



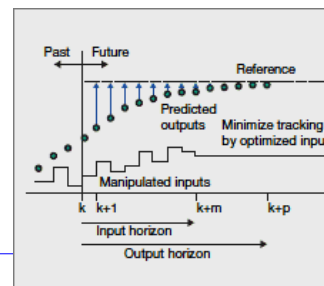
EECI Course on

Nonlinear and Data-based Model Predictive Control

Matthias Müller¹⁾ and Frank Allgöwer²⁾

¹⁾ Institute of Automatic Control
Leibniz University Hannover, Germany

²⁾ Institute for Systems Theory and
Automatic Control
University of Stuttgart, Germany



Structure of Course

MONDAY:

introduction, background **nominal stability (Part 1)**

TUESDAY:

exercise, nominally stable MPC (Part 2), exercise,
nominally stable MPC (Part 3)

WEDNESDAY:

robust MPC, exercise, economic MPC

THURSDAY:

tracking MPC, data-based MPC; selected advanced topics



Nominal Stability of the Closed Loop

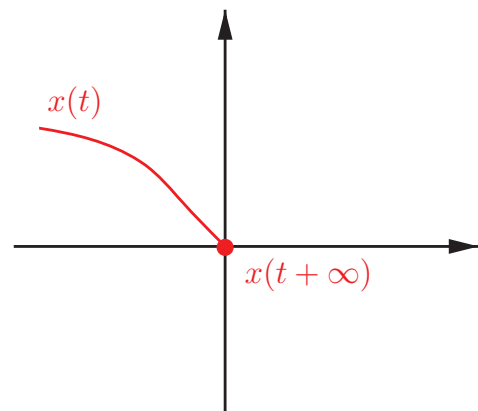
INFINITE HORIZON NMPC

Infinite Horizon NMPC



$$\min_u J(x(t), u)$$
$$J(\cdot) = \int_t^{t+\infty} L(x(\tau), u(\tau)) d\tau$$

subject to: $\dot{x} = f(x, u)$ system dynamics
 $x(t)$ given “state feedback”
 $u(\tau) \in \mathcal{U}$ input constraints
 $x(\tau) \in \mathcal{X}$ state constraints



- + stability/convergence to origin
- + feasibility guaranteed if initially feasible
- + feasibility \Leftrightarrow constrained controllability
- **implementation often not possible**



- **Feasibility** (+optimality) at t_i implies **feasibility** (+optimality) at t_{i+1} :

$$u^*(\tau, t_{i+1}) = u^*(\tau, t_i), \tau \in [t_{i+1}, \infty)$$

(Follows from Bellmans optimality principle)

=> **recursive feasibility**

- Use **value function** $V(x) = J^*(x(t))$ as Lyapunov function candidate:

$$V(x(t_i + \tau)) - V(x(t_i)) \leq - \int_{t_i}^{t_i + \tau} L(x(s), u(s)) ds$$

Value function is strictly decreasing => **stability**

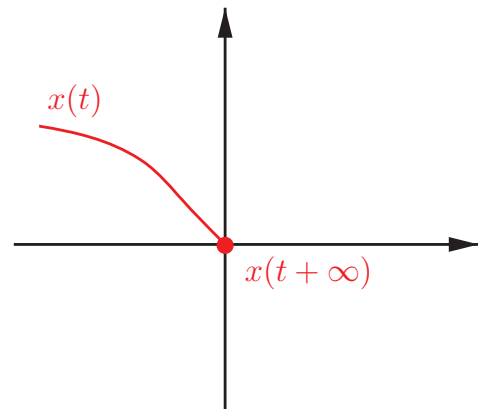
- **attractivity** follows from Barbalat's Lemma



$$\min_u J(x(t), u)$$

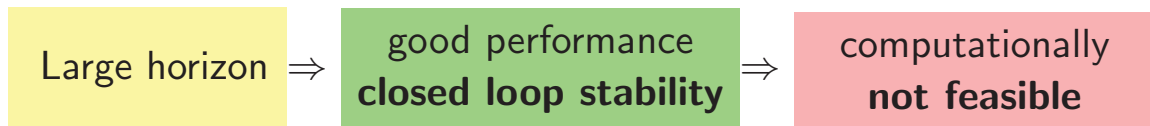
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Dilemma of NMPC

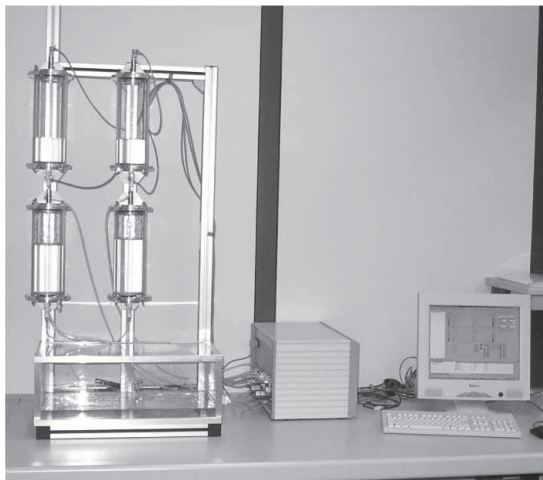


Need for short horizon formulations that achieves good performance and stability

2 possible approaches:

- choose T , F , ... s.t. closed loop is stable

Experimental stability study of NMPC



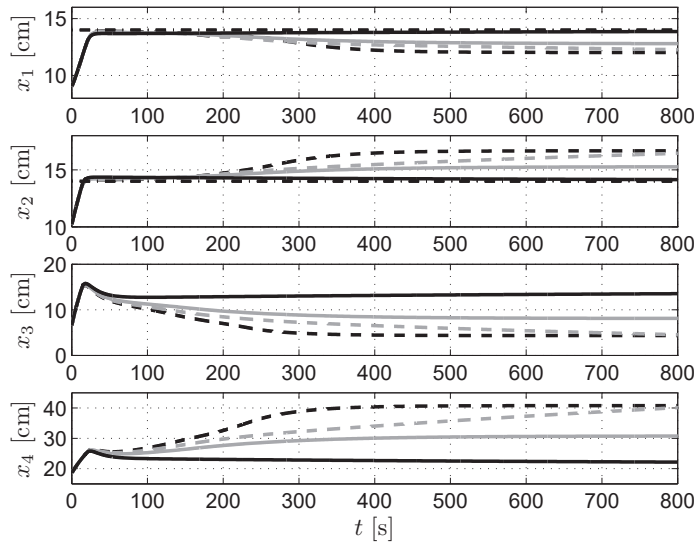
Four tank system at the IST laboratory

Four tank system:

- Nonlinear system
- Input constraints
- State constraints
- “Slow” dynamics

Four tank system is suited for an experimental stability study of NMPC

Four Tank: Simulation and Experiment



- Only simulations
- Setpoint:
 - $x_{1,2s} = 14\text{cm}$
 - $\gamma_{1,2} = 0.4$
- Prediction horizon:
 - $-T = 60\text{s}$: unstab.
 - $-T = 75\text{s}$: unstab.
 - $-T = 90\text{s}$: unstab.
 - $-T = 135\text{s}$: stable
- Stability constraints:
 - **None**
- Input constraints

Closed-loop stability can be achieved with an **long enough prediction horizon**

Problem:

How long is long enough (for an answer see unconstrained NMPC later)

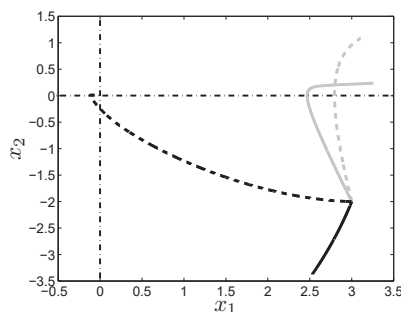
Unstable closed loop for academic example

Example [Primbs '00]: Stabilize the nonlinear system

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = -x_1 \left(\frac{\pi}{2} + \arctan(5x_1) \right) - \frac{5x_1^2}{2(1 + 25x_1^2)} + 4x_2 + 3u$$

via NMPC **without stability constraints** and the cost function $\int_{t_i}^{t_i+T} x_2^2 + u^2 d\tau$.



- $-T = 0.2$: unstable trajectory
- $-T = 0.3$: stable trajectory
- $-T = 0.4$: unstable trajectory
- $-T = 1.0$: unstable trajectory

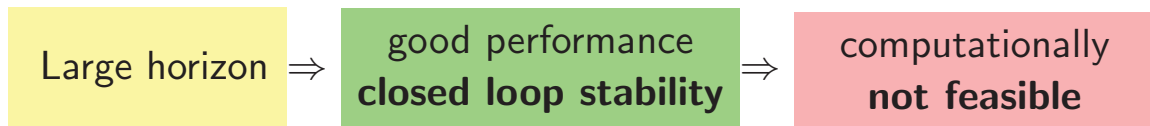
Closed-loop stability can be achieved with an **long enough prediction horizon**

How long is long enough?

This academic example shows that this is not so easy to answer

Dilemma of NMPC

Guaranteed Stability versus Performance



Need for short horizon formulations that achieves good performance and stability

2 possible approaches:

- choose T (L , ...) s.t. closed loop is stable
- modify NMPC setup, s.t. closed loop is stable independent of choice of T , ...

⇒ NMPC scheme with “guaranteed stability”



Nominal Stability of the Closed Loop

ZERO-TERMINAL-CONSTRAINT NMPC



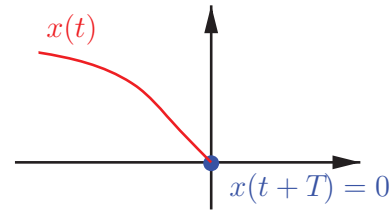
[Kwon '77], [Keerthi & Gilbert '88], [Mayne & Michalska '90]

Simplest finite horizon NMPC scheme with guaranteed stability

Idea: enforce that predicted state reaches origin in finite time

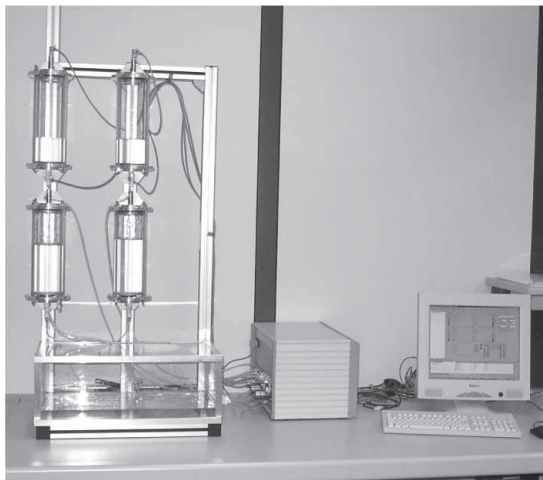
$$\min_u J(x(t), u)$$
$$J(\cdot) = \int_t^{t+T} L(x(\tau), u(\tau)) d\tau$$

subject to: $\dot{x} = f(x, u)$, system dynamics
 $x(t+T) = 0$ zero terminal const.



- + similar to infinite horizon: feasibility once guarantees consecutive decrease of value function and feasibility (supplementing old input with zero) \Rightarrow **stability**
- initial feasibility, performance for short horizons?
- **computationally expensive (boundary value problem)**

Application Example: Four Tank System



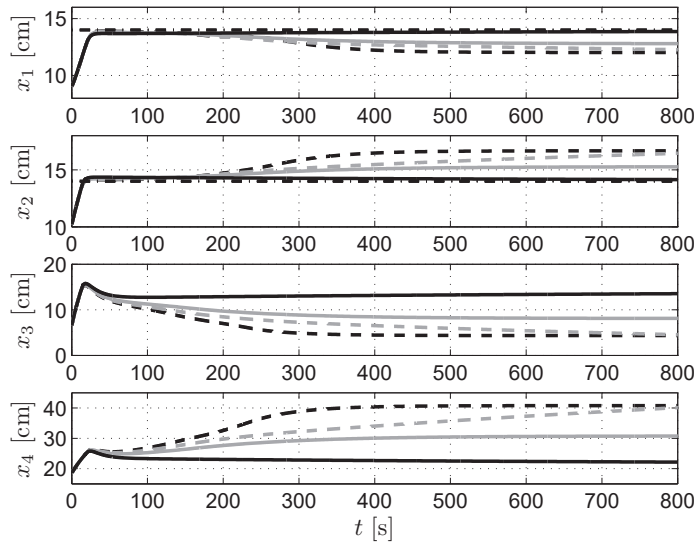
Four tank system of the IST laboratory

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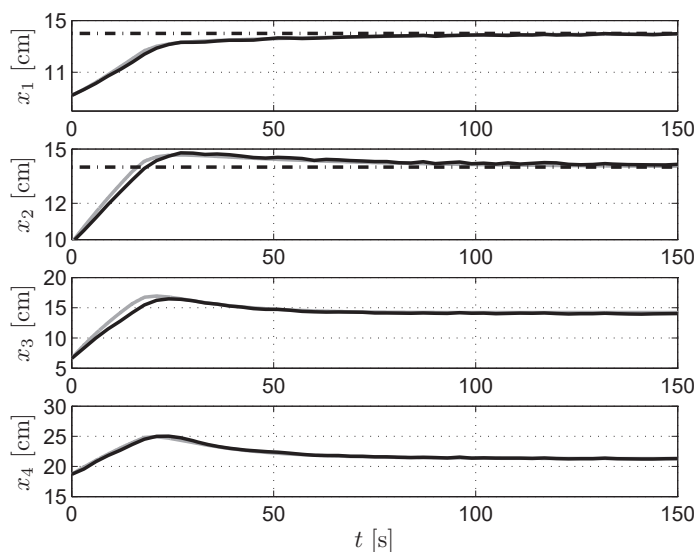
Four tank system is suited for an experimental stability study of NMPC

Recall: Four tank with NMPC with $T=60s$ is unstable



- Only simulations
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- Prediction horizon:
 - $-T = 60s$: unstable
 - $-T = 75s$: unstable
 - $-T = 90s$: unstable
 - $-T = 135s$: stable
- Stability constraints:
 - **None**
- Input constraints

Four Tank: Zero Terminal Constraint MPC



- Sim. —, Exp. —
- Setpoint:
 - $x_{1,2s} = 14cm$
 - $\gamma_{1,2} = 0.4$
- Prediction horizon:
 - $T = 60s$
- Stability constraints:
 - Zero Terminal**
 - Constrained MPC**
- Input constraints
- State constraints

Closed-loop is asymptotically stable with **zero terminal state constraint NMPC**

(for prediction horizon $T=60s$ that led to instability without zero terminal state constraint)