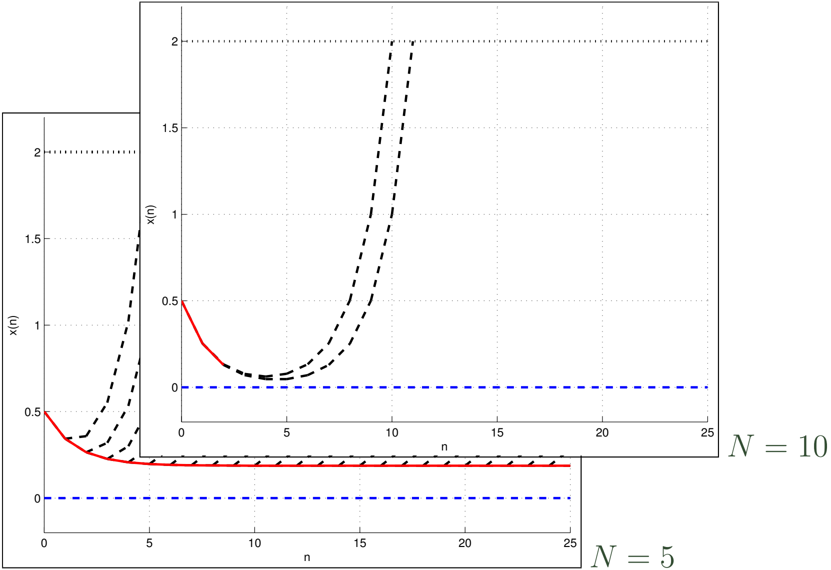
Example 1: trajectories



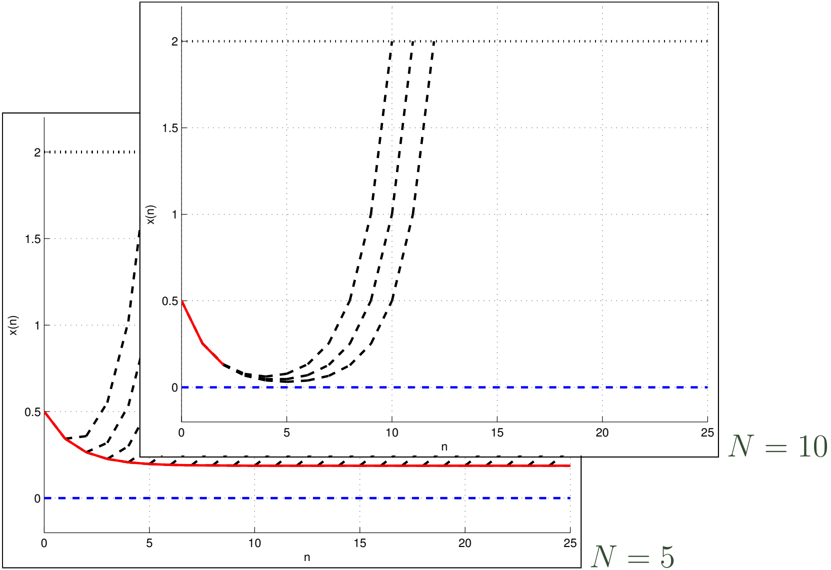
Example 1: trajectories



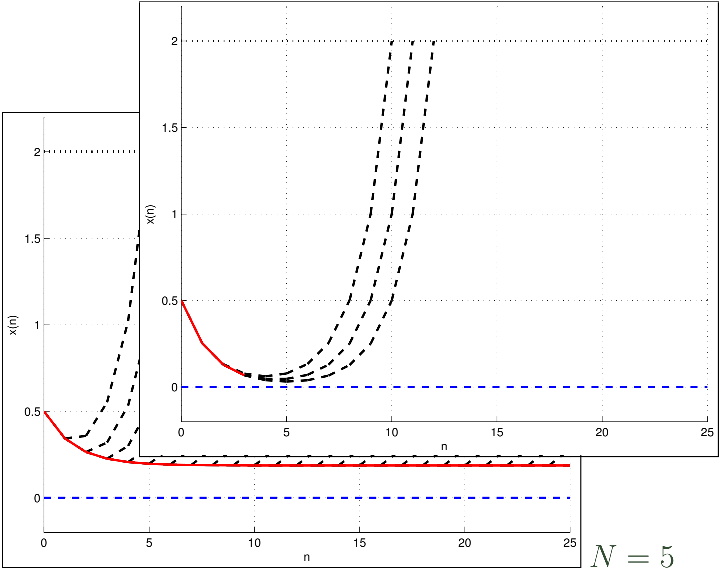
Example 1: trajectories



Example 1: trajectories



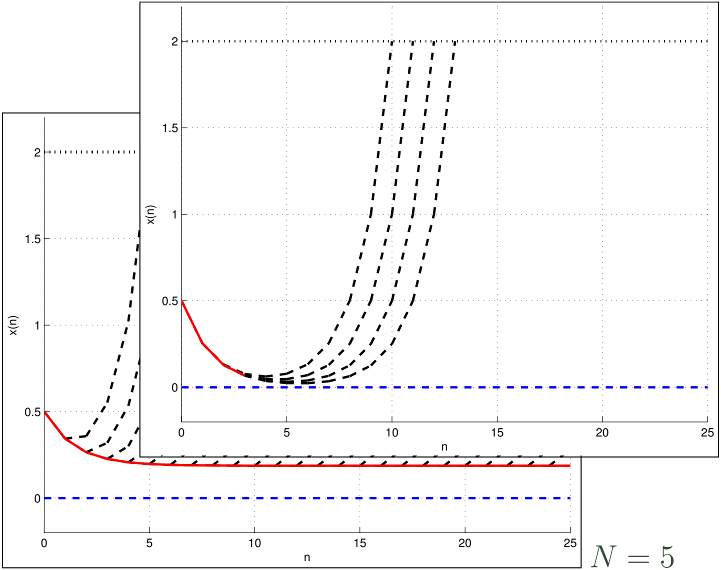
Example 1: trajectories



$N = 10$

$N = 5$

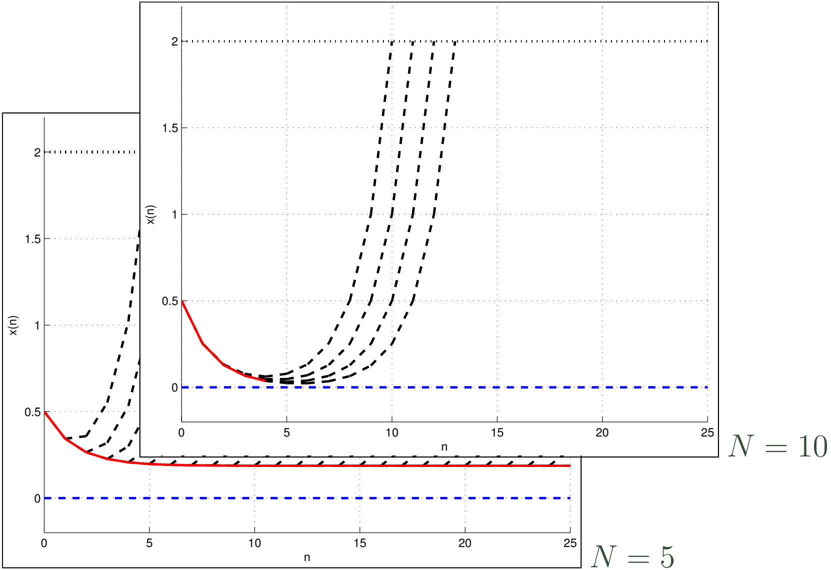
Example 1: trajectories



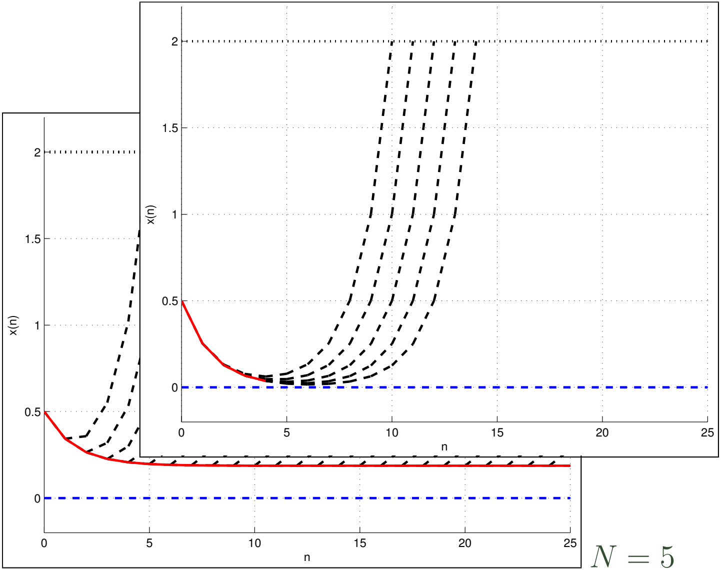
$N = 10$

$N = 5$

Example 1: trajectories



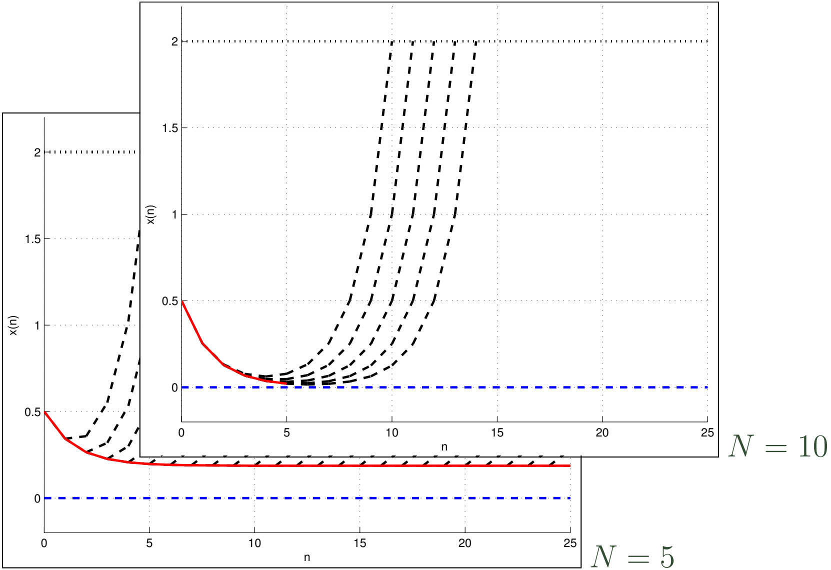
Example 1: trajectories



$N = 10$

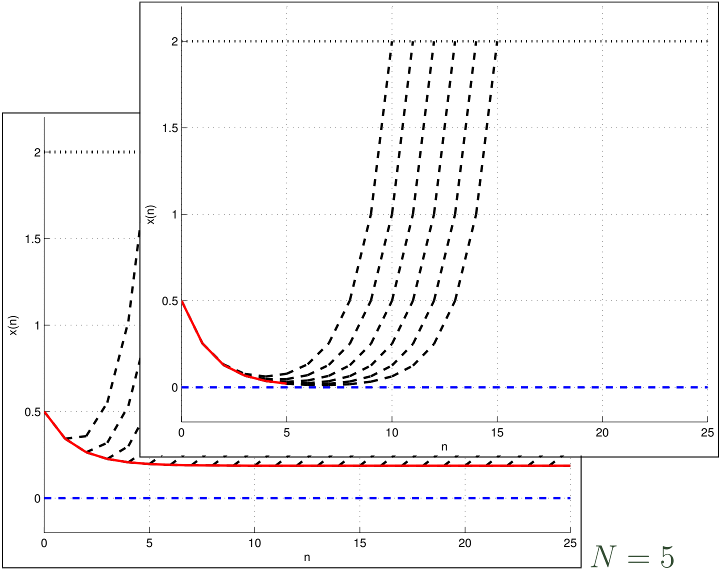
$N = 5$

Example 1: trajectories



UNIVERSITÄT BAYREUTH

Example 1: trajectories

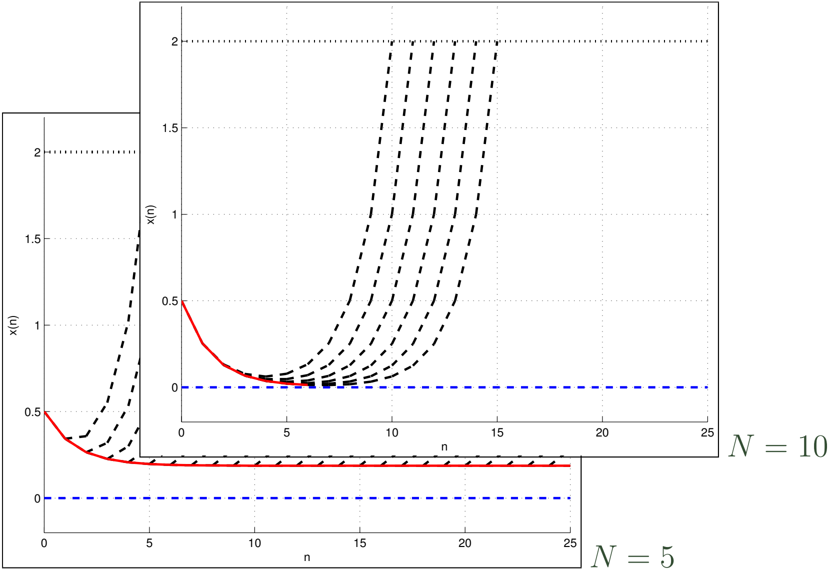


$N = 10$

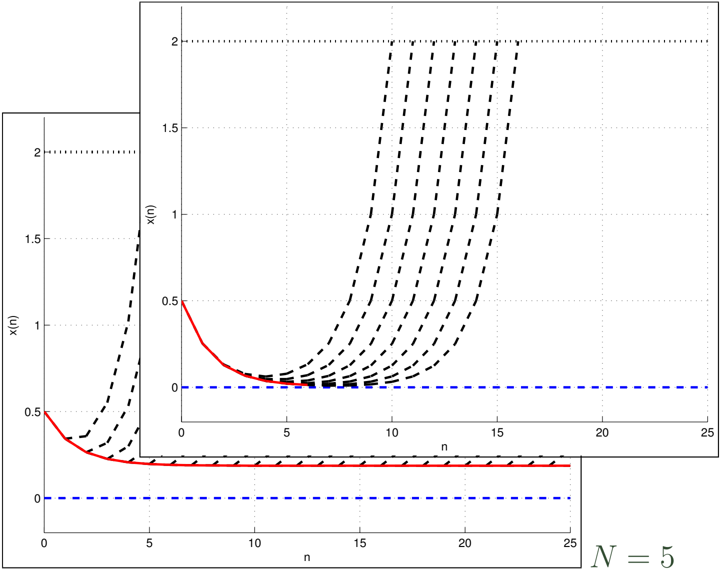
$N = 5$

UNIVERSITÄT BAYREUTH

Example 1: trajectories



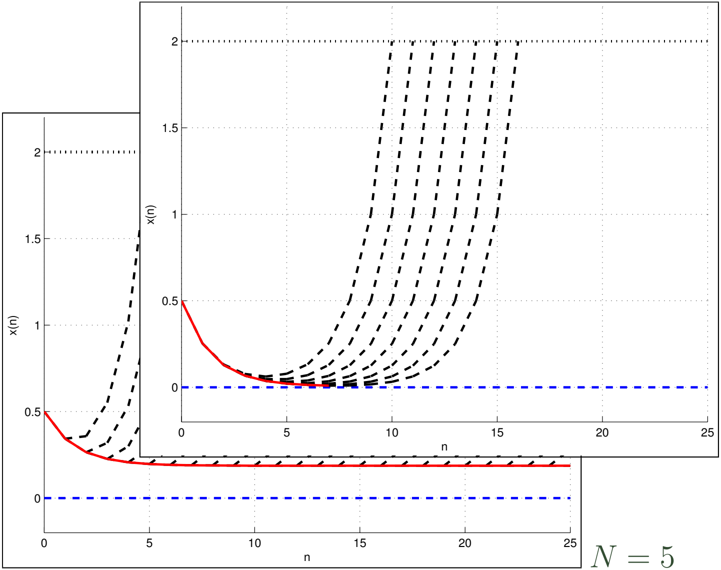
Example 1: trajectories



$N = 10$

$N = 5$

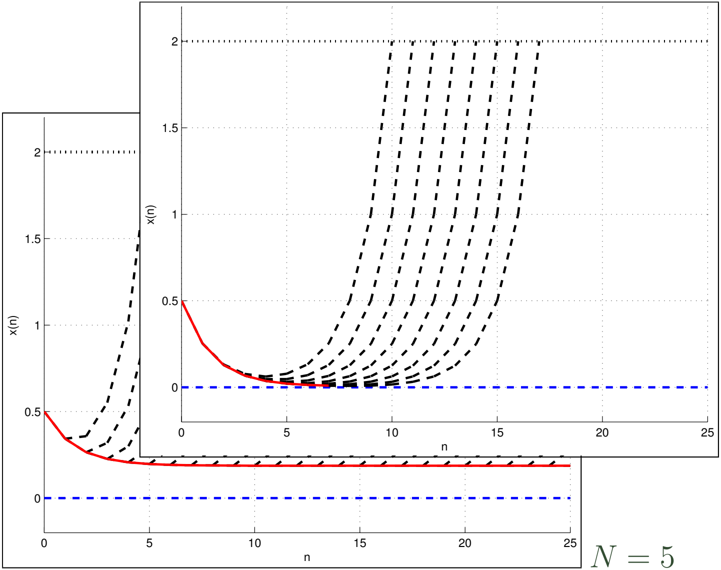
Example 1: trajectories



$N = 10$

$N = 5$

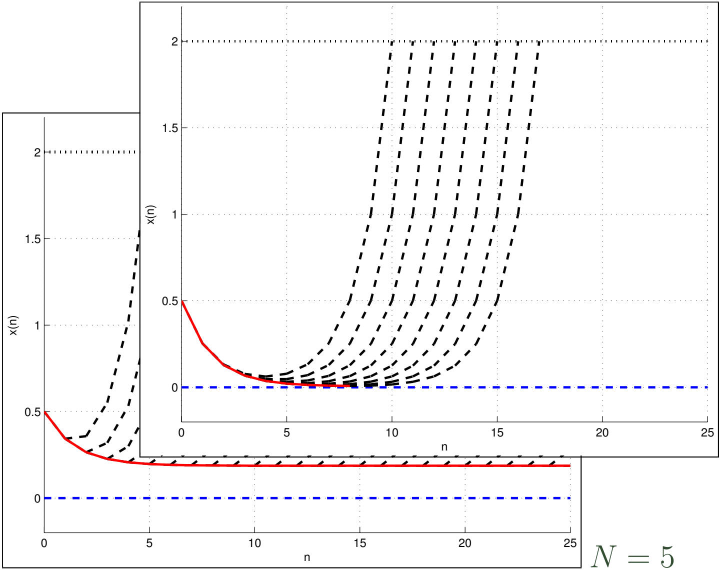
Example 1: trajectories



$N = 10$

$N = 5$

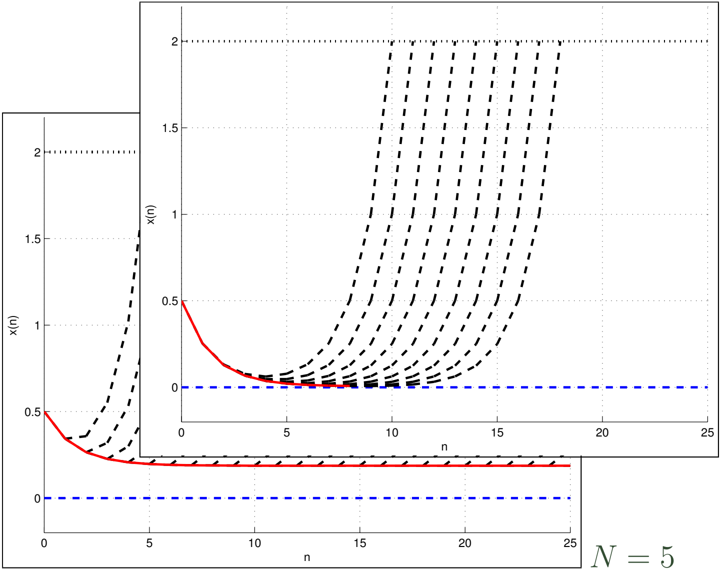
Example 1: trajectories



$N = 10$

$N = 5$

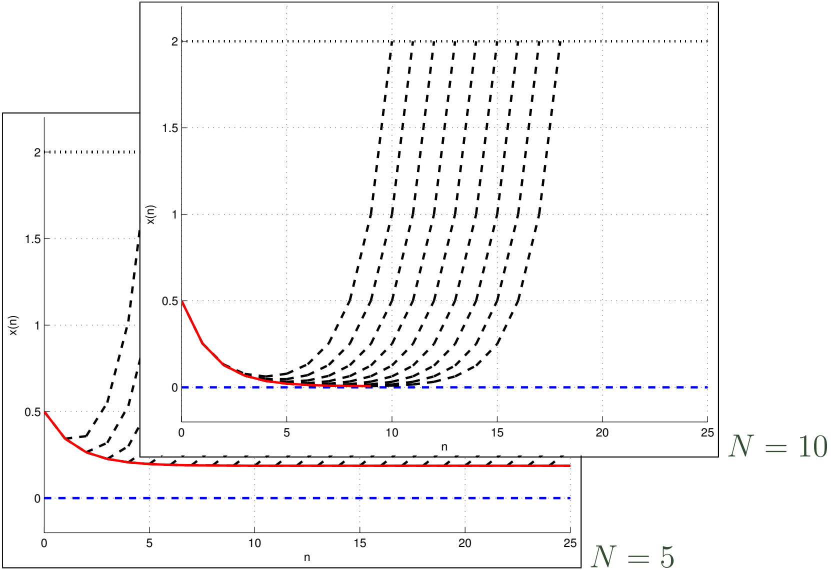
Example 1: trajectories



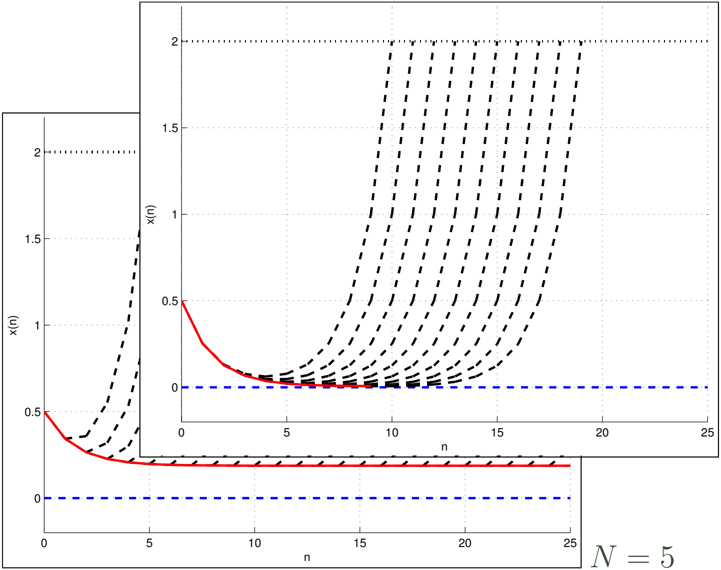
$N = 10$

$N = 5$

Example 1: trajectories



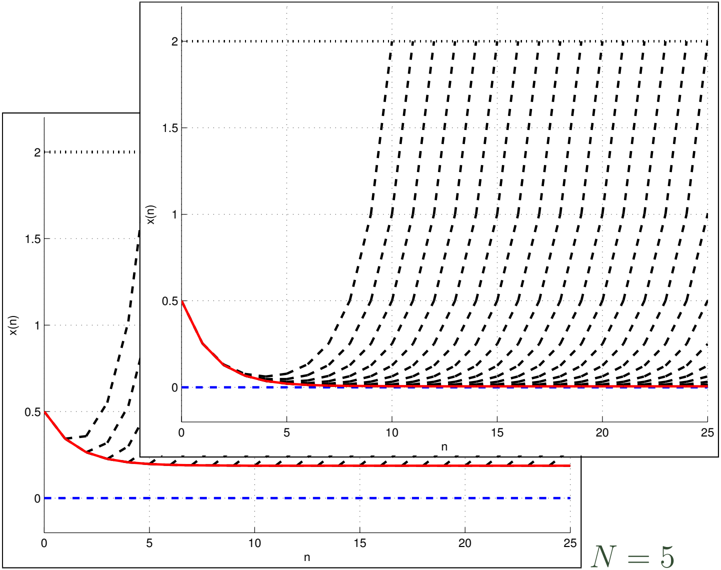
Example 1: trajectories



$N = 10$

$N = 5$

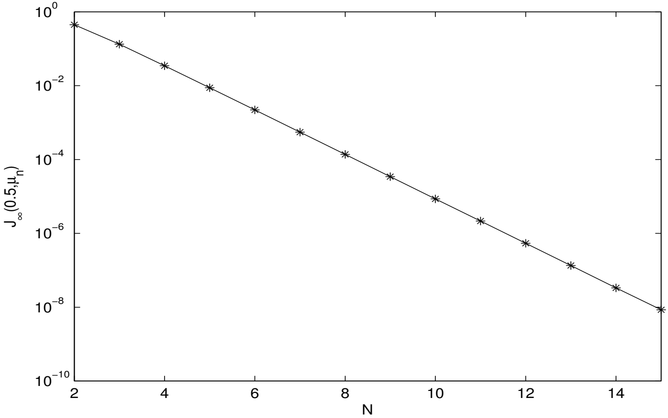
Example 1: trajectories



$N = 10$

$N = 5$

Example: closed loop performance



$J_\infty(0.5, \mu_N)$ depending on N, logarithmic scale

UNIVERSITÄT BAYREUTH

Economic MPC without terminal constraints

Next we look once more at the macroeconomic example [Brock/Mirman '72]

Minimize the average performance with

$$\ell(x,u) = -\ln(Ax^\alpha - u), \quad A = 5,\ \alpha = 0.34$$

with dynamics $x(n+1) = \mathbf{u}(n)$

and constraints $\mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

Economic MPC without terminal constraints

Next we look once more at the macroeconomic example [Brock/Mirman '72]

Minimize the average performance with

$$\ell(x,u) = -\ln(Ax^\alpha - u), \quad A = 5,\ \alpha = 0.34$$

with dynamics $\quad x(n+1) = \mathbf{u}(n)$

and constraints $\quad \mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

This problem exhibits the optimal equilibrium

$$x^e \approx 2.2344 \quad \text{with } \ell(x^e, u^e) \approx 1.4673$$

and is strictly dissipative with $\lambda(x) \approx 0.2306x$

Economic MPC without terminal constraints

Next we look once more at the macroeconomic example [Brock/Mirman '72]

Minimize the average performance with

$$\ell(x,u) = -\ln(Ax^\alpha - u), \quad A = 5,\ \alpha = 0.34$$

with dynamics $x(n+1) = \mathbf{u}(n)$

and constraints $\mathbb{X} = [0.1, 10]$, $\mathbb{U} = [0.1, 5]$

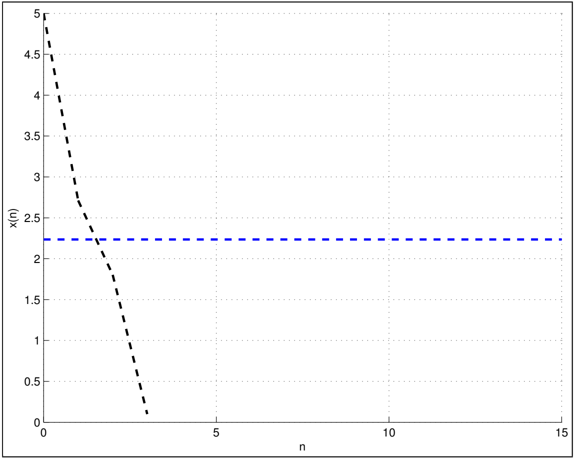
This problem exhibits the optimal equilibrium

$$x^e \approx 2.2344 \quad \text{with } \ell(x^e, u^e) \approx 1.4673$$

and is strictly dissipative with $\lambda(x) \approx 0.2306x$

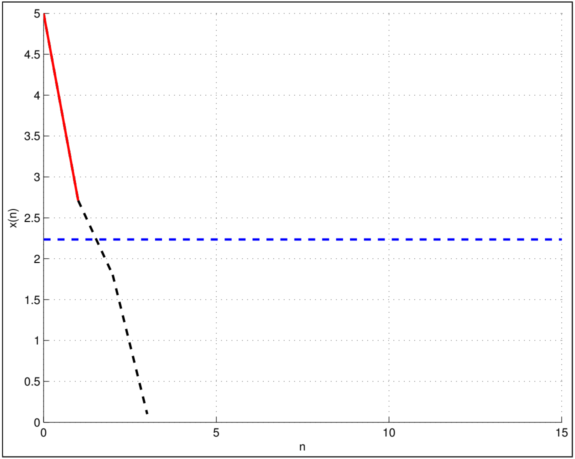
Note: now the NMPC algorithm knows neither x^e nor λ

Example: trajectories



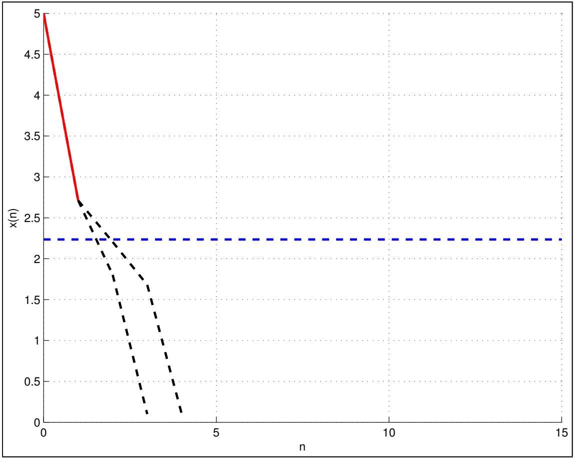
$N = 3$

Example: trajectories



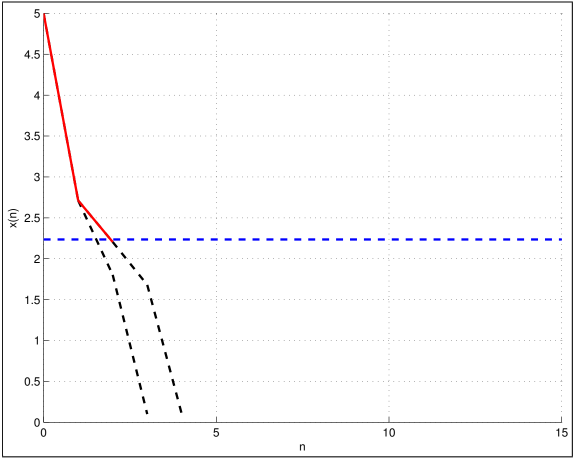
$N = 3$

Example: trajectories



$N = 3$

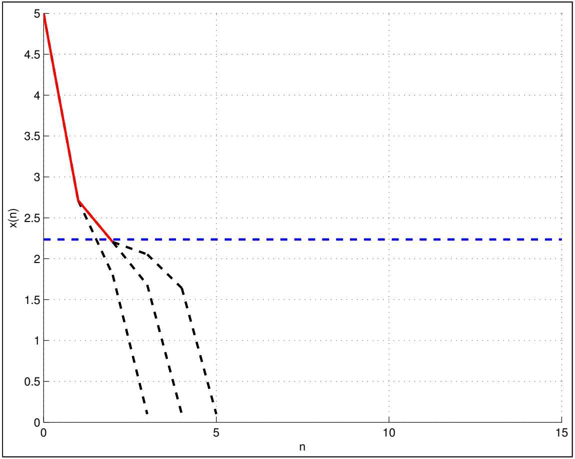
Example: trajectories



$N = 3$

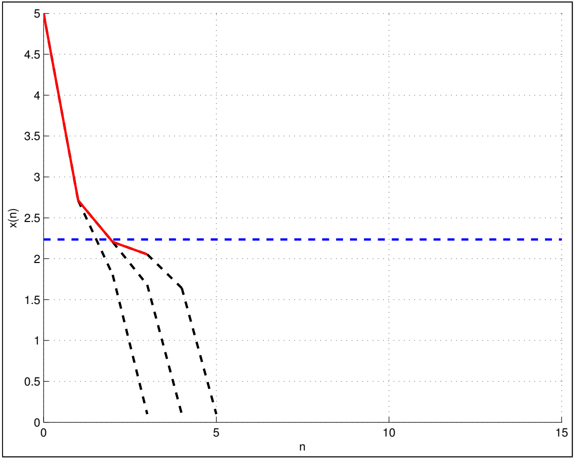
UNIVERSITÄT BAYREUTH

Example: trajectories



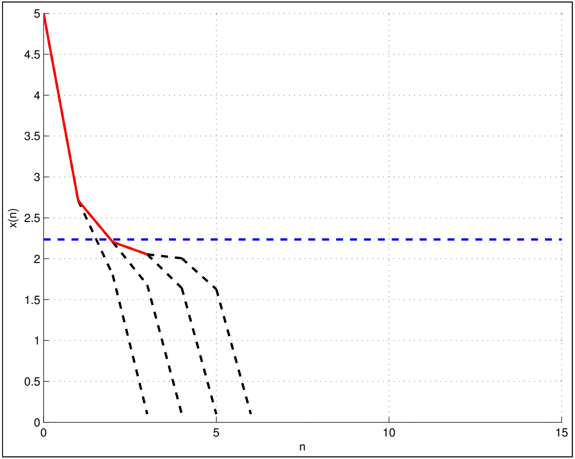
$N = 3$

Example: trajectories



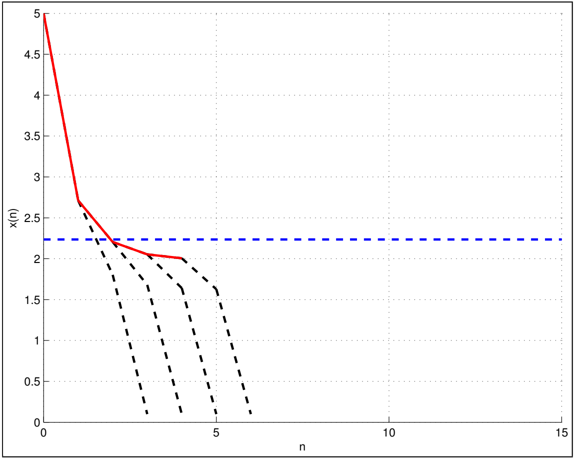
$N = 3$

Example: trajectories



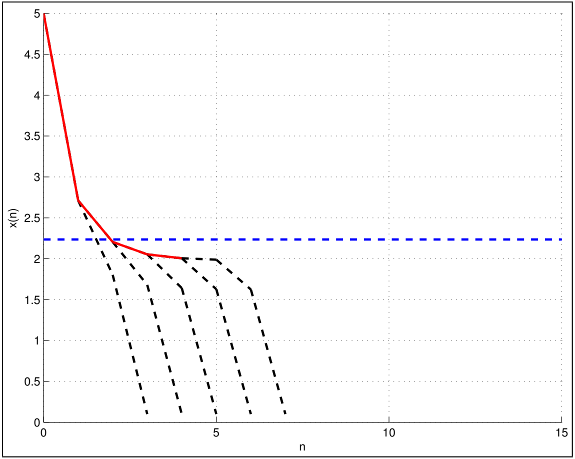
$N = 3$

Example: trajectories



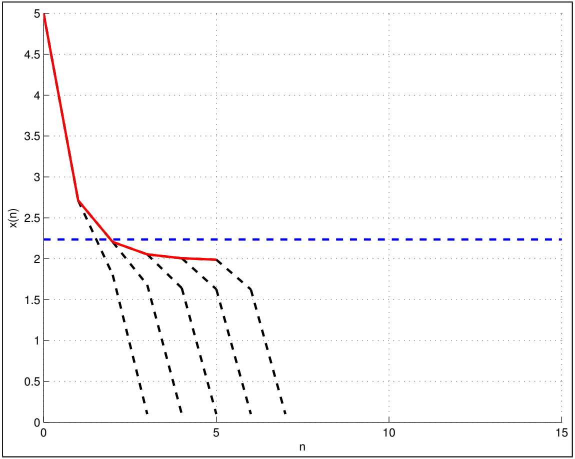
$N = 3$

Example: trajectories



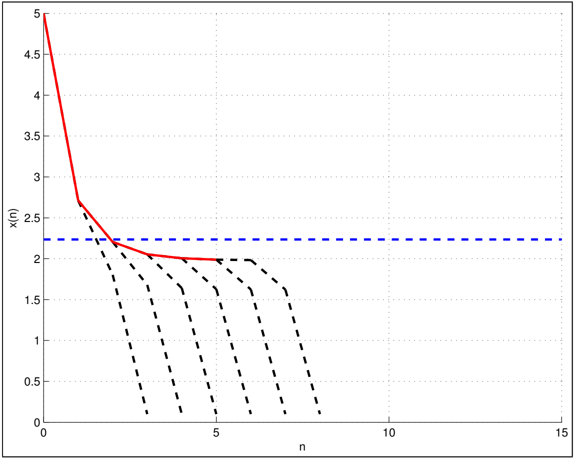
$N = 3$

Example: trajectories



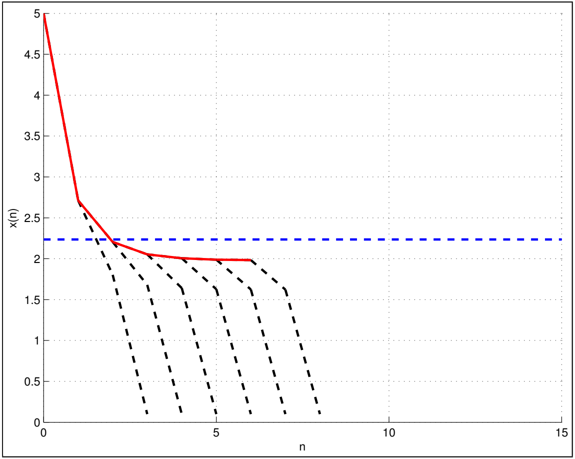
$N = 3$

Example: trajectories



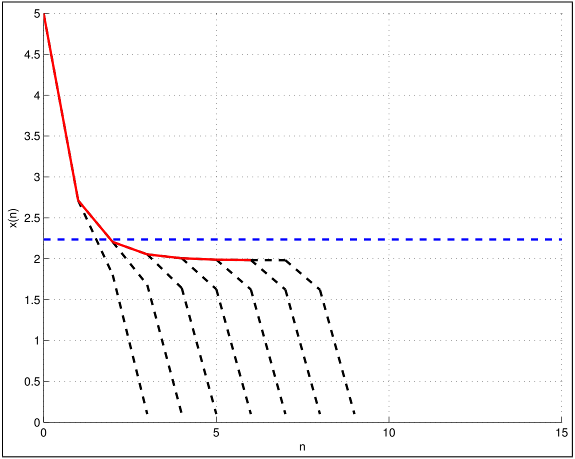
$N = 3$

Example: trajectories



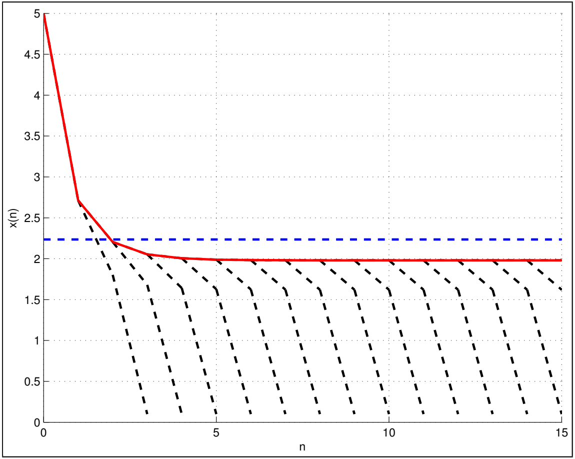
$N = 3$

Example: trajectories



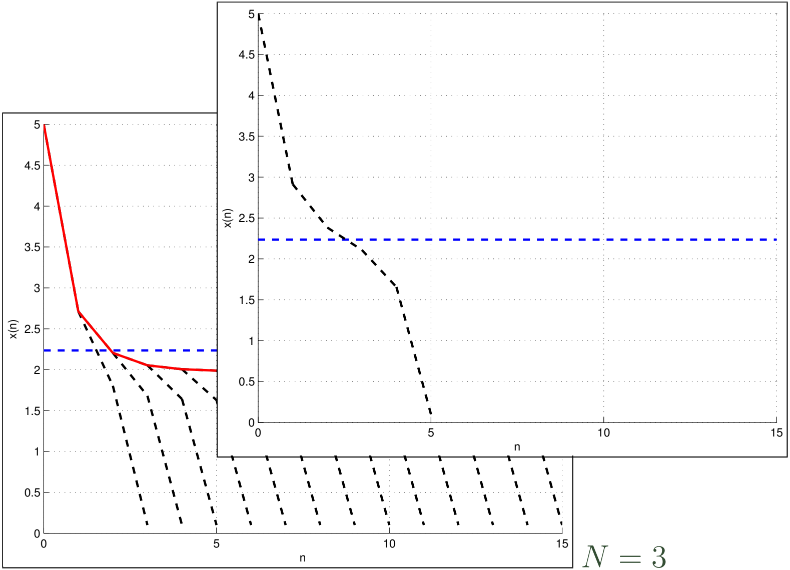
$N = 3$

Example: trajectories



$N = 3$

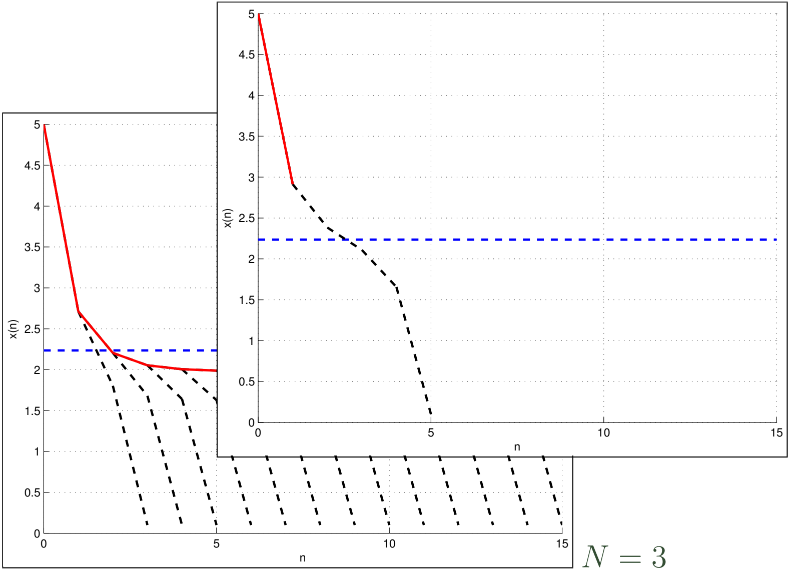
Example: trajectories



$N = 5$

$N = 3$

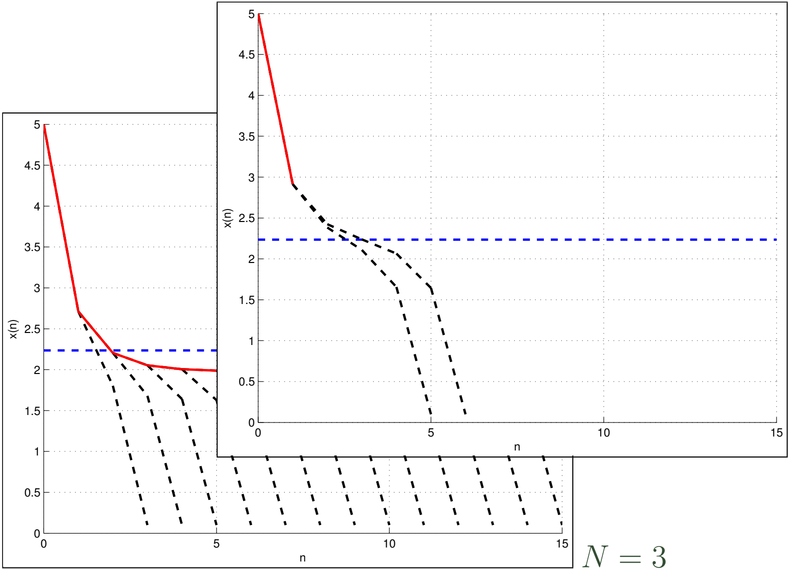
Example: trajectories



$N = 5$

$N = 3$

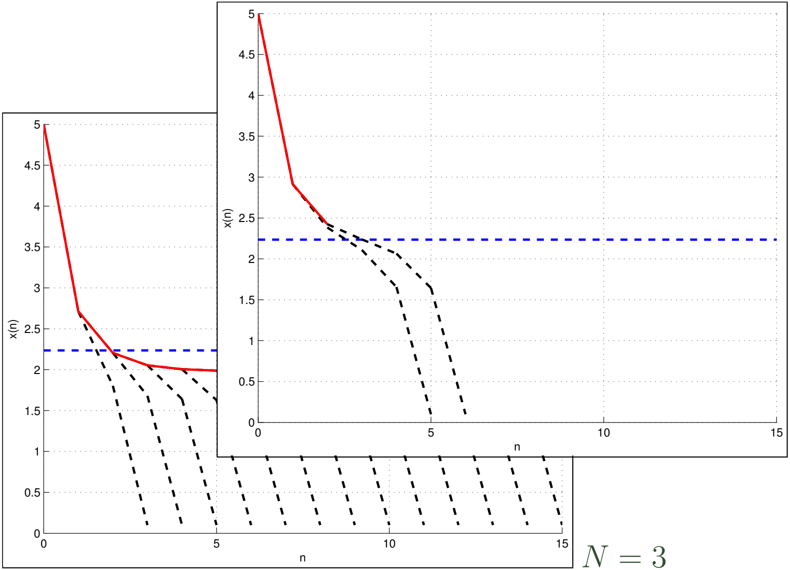
Example: trajectories



$N = 5$

$N = 3$

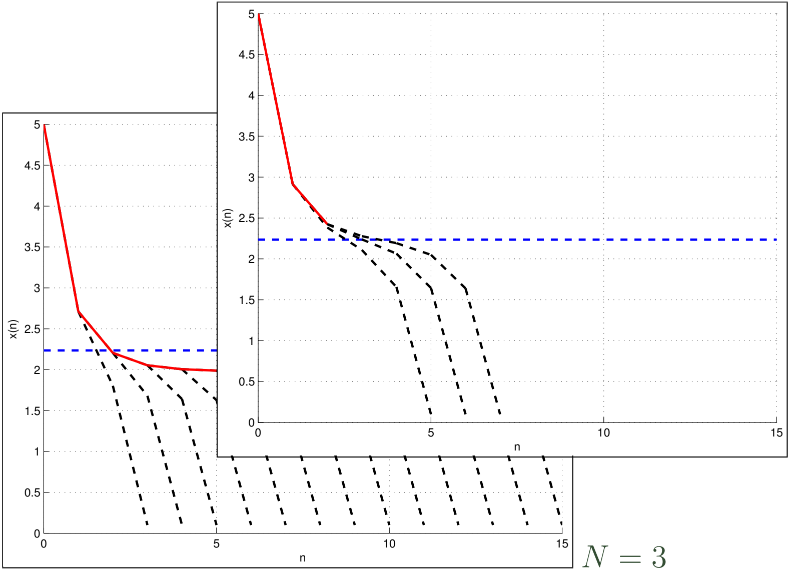
Example: trajectories



$N = 5$

$N = 3$

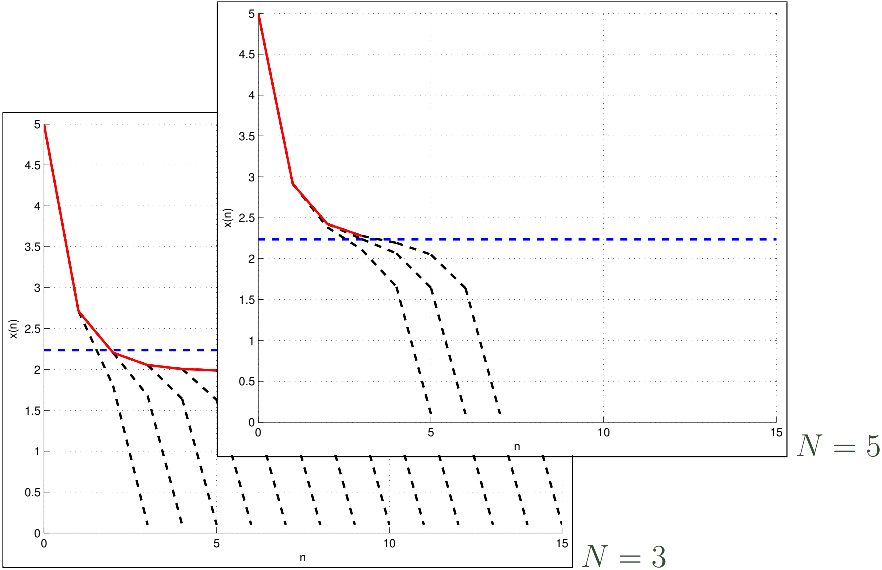
Example: trajectories



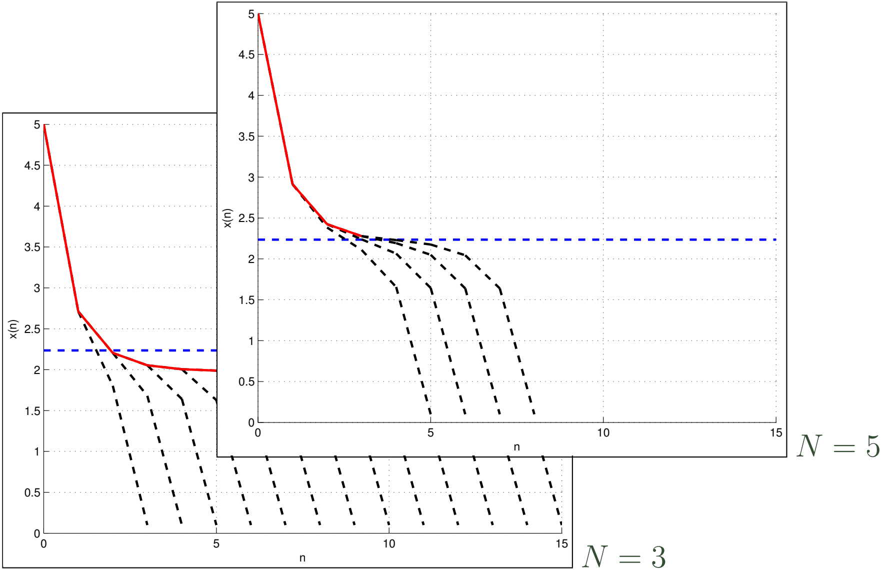
$N = 5$

$N = 3$

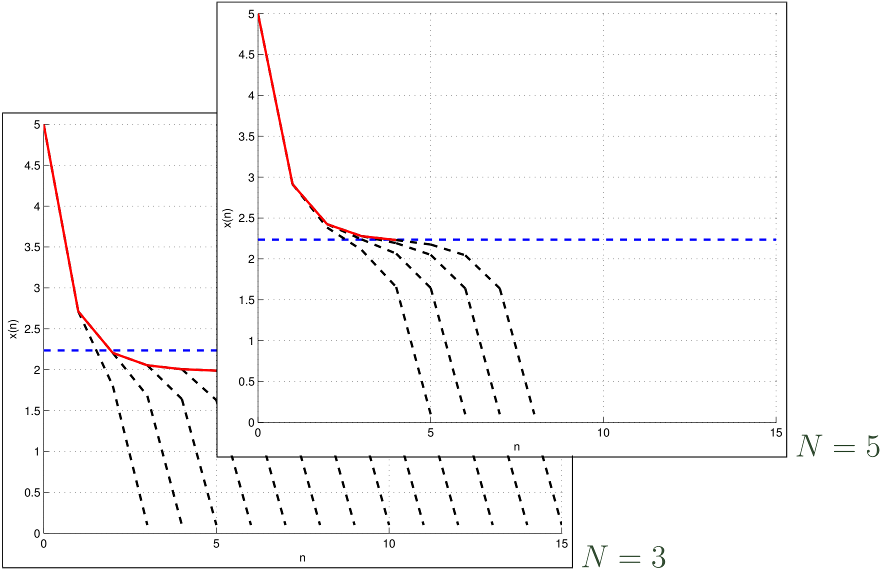
Example: trajectories



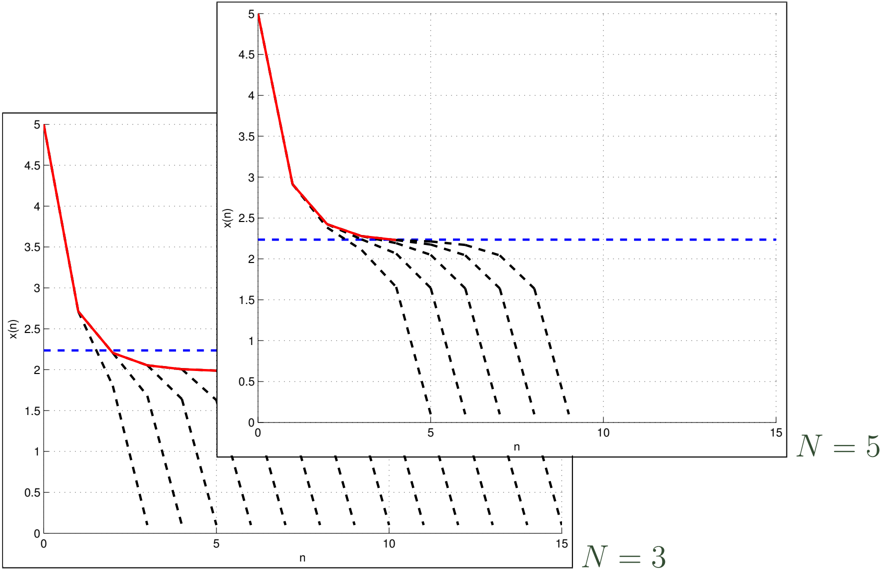
Example: trajectories



Example: trajectories

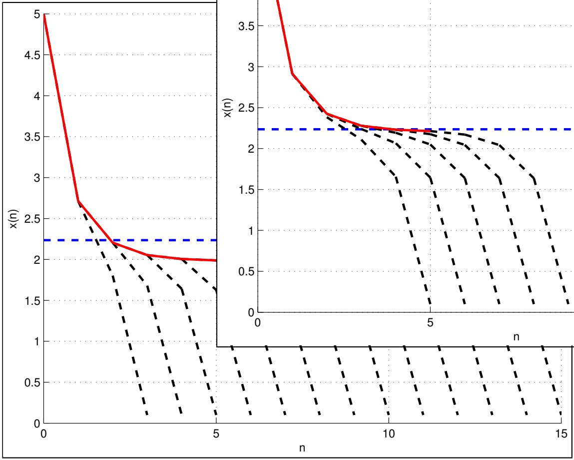


Example: trajectories

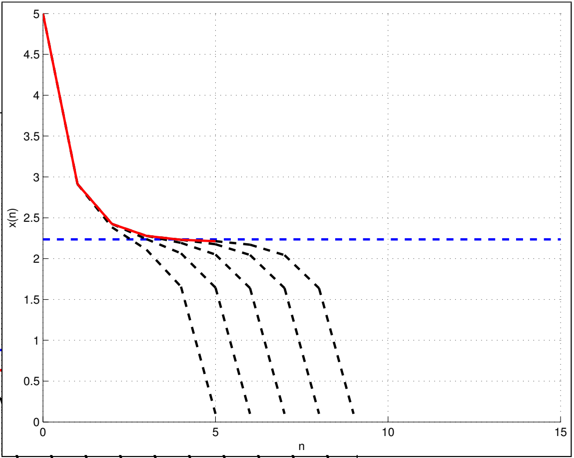


![UNIVERSITÄT BAYREUTH]

Example: trajectories

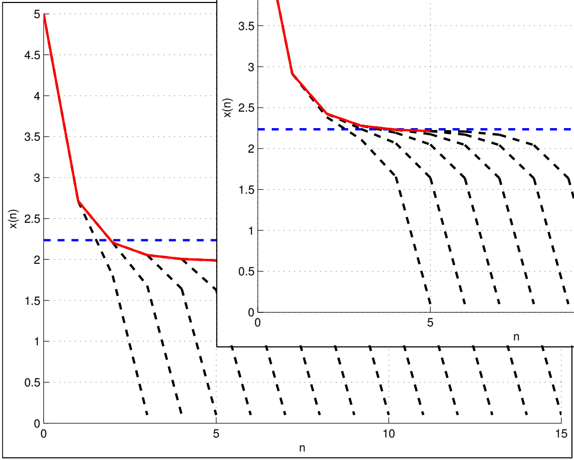


$N = 3$

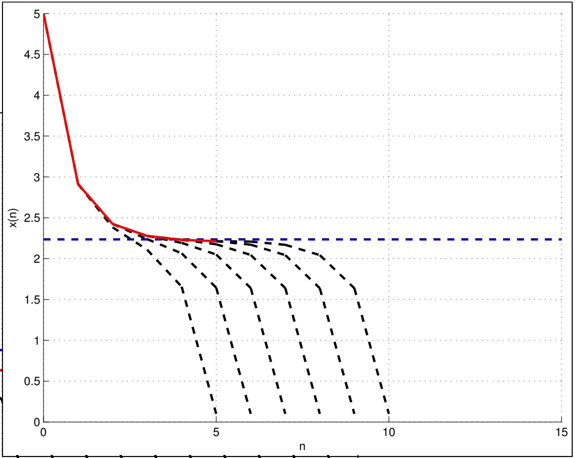


$N = 5$

Example: trajectories



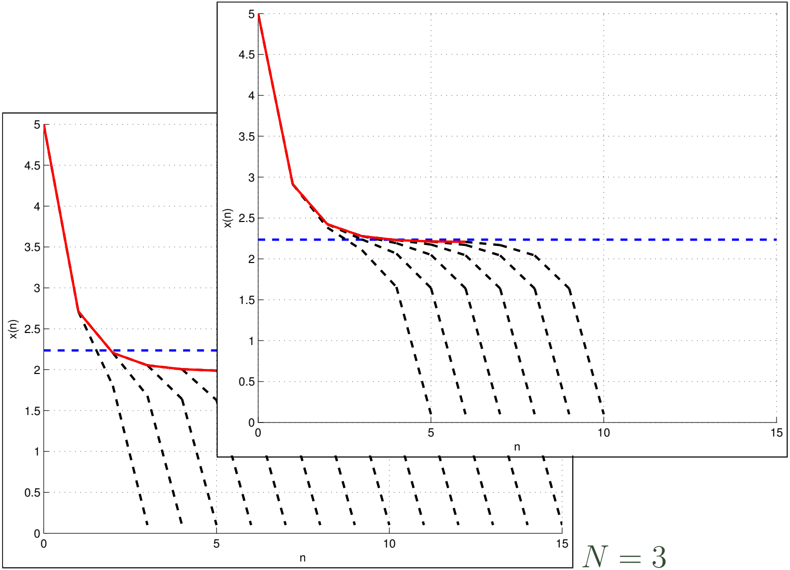
$N = 3$



$N = 5$

UNIVERSITÄT BAYREUTH

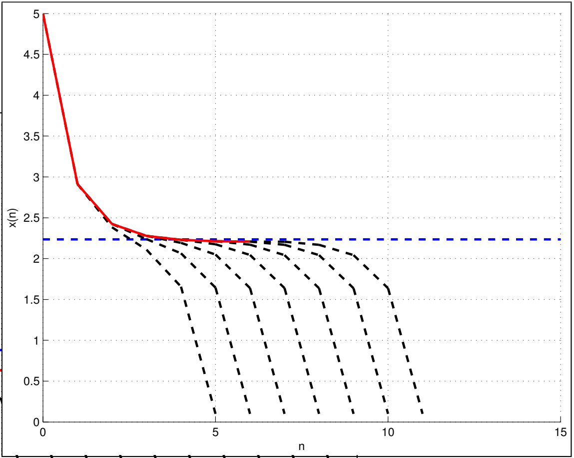
Example: trajectories



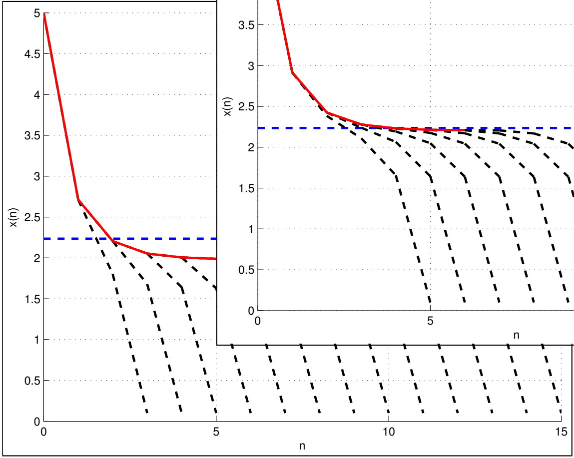
$N = 5$

$N = 3$

Example: trajectories

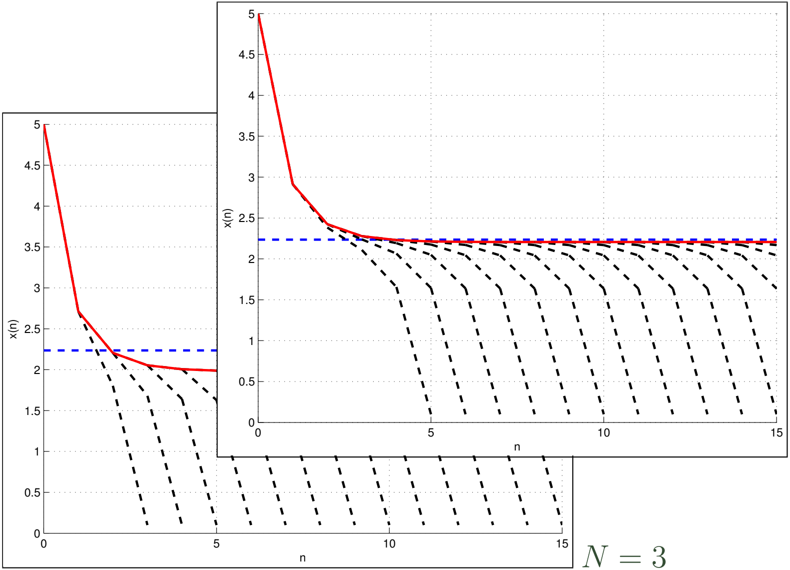


$N = 5$



$N = 3$

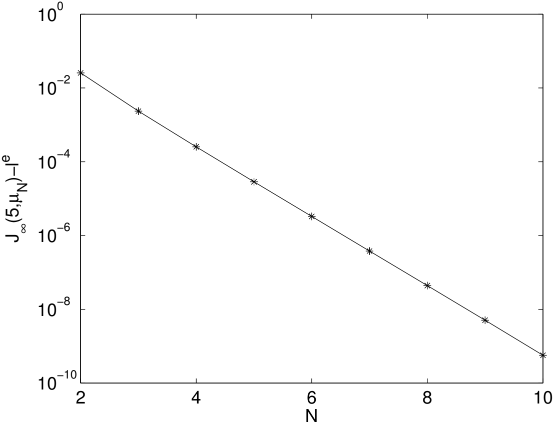
Example: trajectories



$N = 5$

$N = 3$

Example: averaged closed loop performance



$\overline{J}^{cl}_\infty(5,\mu_N) - \ell(x^e,u^e)$ depending on N, logarithmic scale

Example: a linearized tank reactor

[Diehl/Amrit/Rawlings '11]

Minimize the average performance with

$$\ell(x,u) = \|x\|^2 + 0.05u^2$$

with dynamics

$$x(n+1) = \begin{pmatrix} 0.8353 & 0 \\ 0.1065 & 0.9418 \end{pmatrix} x(n) + \begin{pmatrix} 0.00457 \\ -0.00457 \end{pmatrix} \mathbf{u}(n) + \begin{pmatrix} 0.5559 \\ 0.5033 \end{pmatrix}$$

Example: a linearized tank reactor

[Diehl/Amrit/Rawlings '11]

Minimize the average performance with

$$\ell(x,u) = \|x\|^2 + 0.05u^2$$

with dynamics

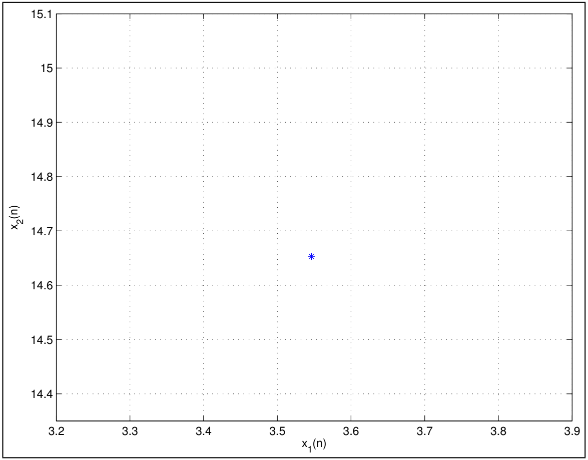
$$x(n+1) = \begin{pmatrix} 0.8353 & 0 \\ 0.1065 & 0.9418 \end{pmatrix} x(n) + \begin{pmatrix} 0.00457 \\ -0.00457 \end{pmatrix} \mathbf{u}(n) + \begin{pmatrix} 0.5559 \\ 0.5033 \end{pmatrix}$$

This problem exhibits the optimal steady state

$$x^e \approx \begin{pmatrix} 3.546 \\ 14.653 \end{pmatrix} \quad \text{with} \quad \ell(x^e, u^e) \approx 229.1876$$

and is dissipative with $\lambda(x) = (-368.6684, -503.5415)^T x$

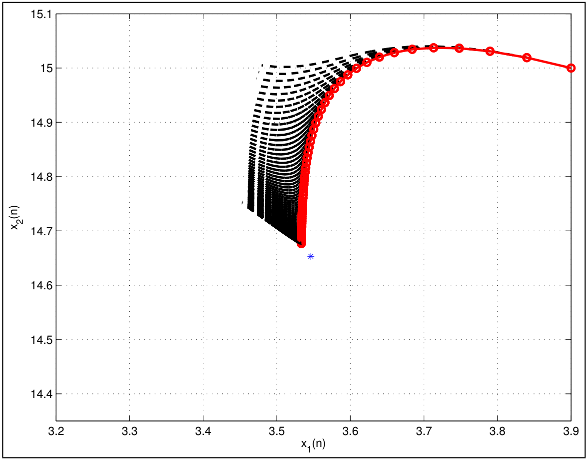
Tank reactor example: trajectories



$N = 15$

UNIVERSITÄT BAYREUTH

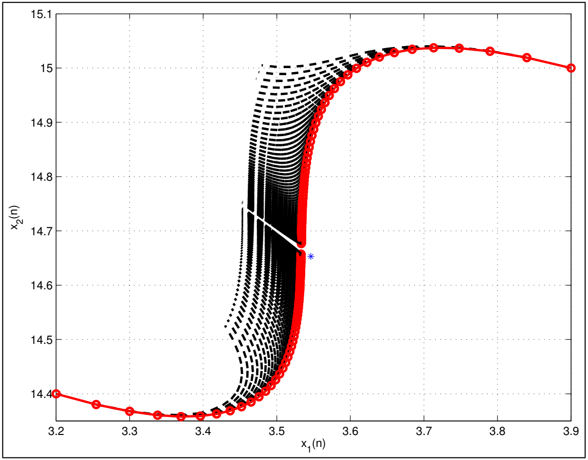
Tank reactor example: trajectories



$N = 15$

UNIVERSITÄT BAYREUTH

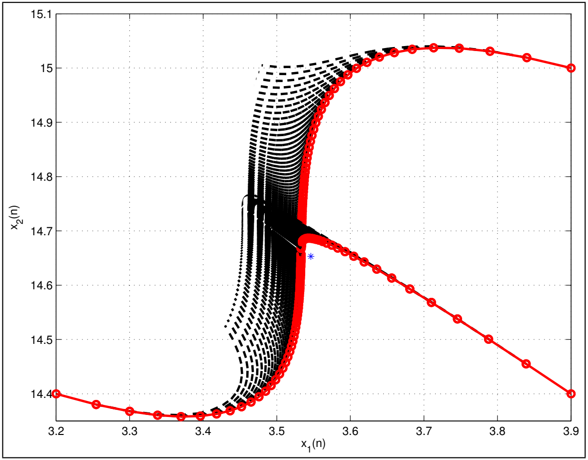
Tank reactor example: trajectories



$N = 15$

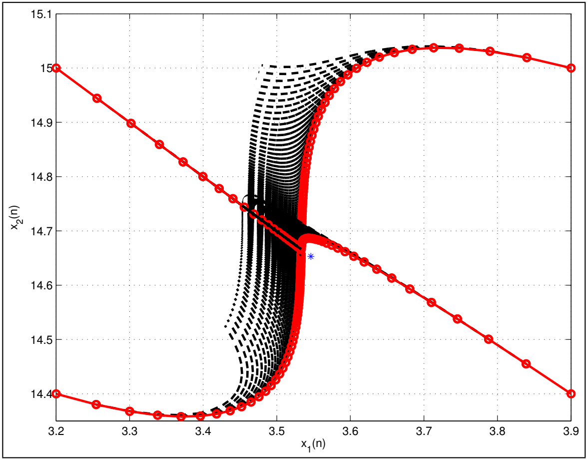
UNIVERSITÄT BAYREUTH

Tank reactor example: trajectories



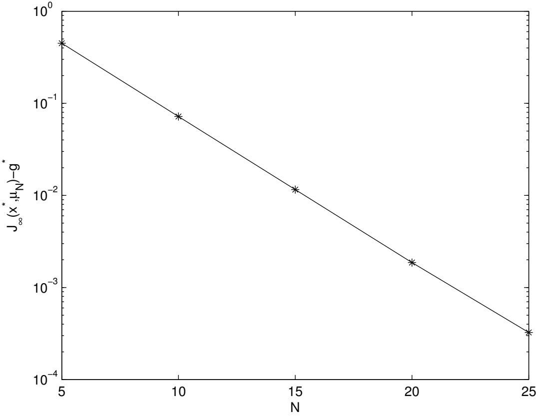
$N = 15$

Tank reactor example: trajectories



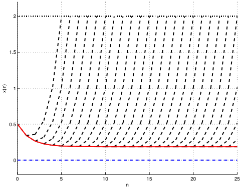
$N = 15$

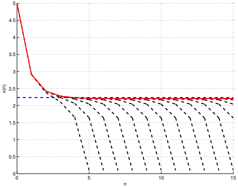
Tank reactor example: averaged closed loop performance

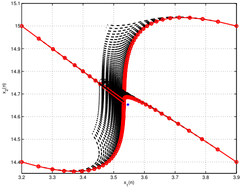


$\overline{J}^{cl}_{\infty}(x^e, \mu_N) - \ell(x^e, u^e)$ depending on N, logarithmic scale

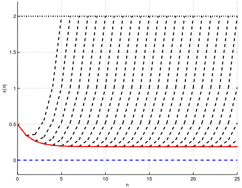
Observations

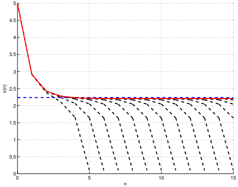


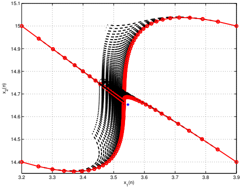




Observations

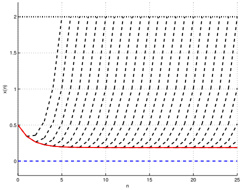


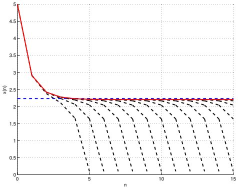


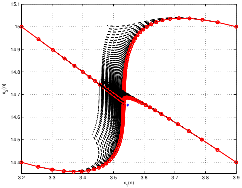


- optimal open loop trajectories first approach the optimal equilibrium and then turn away – "turnpike property"

Observations



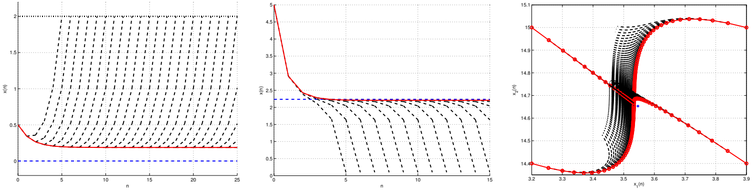




- optimal open loop trajectories first approach the optimal equilibrium and then turn away – “turnpike property”
- closed loop trajectories converge to a neighborhood of the optimal equilibrium whose size tends to 0 as $N \to \infty$

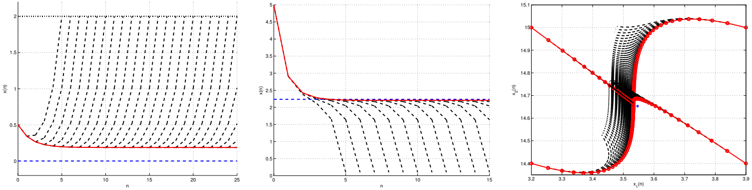
UNIVERSITÄT BAYREUTH

Observations



- optimal open loop trajectories first approach the optimal equilibrium and then turn away – “turnpike property”
- closed loop trajectories converge to a neighborhood of the optimal equilibrium whose size tends to 0 as $N \to \infty$
- the closed loop performance satisfies $\overline{J}^{cl}_{\infty}(x, \mu_N) \to \ell(x^e, u^e)$ as $N \to \infty$, exponentially fast

Observations



- optimal open loop trajectories first approach the optimal equilibrium and then turn away – "turnpike property"
- closed loop trajectories converge to a neighborhood of the optimal equilibrium whose size tends to 0 as $N \to \infty$
- the closed loop performance satisfies $\overline{J}^{cl}_{\infty}(x, \mu_N) \to \ell(x^e, u^e)$ as $N \to \infty$, exponentially fast

Can we prove this behavior?

Idea of proof

The following inequality plays the role of the "α_N–inequality" from stabilizing NMPC:

$$V_{N+1}(x) - V_N(x) \leq \ell(x^e, u^e) + \text{"error"}$$

Idea of proof

The following inequality plays the role of the "α_N–inequality" from stabilizing NMPC:

$$V_{N+1}(x) - V_N(x) \leq \ell(x^e, u^e) + \text{“error”}$$

In stabilizing MPC or under terminal constraints, we have seen that this inequality can be established by "prolonging" the finite horizon optimal trajectory at the end

Idea of proof

The following inequality plays the role of the "α_N–inequality" from stabilizing NMPC:

$$V_{N+1}(x) - V_N(x) \leq \ell(x^e, u^e) + \text{"error"}$$

In stabilizing MPC or under terminal constraints, we have seen that this inequality can be established by "prolonging" the finite horizon optimal trajectory at the end

But: this method does not work here, since at the end the finite horizon optimal trajectories are far away from x^e

Idea of proof

The following inequality plays the role of the "α_N–inequality" from stabilizing NMPC:

$$V_{N+1}(x) - V_N(x) \leq \ell(x^e, u^e) + \text{“error”}$$

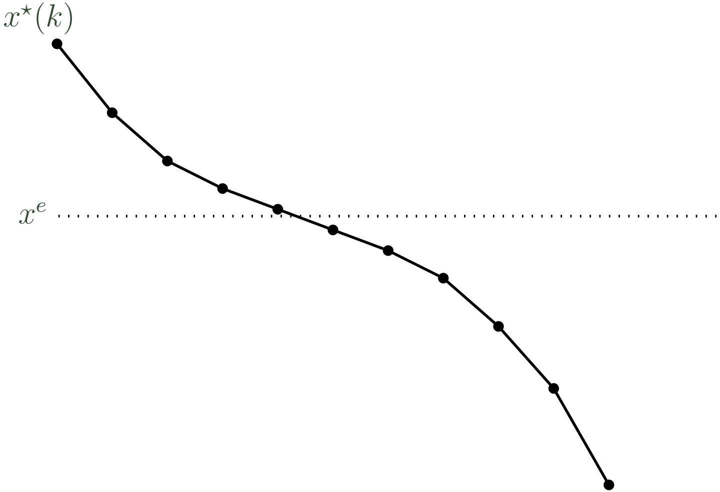
In stabilizing MPC or under terminal constraints, we have seen that this inequality can be established by "prolonging" the finite horizon optimal trajectory at the end

But: this method does not work here, since at the end the finite horizon optimal trajectories are far away from x^e

Remedy: prolong the optimal trajectory in the middle

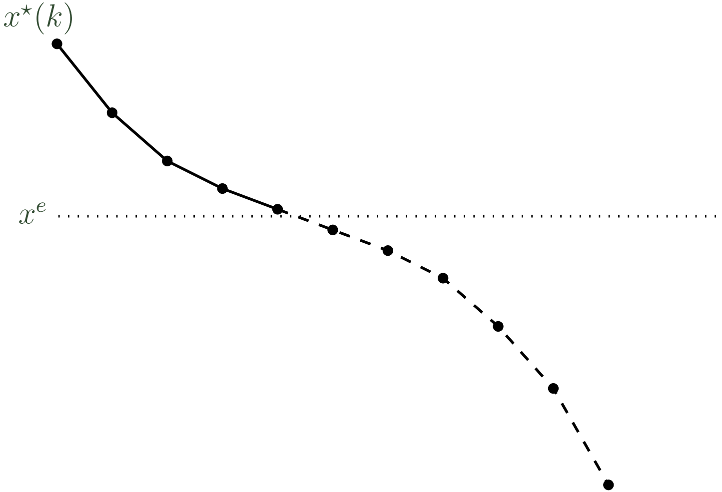
Prolonging in the middle

Sketch of the idea:



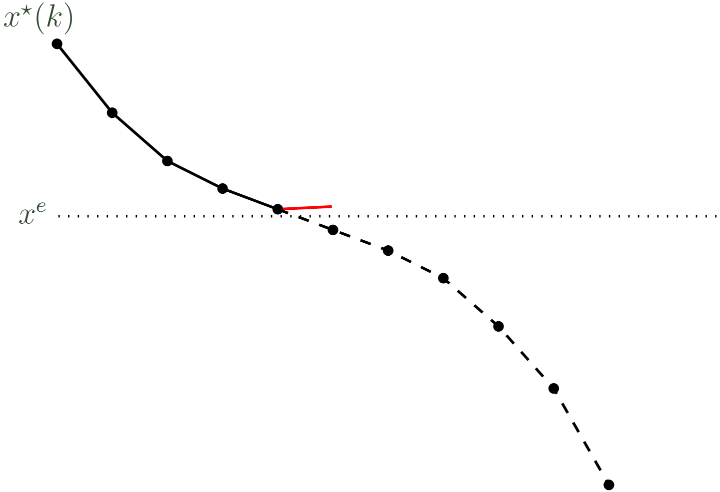
Prolonging in the middle

Sketch of the idea:



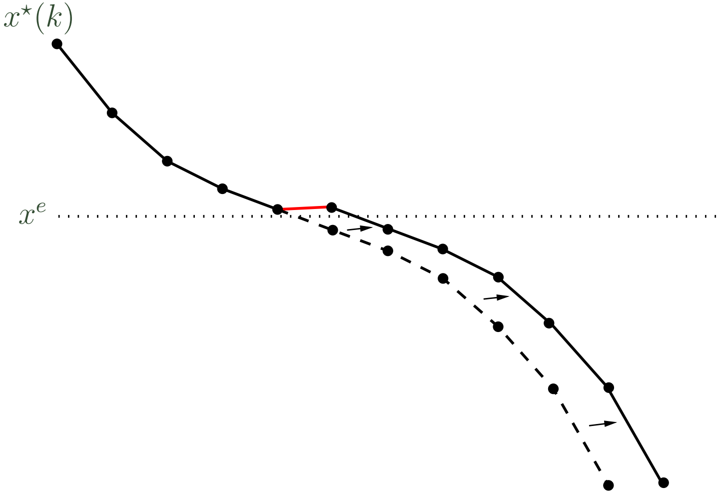
Prolonging in the middle

Sketch of the idea:



Prolonging in the middle

Sketch of the idea:



Assumptions needed for this construction

What do we need to make this construction work? [Gr. '13]

Assumptions needed for this construction

What do we need to make this construction work? [Gr. '13]

(1) Continuity of V_N near x^e (uniform in x and N)

- ensures that we can prolong the trajectory in the middle without changing the value of the tail too much

Assumptions needed for this construction

What do we need to make this construction work? [Gr. '13]

(1) Continuity of V_N near x^e (uniform in x and N)

- ensures that we can prolong the trajectory in the middle without changing the value of the tail too much

(2) Turnpike property

- ensures that the finite horizon optimal trajectory satisfies

$$\min_{k \in \{0,\dots,N\}} \|x^\star(k) - x^e\| \le \sigma(N)$$

with $\sigma(N) \to 0$ as $N \to \infty$

Assumptions needed for this construction

What do we need to make this construction work? [Gr. '13]

(1) Continuity of V_N near x^e (uniform in x and N)

- ensures that we can prolong the trajectory in the middle without changing the value of the tail too much

(2) Turnpike property

- ensures that the finite horizon optimal trajectory satisfies

$$\min_{k\in\{0,\dots,N\}} \|x^\star(k) - x^e\| \le \sigma(N)$$

with $\sigma(N) \to 0$ as $N \to \infty$

- note: in numerical examples we often observe exponential turnpike, i.e., $\sigma(N) = \theta^N$

The next theorem provides checkable sufficient conditions for these properties

Economic MPC theorem

Theorem: [Gr./Stieler '14]

Let f and ℓ be Lipschitz, $\mathbb{X}$ and $\mathbb{U}$ be compact and assume

(i) local controllability near x^e

(ii) strict dissipativity

(iii) reachability of x^e from all $x \in \mathbb{X}$

Economic MPC theorem

Theorem: [Gr./Stieler '14]

Let f and ℓ be Lipschitz, $\mathbb{X}$ and $\mathbb{U}$ be compact and assume

(i) local controllability near x^e

(ii) strict dissipativity

(iii) reachability of x^e from all $x \in \mathbb{X}$

(iv) polynomial growth conditions for $\tilde{\ell}$

Economic MPC theorem

Theorem: [Gr./Stieler '14]

Let f and ℓ be Lipschitz, $\mathbb{X}$ and $\mathbb{U}$ be compact and assume

(i) local controllability near x^e
(ii) strict dissipativity

(i) and (ii) $\Rightarrow$ uniform continuity of V_N

(iii) reachability of x^e from all $x \in \mathbb{X}$

(iv) polynomial growth conditions for $\tilde{\ell}$

Economic MPC theorem

Theorem: [Gr./Stieler '14]

Let f and ℓ be Lipschitz, $\mathbb{X}$ and $\mathbb{U}$ be compact and assume

(i) local controllability near x^e

(ii) strict dissipativity

} $\Rightarrow$ uniform continuity of V_N

(iii) reachability of x^e from all $x \in \mathbb{X}$

} $\Rightarrow$ turnpike property

(iv) polynomial growth conditions for $\tilde{\ell}$

Economic MPC theorem

Theorem: [Gr./Stieler '14]

Let f and ℓ be Lipschitz, $\mathbb{X}$ and $\mathbb{U}$ be compact and assume

(i) local controllability near x^e
(ii) strict dissipativity

(i) + (ii) $\Rightarrow$ uniform continuity of V_N

(iii) reachability of x^e from all $x \in \mathbb{X}$

(i) + (ii) + (iii) $\Rightarrow$ turnpike property

(iv) polynomial growth conditions for $\tilde{\ell}$

(i)–(iv) $\Rightarrow$ exponential turnpike
[Damm/Gr./Stieler/Worthmann '14]

Economic MPC theorem

Theorem: [Gr./Stieler '14]

Let f and ℓ be Lipschitz, $\mathbb{X}$ and $\mathbb{U}$ be compact and assume

(i) local controllability near x^e
(ii) strict dissipativity
(i)+(ii) $\Rightarrow$ uniform continuity of V_N

(iii) reachability of x^e from all $x \in \mathbb{X}$
uniform continuity of V_N + (iii) $\Rightarrow$ turnpike property

(iv) polynomial growth conditions for $\tilde{\ell}$

(i)–(iv) $\Rightarrow$ exponential turnpike
[Damm/Gr./Stieler/Worthmann '14]
(for alternative conditions see also [Porretta/Zuazua '13])

Economic MPC theorem

Under assumptions (i)–(iii), there exist $\varepsilon_1(N), \varepsilon_2(K) \to 0$ as $N \to \infty$ and $K \to \infty$, exponentially fast if additionally (iv) holds, such that the following properties hold

Economic MPC theorem

Under assumptions (i)–(iii), there exist $\varepsilon_1(N), \varepsilon_2(K) \to 0$ as $N \to \infty$ and $K \to \infty$, exponentially fast if additionally (iv) holds, such that the following properties hold

(1) Approximate average optimality:

$$\overline{J}^{cl}_{\infty}(x, \mu_N) \leq \ell(x^e, u^e) + \varepsilon_1(N)$$

Economic MPC theorem

Under assumptions (i)–(iii), there exist $\varepsilon_1(N), \varepsilon_2(K) \to 0$ as $N \to \infty$ and $K \to \infty$, exponentially fast if additionally (iv) holds, such that the following properties hold

(1) Approximate average optimality:

$$\overline{J}^{cl}_\infty(x, \mu_N) \leq \ell(x^e, u^e) + \varepsilon_1(N)$$

(2) Practical asymptotic stability: there is $\beta \in \mathcal{KL}$:

$$\|x_{\mu_N}(k, x) - x^e\| \leq \beta(\|x - x^e\|, k) + \varepsilon_1(N) \text{ for all } k \in \mathbb{N}$$

Economic MPC theorem

Under assumptions (i)–(iii), there exist $\varepsilon_1(N), \varepsilon_2(K) \to 0$ as $N \to \infty$ and $K \to \infty$, exponentially fast if additionally (iv) holds, such that the following properties hold

(1) Approximate average optimality:

$$\overline{J}^{cl}_\infty(x, \mu_N) \leq \ell(x^e, u^e) + \varepsilon_1(N)$$

(2) Practical asymptotic stability: there is $\beta \in \mathcal{KL}$:

$$\|x_{\mu_N}(k, x) - x^e\| \leq \beta(\|x - x^e\|, k) + \varepsilon_1(N) \text{ for all } k \in \mathbb{N}$$

(3) Approximate transient optimality: for all $K \in \mathbb{N}$:

$$J^{cl}_K(x, \mu_N(x)) \leq J_K(x, \mathbf{u}) + K\varepsilon_1(N) + \varepsilon_2(K)$$

for all admissible $\mathbf{u}$ with $\|x_{\mathbf{u}}(K, x) - x^e\| \leq \beta(\|x - x^e\|, K) + \varepsilon_1(N)$

Illustration of (2) and (3)

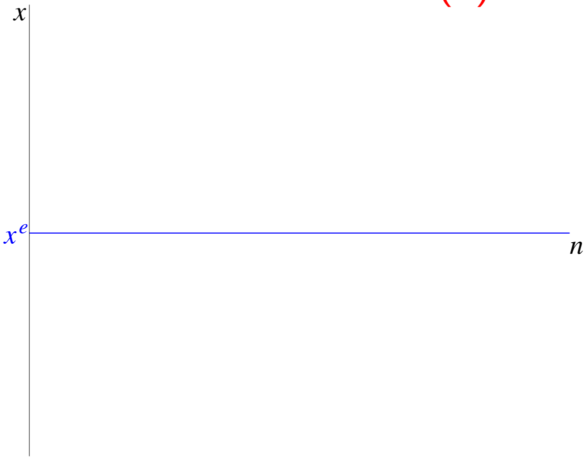


Illustration of (2) and (3)

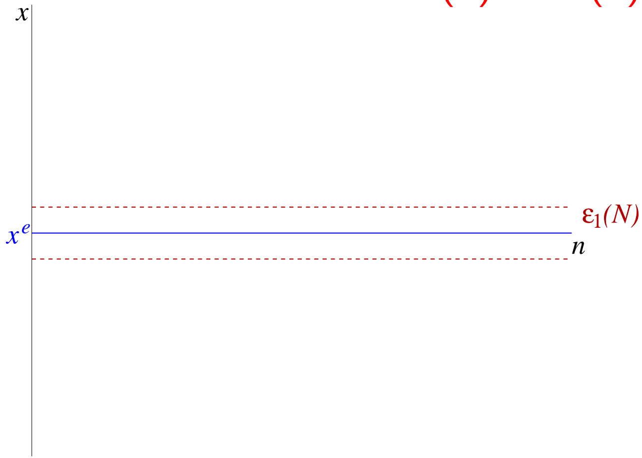
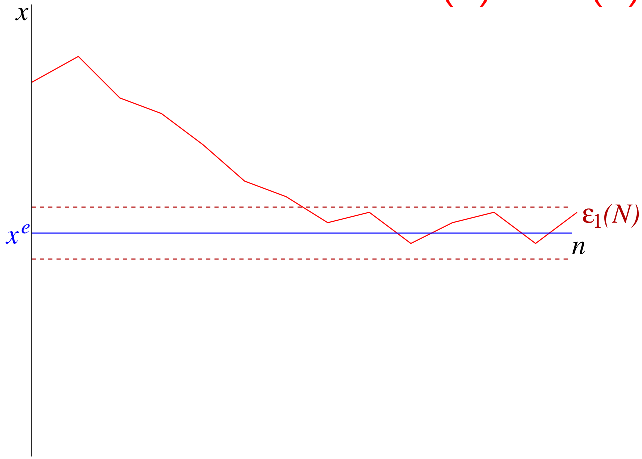
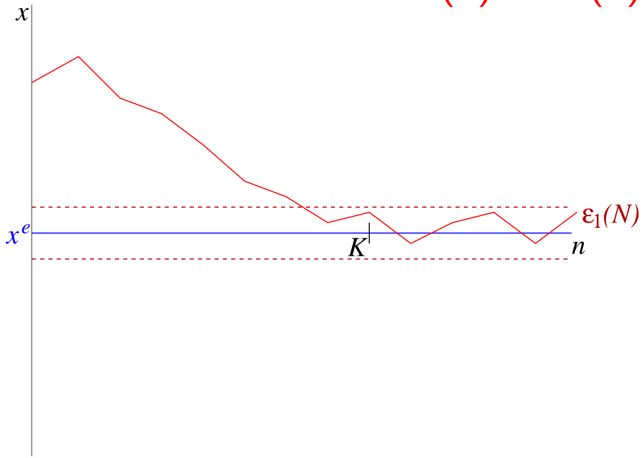


Illustration of (2) and (3)



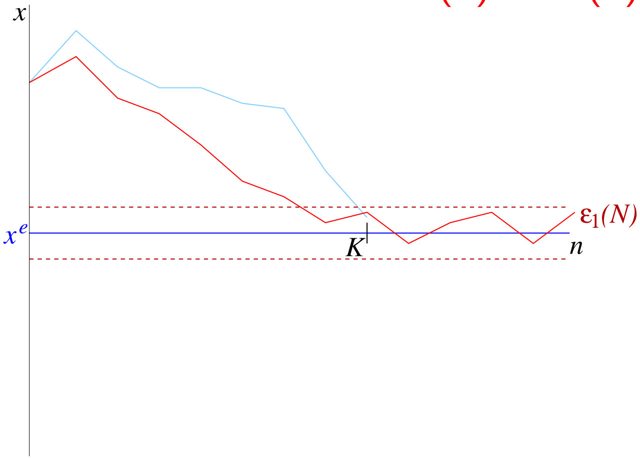
(2): $x_{\mu_N}(n)$ converges to the $\varepsilon_1(N)$-ball around x^e

Illustration of (2) and (3)



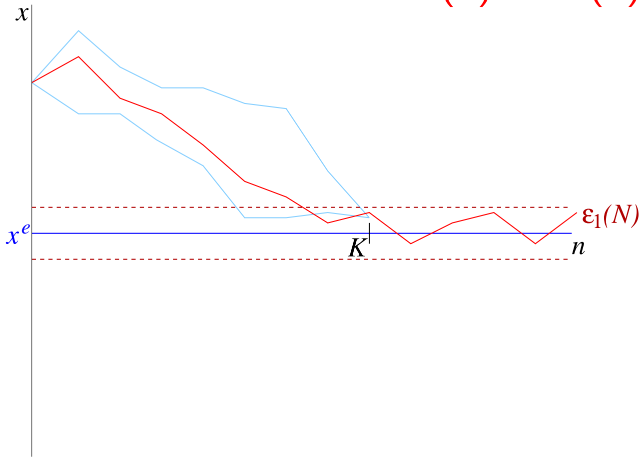
(2): $x_{\mu_N}(n)$ converges to the $\varepsilon_1(N)$-ball around x^e

Illustration of (2) and (3)



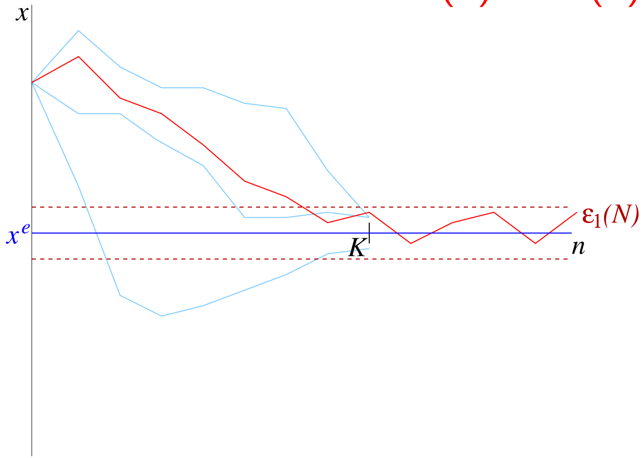
(2): $x_{\mu_N}(n)$ converges to the $\varepsilon_1(N)$-ball around x^e

Illustration of (2) and (3)



(2): $x_{\mu_N}(n)$ converges to the $\varepsilon_1(N)$-ball around x^e

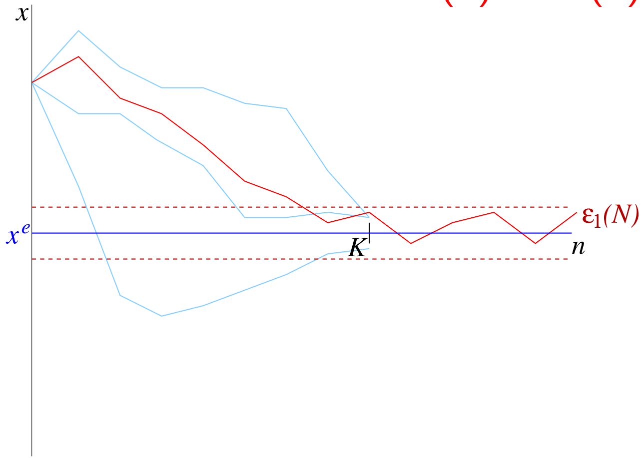
Illustration of (2) and (3)



(2): $x_{\mu_N}(n)$ converges to the $\varepsilon_1(N)$-ball around x^e

UNIVERSITÄT BAYREUTH

Illustration of (2) and (3)



(2): $x_{\mu_N}(n)$ converges to the $\varepsilon_1(N)$-ball around x^e

(3): cost of light blue trajectories is higher than that of $x_{\mu_N}(n)$ up to error terms $K\varepsilon_1(N) + \varepsilon_2(K)$

UNIVERSITÄT BAYREUTH

Linear quadratic convex problems

Theorem: [Gr./Stieler '14] For $\mathbb{X} = \mathbb{R}^n$, $U = \mathbb{R}^m$ and

$$\begin{aligned} f(x,u) &= Ax + Bu + c \\ \ell(x,u) &= x^T R x + u^T Q u + d^T x + e^T u, \quad R, Q > 0 \end{aligned}$$

the condition

(A,B) is stabilizable

is necessary and sufficient for practical asymptotic stability and approximate optimality of the MPC closed loop.

Linear quadratic convex problems

Theorem: [Gr./Stieler '14] For $\mathbb{X} = \mathbb{R}^n$, $U = \mathbb{R}^m$ and

$$\begin{aligned} f(x,u) &= Ax + Bu + c \\ \ell(x,u) &= x^T Rx + u^T Qu + d^T x + e^T u, \quad R, Q > 0 \end{aligned}$$

the condition

(A, B) is stabilizable

is necessary and sufficient for practical asymptotic stability and approximate optimality of the MPC closed loop.

Moreover, all error terms converge to 0 exponentially fast

Summary of Section (9)

- Without terminal constraints, average performance is only achieved approximately — the larger N, the better

Summary of Section (9)

- Without terminal constraints, average performance is only achieved approximately — the larger N, the better
- Likewise, asymptotic stability is only achieved up to a small neighborhood of x^e, i.e., "practically"

Summary of Section (9)

- Without terminal constraints, average performance is only achieved approximately — the larger N, the better
- Likewise, asymptotic stability is only achieved up to a small neighborhood of x^e, i.e., "practically"
- On the other hand, no a priori knowledge of the optimal equilibrium is needed

UNIVERSITÄT BAYREUTH

Summary of Section (9)

- Without terminal constraints, average performance is only achieved approximately — the larger N, the better
- Likewise, asymptotic stability is only achieved up to a small neighborhood of x^e, i.e., "practically"
- On the other hand, no a priori knowledge of the optimal equilibrium is needed
- In addition, transient optimality is achived (recently also established for terminal constrained variant)

Summary of Section (9)

- Without terminal constraints, average performance is only achieved approximately — the larger N, the better
- Likewise, asymptotic stability is only achieved up to a small neighborhood of x^e, i.e., “practically”
- On the other hand, no a priori knowledge of the optimal equilibrium is needed
- In addition, transient optimality is achived (recently also established for terminal constrained variant)
- Exponential turnpike plus polynomial bounds in addition ensure exponential decay of the error terms

Summary of Section (9)

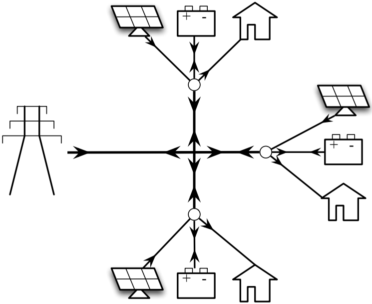
- Without terminal constraints, average performance is only achieved approximately — the larger N, the better
- Likewise, asymptotic stability is only achieved up to a small neighborhood of x^e, i.e., "practically"
- On the other hand, no a priori knowledge of the optimal equilibrium is needed
- In addition, transient optimality is achived (recently also established for terminal constrained variant)
- Exponential turnpike plus polynomial bounds in addition ensure exponential decay of the error terms
- As in the case with terminal constraints dissipativity plus controllability (or stabilizability) are the important structural conditions

(10) Application to a smart grid control problem

with Philipp Braun (Bayreuth), Chris Kellett (Newcastle),
Steve Weller (Newcastle) and Karl Worthmann (Ilmenau)

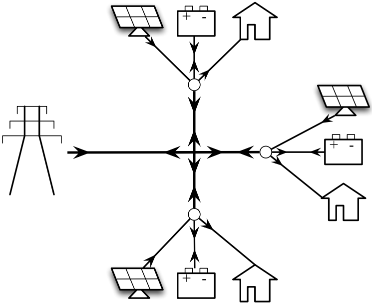
An application to a smart grid control problem

Consider the following setting in a future smart grid:



An application to a smart grid control problem

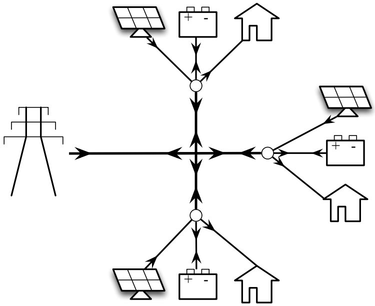
Consider the following setting in a future smart grid:



(batteries could be replaced by other storage devices)

An application to a smart grid control problem

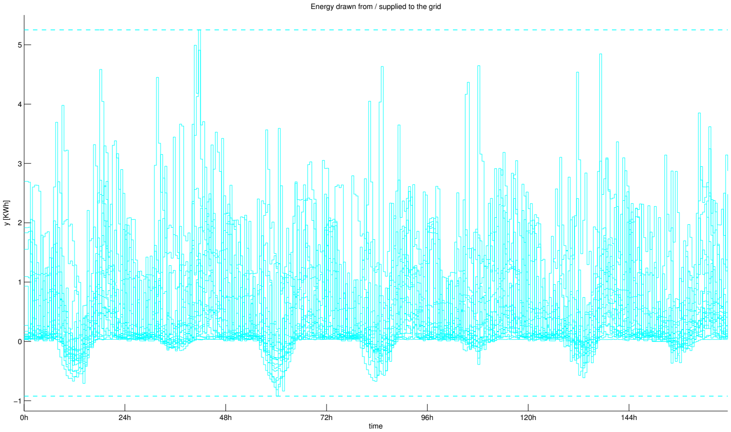
Consider the following setting in a future smart grid:



(batteries could be replaced by other storage devices)

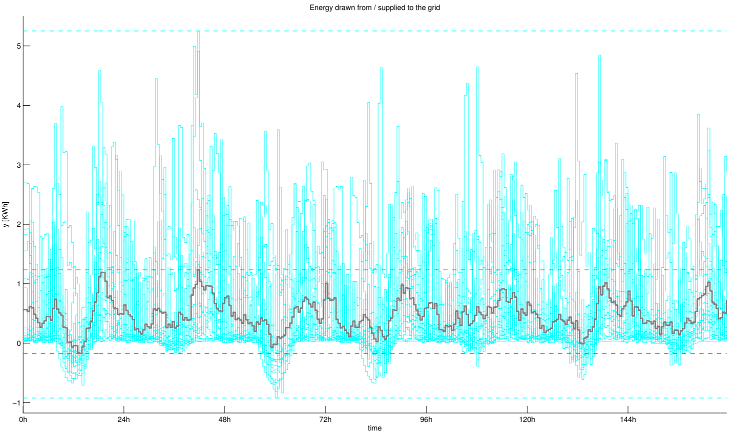
Control goal: Use the batteries as buffer in order to avoid large variations in demand and supply

Data: net energy demand



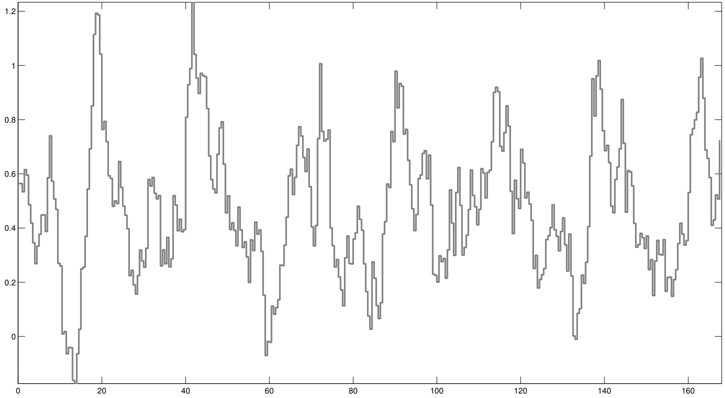
Ausgrid Data: individual units

Data: net energy demand



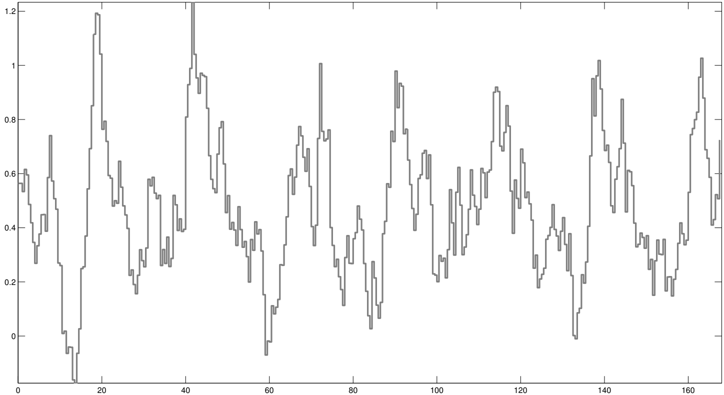
Ausgrid Data: individual units, averaged

Data: net energy demand



Ausgrid Data: averaged

Data: net energy demand



Ausgrid Data: averaged

In practice, forecasted data will be used

Model

For each unit $i = 1, \ldots, P$ we define

Model

For each unit $i = 1, \ldots, P$ we define

x_i = state of battery of ith unit

Model

For each unit $i = 1, \ldots, P$ we define

x_i = state of battery of ith unit $\qquad 0 \le x_i \le C_i$

u_i = battery charge/discharge

Model

For each unit $i = 1, \ldots, P$ we define

x_i = state of battery of ith unit $\qquad 0 \leq x_i \leq C_i$

u_i = battery charge/discharge $\qquad \underline{u}_i \leq u_i \leq \overline{u}_i$

Model

For each unit $i = 1, \ldots, P$ we define

$x_i =$ state of battery of ith unit $\qquad 0 \le x_i \le C_i$

$u_i =$ battery charge/discharge $\qquad \underline{u}_i \le u_i \le \overline{u}_i$

$w_i =$ energy load minus production in ith unit

Model

For each unit $i = 1, \dots, P$ we define

$x_i =$ state of battery of ith unit $\qquad 0 \le x_i \le C_i$

$u_i =$ battery charge/discharge $\qquad \underline{u}_i \le u_i \le \overline{u}_i$

$w_i =$ energy load minus production in ith unit

$y_i =$ power drawn from/supplied to the outside

UNIVERSITÄT BAYREUTH

Model

For each unit $i = 1, \ldots, P$ we define

$x_i =$ state of battery of ith unit $\qquad 0 \leq x_i \leq C_i$

$u_i =$ battery charge/discharge $\qquad \underline{u}_i \leq u_i \leq \overline{u}_i$

$w_i =$ energy load minus production in ith unit

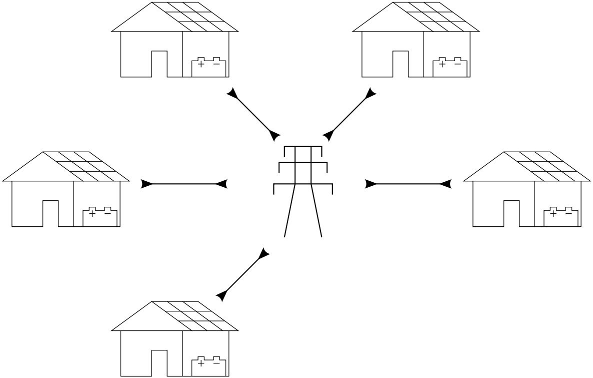
$y_i =$ power drawn from/supplied to the outside

$$\begin{aligned} x_i(k+1) &= x_i(k) + T u_i(k) \\ y_i(k) &= w_i(k) + u_i(k) \end{aligned}$$

sampling time $T = 30\,$min

UNIVERSITÄT BAYREUTH

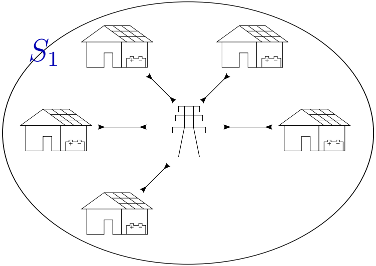
MPC approach



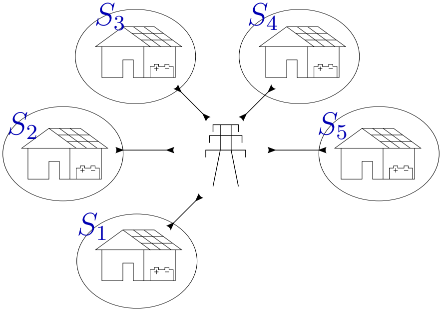
Objective: keep y_i close to average (in time) consumption
using MPC with ℓ penalizing the deviation from the average

Control Schemes

Centralized Control

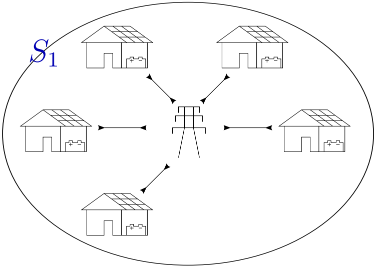


Decentralized Control



Control Schemes

Centralized Control



Compute at sampling instant n

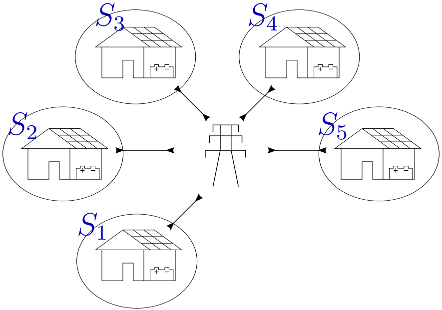
$$\overline{\zeta}(n) = \frac{1}{NP}\sum_{i=1}^{P}\sum_{j=0}^{N-1} w_i(n+j)$$

and minimize over $(u_1, \dots, u_P)$

$$\sum_{j=0}^{N-1}\left(\overline{\zeta}(n) - \frac{1}{P}\sum_{i=1}^{P} y_i(n+j)\right)^2$$

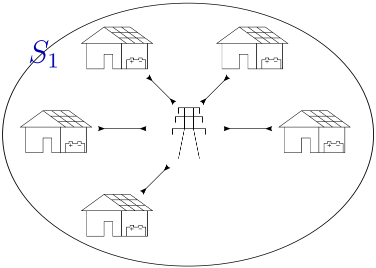
w.r.t. global constraints

Decentralized Control



Control Schemes

Centralized Control



Compute at sampling instant n

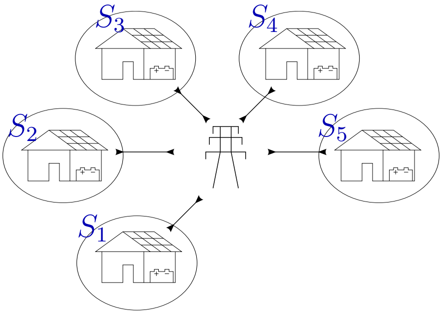
$$\bar{\zeta}(n) = \frac{1}{NP}\sum_{i=1}^{P}\sum_{j=0}^{N-1} w_i(n+j)$$

and minimize over $(u_1, \ldots, u_P)$

$$\sum_{j=0}^{N-1}\left(\bar{\zeta}(n) - \frac{1}{P}\sum_{i=1}^{P} y_i(n+j)\right)^2$$

w.r.t. global constraints

Decentralized Control



For each unit i compute

$$\bar{\zeta}_i(n) = \frac{1}{N}\sum_{j=0}^{N-1} w_i(n+j)$$

and minimize over u_i

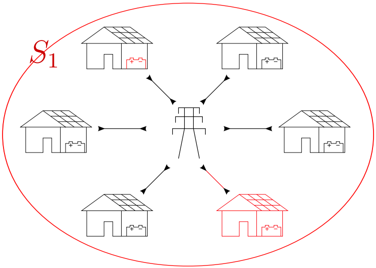
$$\sum_{j=0}^{N-1}\left(\bar{\zeta}_i(n) - y_i(n+j)\right)^2$$

w.r.t. local constraints

UNIVERSITÄT BAYREUTH

Control Schemes

Centralized Control



Compute at sampling instant n

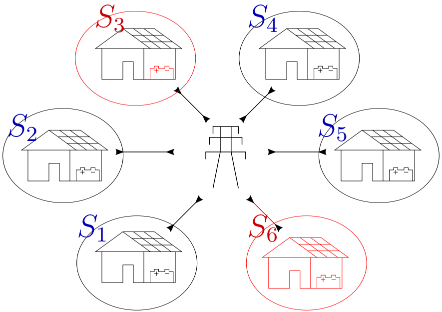
$$\bar{\zeta}(n) = \frac{1}{NP} \sum_{i=1}^{P} \sum_{j=0}^{N-1} w_i(n+j)$$

and minimize over $(u_1, \ldots, u_P)$

$$\sum_{j=0}^{N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} y_i(n+j) \right)^2$$

w.r.t. global constraints

Decentralized Control



For each unit i compute

$$\bar{\zeta}_i(n) = \frac{1}{N} \sum_{j=0}^{N-1} w_i(n+j)$$

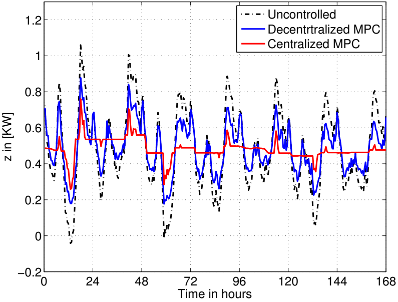
and minimize over u_i

$$\sum_{j=0}^{N-1} \left(\bar{\zeta}_i(n) - y_i(n+j) \right)^2$$

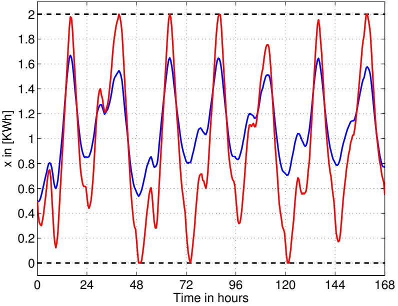
w.r.t. local constraints

Numerical Results

Performance



Average Battery Profiles



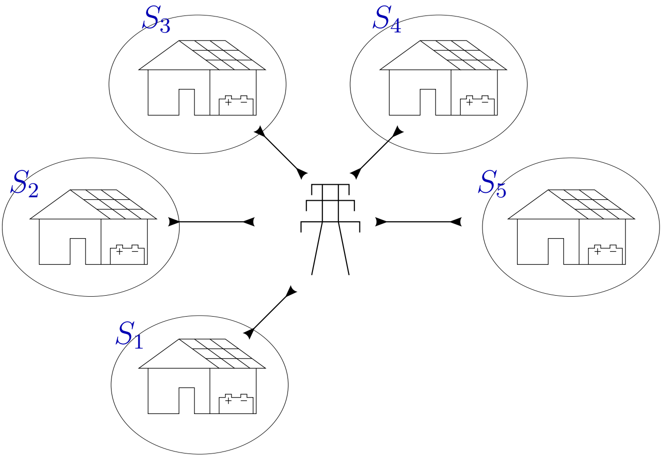
Setting:

- 100 units; 1 week simulation length
- prediction horizon 24[h]; sampling time 0.5[h]
- maximal charging/discharging rates per hour: 0.3[kWh]

Control Schemes

Alternative: Distributed Control

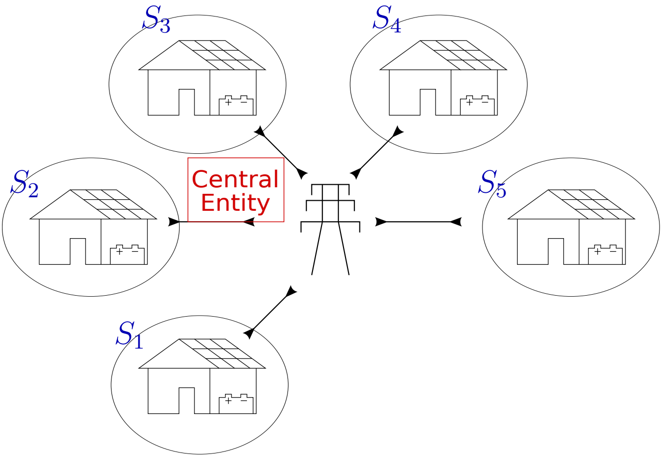
(Optimization in units with communication via Central Entity)



Control Schemes

Alternative: Distributed Control

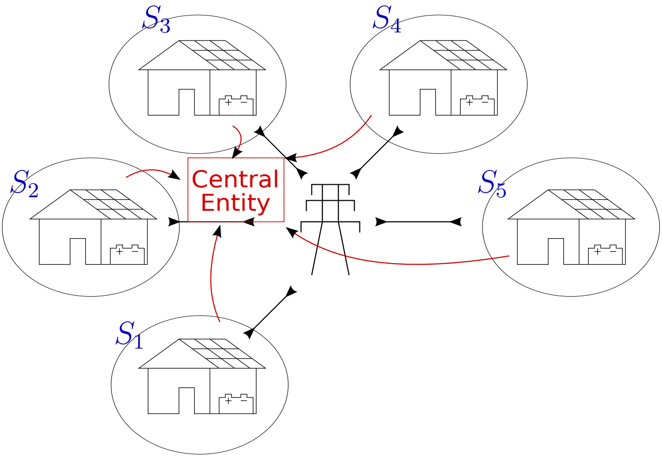
(Optimization in units with communication via Central Entity)



Control Schemes

Alternative: Distributed Control

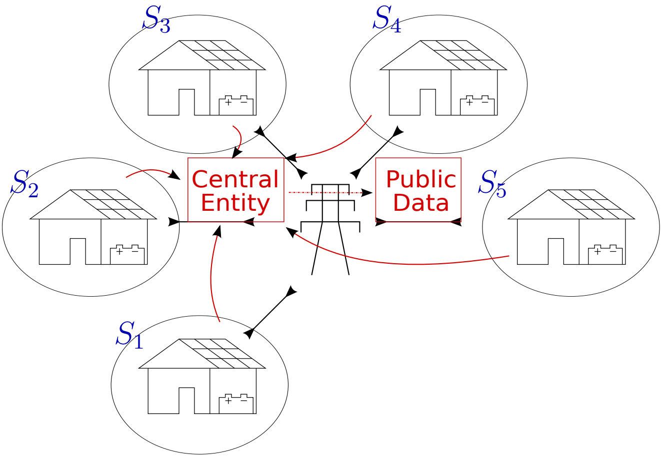
(Optimization in units with communication via Central Entity)



Control Schemes

Alternative: Distributed Control

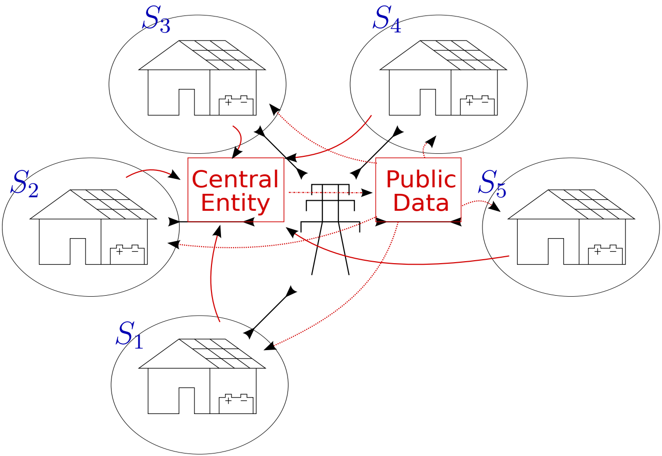
(Optimization in units with communication via Central Entity)



Control Schemes

Alternative: Distributed Control

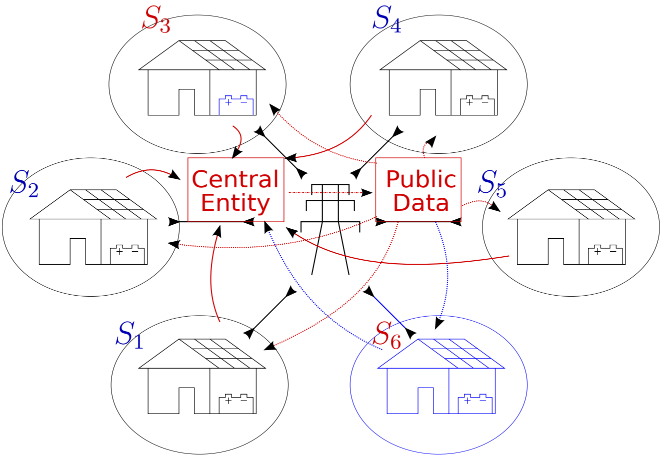
(Optimization in units with communication via Central Entity)



Control Schemes

Alternative: Distributed Control

(Optimization in units with communication via Central Entity)



The Centralized Optimization Algorithm

At each sampling instant n:

1. Set $x_0 = [x_1(n), \ldots, x_P(n)]^T$
2. Compute $\bar{\zeta}(n) = \frac{1}{NP} \sum_{i=1}^{P} \sum_{j=0}^{N-1} w_i(n+k)$
3. Minimize

$$J_N(x_0, u(\cdot)) = \sum_{k=0}^{N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} (u_i(k) + w_i(n+k)) \right)^2$$

s.t.

- $x_i(0) = x_{\mu_N, i}(n)$ and $x_i(k+1) = x_i(k) + Tu_i(k)$
- $y_i(n+k) = w_i(n+k) + u_i(k)$
- $0 \le x_i(k+1) \le C_i$ and $\underline{u}_i \le u_i(k) \le \overline{u}_i$

for $k = 0, \ldots, N-1$ and $i = 1, \ldots, P$

$\rightsquigarrow \begin{cases} \text{optimal control sequence} & u^\star(0), \ldots, u^\star(N-1) \\ \text{performance output} & y^\star(0), \ldots, y^\star(N-1) \end{cases}$

The Centralized Optimization Algorithm

At each sampling instant n:

1. Set $x_0 = [x_1(n), \ldots, x_P(n)]^T$
2. Compute $\quad \bar{\zeta}(n) = \frac{1}{NP} \sum_{i=1}^{P} \sum_{j=0}^{N-1} w_i(n+k)$
3. Minimize
   $$J_N(x_0, y(n+\cdot)) = \sum_{k=0}^{N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} y_i(n+k) \right)^2$$
   s.t.
   - $x_i(0) = x_{\mu_N,i}(n)$ and $x_i(k+1) = x_i(k) + T u_i(k)$
   - $y_i(n+k) = w_i(n+k) + u_i(k)$
   - $0 \le x_i(k+1) \le C_i$ and $\underline{u}_i \le u_i(k) \le \overline{u}_i$

   for $k = 0, \ldots, N-1$ and $i = 1, \ldots, P$

$$\rightsquigarrow \begin{cases} \text{optimal control sequence} & u^\star(0), \ldots, u^\star(N-1) \\ \text{performance output} & y^\star(0), \ldots, y^\star(N-1) \end{cases}$$

The Distributed Optimization Algorithm

At each sampling instant n:

1. Initialize $y_i^0(j) := w_i(j)$, $j = n, \dots, n+N-1$ (i.e., $u_i \equiv 0$)
2. Perform iteratively for $\ell = 0, 1, \dots$
   a. Units: send y_i^ℓ to the Central Entity
   b. Central Entity: Compute and broadcast $\bar{\zeta}(n)$ and
   $$Y^\ell(j) := \sum_{i=1}^P y_i^\ell(j), \qquad j = n, 1, \dots, n+N-1$$
   c. Units: For each $i \in \{1, \dots, P\}$ minimize (in parallel)
   $$J_{N,i}(x_i, y_i(\cdot)) = \sum_{j=n}^{n+N-1} \left(P\bar{\zeta}(n) - Y^\ell(j) + y_i^\ell(j) - y_i(j)\right)^2,$$
   send the (unique) minimizer $y_i^{\ell,\star}(\cdot)$ to the Central Entity
   d. Central Entity: Compute and broadcast
   $$\theta = \operatorname*{argmin}_{\theta \in [0,1]} \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^P \left[(1-\theta) y_i^\ell(j) + \theta y_i^{\ell,\star}(j)\right]\right)^2$$
   e. Units: Set $y_i^{\ell+1}(\cdot) = (1-\theta) y_i^\ell(\cdot) + \theta y_i^{\ell,\star}(\cdot)$

Convergence of Distributed Optimization (1)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

UNIVERSITÄT BAYREUTH

Convergence of Distributed Optimization (1)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\overline{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Proof:

$V^{\ell+1} = \sum_{j=n}^{n+N-1} \left(\overline{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell+1}(j) \right)^2$

UNIVERSITÄT BAYREUTH

Convergence of Distributed Optimization (1)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^\ell(\cdot)$, then $V^{\ell+1} < V^\ell$ holds for

$$V^\ell := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^\ell(j) \right)^2$$

Proof:

$$\begin{aligned} V^{\ell+1} &= \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \tfrac{1}{P} \sum_{i=1}^{P} Y^{\ell+1}(j) \right)^2 \\ &= \sum_j \left(\bar{\zeta}(n) - Y^\ell(j) + \tfrac{1}{P} \sum_i \theta \left(y_i^{\ell,\star}(j) - y_i^\ell(j) \right) \right)^2 \end{aligned}$$

Convergence of Distributed Optimization (1)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Proof:

$$\begin{aligned} V^{\ell+1} &= \textstyle\sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell+1}(j) \right)^2 \\ &= \textstyle\sum_j \left(\bar{\zeta}(n) - Y^{\ell}(j) + \frac{1}{P} \sum_i \theta \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right)^2 \\ &\leq \textstyle\sum_j \left(\sum_i \frac{1}{P} \left(\bar{\zeta} - Y^{\ell}(j) + \frac{1}{P} \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right) \right)^2 \qquad \theta = \frac{1}{P} \end{aligned}$$

Convergence of Distributed Optimization (1)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Proof:

$$\begin{aligned}
V^{\ell+1} &= \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \tfrac{1}{P} \sum_{i=1}^{P} Y^{\ell+1}(j) \right)^2 \\
&= \sum_j \left(\bar{\zeta}(n) - Y^{\ell}(j) + \tfrac{1}{P} \sum_i \theta \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right)^2 \\
&\leq \sum_j \left(\sum_i \tfrac{1}{P} \left(\bar{\zeta} - Y^{\ell}(j) + \tfrac{1}{P} \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right) \right)^2 \quad \theta = \tfrac{1}{P} \\
&\leq \sum_j \sum_i \tfrac{1}{P} \left(\bar{\zeta} - Y^{\ell}(j) + \tfrac{1}{P} \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right)^2 \text{ Jen.'s Ineq.}
\end{aligned}$$

Convergence of Distributed Optimization (1)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Proof:

$$\begin{aligned}
V^{\ell+1} &= \textstyle\sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell+1}(j) \right)^2 \\
&= \textstyle\sum_j \left(\bar{\zeta}(n) - Y^{\ell}(j) + \frac{1}{P} \sum_i \theta \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right)^2 \\
&\leq \textstyle\sum_j \left(\sum_i \frac{1}{P} \left(\bar{\zeta} - Y^{\ell}(j) + \frac{1}{P} \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right) \right)^2 \qquad \theta = \frac{1}{P} \\
&\leq \textstyle\sum_j \sum_i \frac{1}{P} \left(\bar{\zeta} - Y^{\ell}(j) + \frac{1}{P} \left(y_i^{\ell,\star}(j) - y_i^{\ell}(j) \right) \right)^2 \quad \text{Jen.'s Ineq.} \\
&< \textstyle\frac{1}{P} \sum_i \sum_j \left(\bar{\zeta}(n) - Y^{\ell}(j) \right)^2 \quad = \quad V^{\ell}. \qquad \text{Local Minimization}
\end{aligned}$$

Convergence of Distributed Optimization (2)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\overline{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

UNIVERSITÄT BAYREUTH

Convergence of Distributed Optimization (2)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Corollary: $\lim_{\ell \to \infty} V^{\ell}$ exists

UNIVERSITÄT BAYREUTH

Convergence of Distributed Optimization (2)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Corollary: $\lim_{\ell\to\infty} V^{\ell}$ exists

Proof: $V^{\ell} \geq 0$ is bounded from below and decreasing.

Convergence of Distributed Optimization (2)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^\ell(\cdot)$, then $V^{\ell+1} < V^\ell$ holds for

$$V^\ell := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^\ell(j) \right)^2$$

Corollary: $\lim_{\ell\to\infty} V^\ell$ exists

Proof: $V^\ell \geq 0$ is bounded from below and decreasing.

Theorem: The limit $V^\star = \lim_{\ell\to\infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization

Convergence of Distributed Optimization (2)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Corollary: $\lim_{\ell \to \infty} V^{\ell}$ exists

Proof: $V^{\ell} \geq 0$ is bounded from below and decreasing.

Theorem: The limit $V^{\star} = \lim_{\ell \to \infty} V^{\ell}$ generated by distributed optimization coincides with the optimal value $V^{\sharp}$ of the centralized optimization

Proof (by contradiction): Assume $V^{\sharp} < V^{\star}$

Convergence of Distributed Optimization (2)

Lemma: If $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$, then $V^{\ell+1} < V^{\ell}$ holds for

$$V^{\ell} := \sum_{j=n}^{n+N-1} \left(\bar{\zeta}(n) - \frac{1}{P} \sum_{i=1}^{P} Y^{\ell}(j) \right)^2$$

Corollary: $\lim_{\ell\to\infty} V^{\ell}$ exists

Proof: $V^{\ell} \geq 0$ is bounded from below and decreasing.

Theorem: The limit $V^{\star} = \lim_{\ell\to\infty} V^{\ell}$ generated by distributed optimization coincides with the optimal value $V^{\sharp}$ of the centralized optimization

Proof (by contradiction): Assume $V^{\sharp} < V^{\star}$

Local minimization leads to $y^{\ell,\star}(\cdot) \neq y^{\ell}(\cdot)$ in the limit which by the lemma above implies an improvement of $V^{\star}$. $\lightning$

UNIVERSITÄT BAYREUTH

Convergence of Distributed Optimization (3)

Theorem: The limit $V^\star = \lim_{\ell\to\infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization.

Convergence of Distributed Optimization (3)

Theorem: The limit $V^\star = \lim_{\ell\to\infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization.

Question: Do the minimizers also converge?

Convergence of Distributed Optimization (3)

Theorem: The limit $V^\star = \lim_{\ell\to\infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization.

Question: Do the minimizers also converge?

Answer: Not necessarily, because the centralized minimizer is not unique. But we obtain something slightly weaker:

Convergence of Distributed Optimization (3)

Theorem: The limit $V^\star = \lim_{\ell\to\infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization.

Question: Do the minimizers also converge?

Answer: Not necessarily, because the centralized minimizer is not unique. But we obtain something slightly weaker:

Lemma Let $(y^\ell)_{\ell\in\mathbb{N}_0}$ be the sequence of minimizers generated by distributed optimization. Then

$$\|y^\ell - y^{\ell-1}\| \to 0 \qquad \text{for } \ell \to \infty.$$

UNIVERSITÄT BAYREUTH

Convergence of Distributed Optimization (3)

Theorem: The limit $V^\star = \lim_{\ell \to \infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization.

Question: Do the minimizers also converge?

Answer: Not necessarily, because the centralized minimizer is not unique. But we obtain something slightly weaker:

Lemma Let $(y^\ell)_{\ell \in \mathbb{N}_0}$ be the sequence of minimizers generated by distributed optimization. Then

$$\|y^\ell - y^{\ell-1}\| \to 0 \qquad \text{for } \ell \to \infty.$$

The proof is based on sensitivity analysis [Fiacco]

Convergence of Distributed Optimization (3)

Theorem: The limit $V^\star = \lim_{\ell\to\infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization.

Question: Do the minimizers also converge?

Answer: Not necessarily, because the centralized minimizer is not unique. But we obtain something slightly weaker:

Lemma Let $(y^\ell)_{\ell\in\mathbb{N}_0}$ be the sequence of minimizers generated by distributed optimization. Then

$$\|y^\ell - y^{\ell-1}\| \to 0 \qquad \text{for } \ell \to \infty.$$

The proof is based on sensitivity analysis [Fiacco]

Question: When should the iterative distributed optimization be terminated?

Convergence of Distributed Optimization (3)

Theorem: The limit $V^\star = \lim_{\ell\to\infty} V^\ell$ generated by distributed optimization coincides with the optimal value $V^\sharp$ of the centralized optimization.

Question: Do the minimizers also converge?

Answer: Not necessarily, because the centralized minimizer is not unique. But we obtain something slightly weaker:

Lemma Let $(y^\ell)_{\ell\in\mathbb{N}_0}$ be the sequence of minimizers generated by distributed optimization. Then

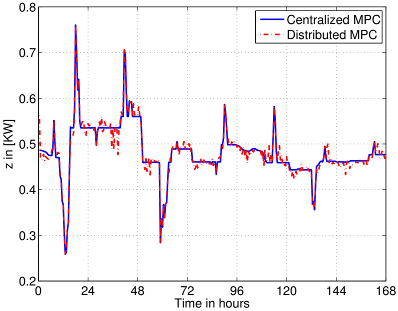
$$\|y^\ell - y^{\ell-1}\| \to 0 \qquad \text{for } \ell \to \infty.$$

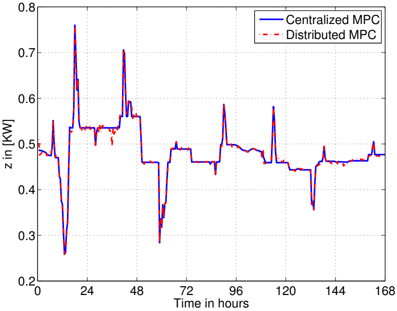
The proof is based on sensitivity analysis [Fiacco]

Question: When should the iterative distributed optimization be terminated? $\to$ numerical simulation studies

Numerical Results

Closed loop (MPC) performance with incomplete optimization





- iteration until $\ell = 3$ (left) and $\ell = 10$ (right) at every sampling instant
- Simulation for 100 units, simulation length one week

Summary of Section (10)

For the particular networked situation, we were able to derive a distributed optimization routine (to be carried out in each step of the MPC scheme) providing

Summary of Section (10)

For the particular networked situation, we were able to derive a distributed optimization routine (to be carried out in each step of the MPC scheme) providing

- Flexibility due to local optimization

Summary of Section (10)

For the particular networked situation, we were able to derive a distributed optimization routine (to be carried out in each step of the MPC scheme) providing

- Flexibility due to local optimization
- Rather fast convergence to the centralized optimum

Summary of Section (10)

For the particular networked situation, we were able to derive a distributed optimization routine (to be carried out in each step of the MPC scheme) providing

- Flexibility due to local optimization
- Rather fast convergence to the centralized optimum
- Price to pay: existence of a Central Entity and communication during the iteration

Open Questions for MPC

Independent from the optimization algorithm developed for this application, there are several open questions for MPC:

Open Questions for MPC

Independent from the optimization algorithm developed for this application, there are several open questions for MPC:

- Can we derive a performance bound for the time varying situation of this example?

Open Questions for MPC

Independent from the optimization algorithm developed for this application, there are several open questions for MPC:

- Can we derive a performance bound for the time varying situation of this example?
- What replaces the optimal equilibrium for this time-varying problem? Is there a suitable dissipativity notion?

Open Questions for MPC

Independent from the optimization algorithm developed for this application, there are several open questions for MPC:

- Can we derive a performance bound for the time varying situation of this example?
- What replaces the optimal equilibrium for this time-varying problem? Is there a suitable dissipativity notion?
- What can we say about the MPC closed loop if the units cannot reach an optimum but, e.g., only a Nash equilibrium?

Selected literature

D.Q. Mayne, J.B. Rawlings, C.V. Rao, P.O.M. Scokaert, Constrained model predictive control: stability and optimality, Automatica, 36(2000), 789–814 ("The" classical reference)

L. Grüne and J. Pannek, Nonlinear Model Predictive Control, Springer, 2011 (contains most of the material from Part A)

L. Grüne, NMPC without terminal constraints, Proceedings of the IFAC Conference on Nonlinear Model Predictive Control, 2012, 1–13 (survey of some results from Part A and B)

D. Angeli, R. Amrit, J.B. Rawlings, On average performance and stability of economic model predictive control, IEEE Trans. Autom. Control, 57 (2012), 1615–1626 (results from Section (8))

L. Grüne and M. Stieler, Asymptotic stability and transient optimality of economic MPC without terminal conditions, Journal of Process Control, 24 (2014), 1187–1196 (results from Section (9))

K. Worthmann, C.M. Kellett, P. Braun, L. Grüne, S.R. Weller, Distributed and decentralized control of residential energy systems incorporating battery storage, IEEE Transactions on Smart Grid, to appear (results from Section (10))