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Model Predictive Control in the Chemical Process Industry hosted by Industrial Controllers

Modelgebaseerde regeling van industriële chemische processen op industriële regelaars

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BioTeC BIOPROCESS TECHNOLOGY & CONTROL

SCD

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Outline

- Introduction – aim of this PhD
  - What – Why - How
- Background
  - Model identification
  - Model predictive control
  - Employed devices
- Results:
  - Case I: Air heating set-up
  - Case II: Pilot-scale distillation column
- Discussion & Conclusions

What? This PhD…

Optimal control is
calculated *online.*

A model is required
to predict future behavior
of the system.

Slow systems

Model Predictive Control

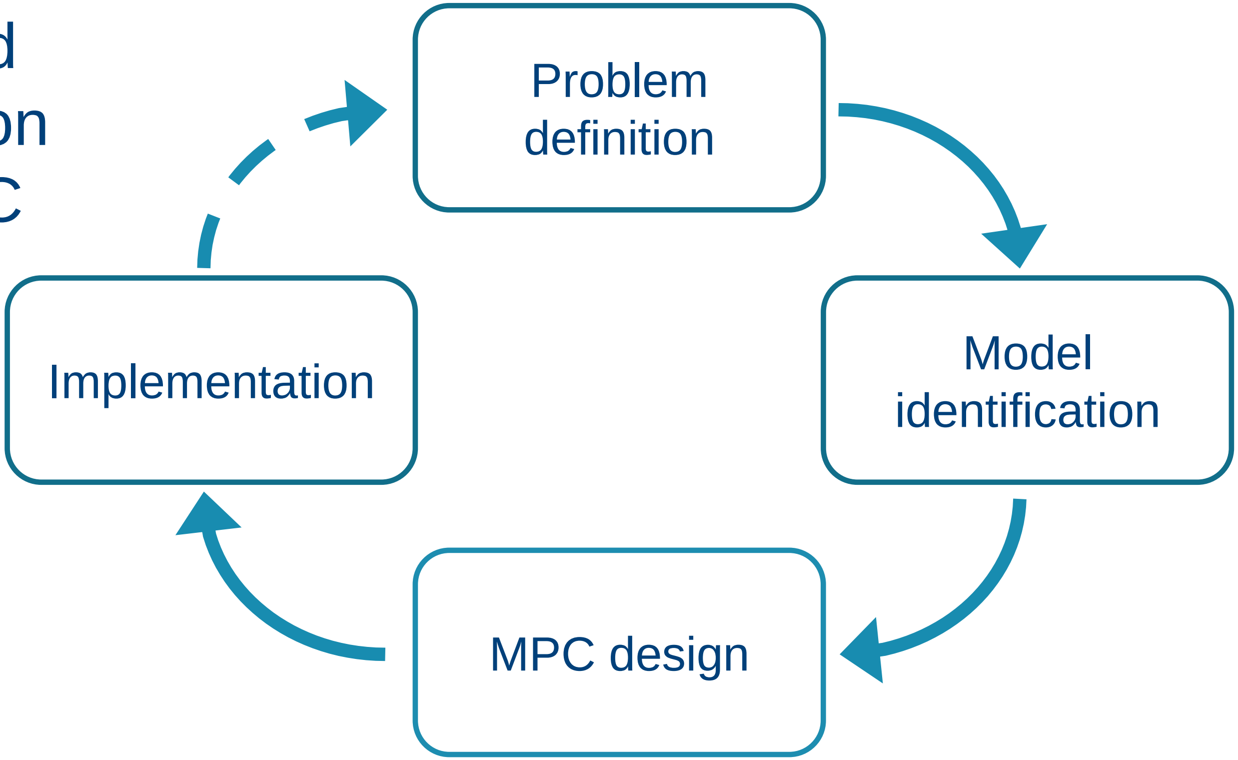
in the Chemical **Process Industry**

hosted by **Industrial Controllers**

Programmable Automation Controller (PAC)
Programmable Logic Controller (PLC)

…completes the loop …

- All steps required for implementation of MPC on a PAC and PLC.
- NOT an in-depth analysis of one aspect



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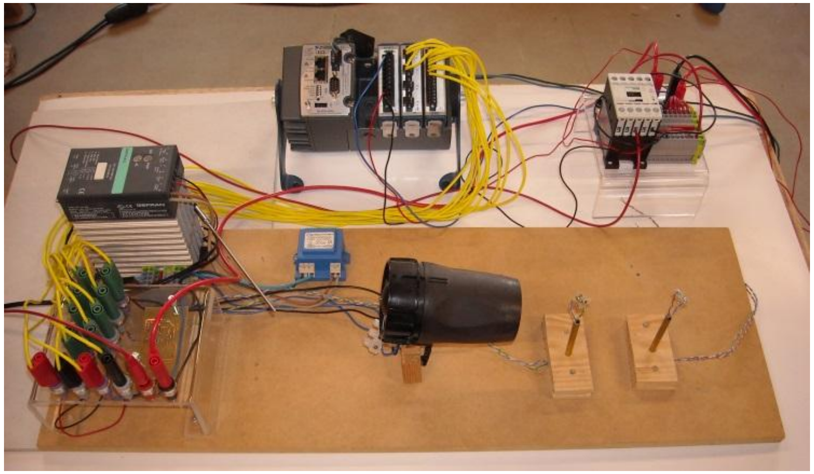
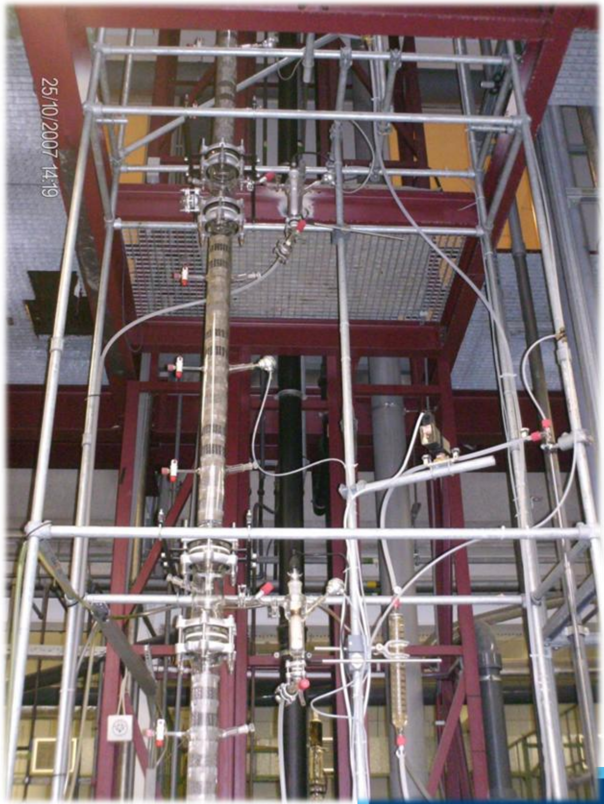
… for MPC on 2 experimental set-ups …

Increasing complexity of the system

Air heating set-up



Pilot-scale distillation column



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…using three different devices.

Decreasing computational power

Personal Computer (PC)

Programmable Automation Controller (PAC)

Programmable Logic Controller (PLC)

Why?

- In the past: MPC custom build
  - Large installations
  - Slow processes
- Evolution to (very) fast MPC (applications)
- Idea:
  - Use existing industrial controller hardware
  - Employ ‘fast’ algorithms on ‘slow’ devices

This to introduce MPC in a typical industrial environment on ‘known devices’

How?

- Collect necessary information:
  - Model for control
  - Choose desired temperature profiles
  - Choose MPC controller objective

- Simulation on PC

- Implementation on an experimental set-up following a decreasing computational power: PC → PAC → PLC

Overview of this PhD

Decreasing computational power

	Air heating set-up	Distillation column
Model identification	v	v
MPC design	v	v
Computer hardware (PC)		
- Simulation	o	v
- Experiment on the set-up	o	v
Programmable automation controller (PAC)		
- Simulation	v	o
- Hardware-In-the-Loop experiments	v	v
- Experiments on the set-up	v	v
Programmable logic controller (PLC)		
- Hardware-In-the-Loop experiment	o	v
- Experiments on the set-up	v	v

o = not performed
v = completed
v = completed and will be presented now

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Obtaining a model

- A model describes the relation between the inputs and a outputs of a system.
- Many model types exist:
  - White box modeling
  - Gray box modeling
  - Black-box modeling
- Different properties
  - Linear versus non–linear
  - Parametric versus non parametric
  - …

Finally, a simple but accurate model is required

Model identification in this work

- Black-box model based on transfer functions, subspace state-space modeling and polynomial models according to the Box-Jenkins model structure.

- Model selection based on
  - Akaike Information Criterion
  - Operator knowledge

- Resulting model has been converted to state-space.
- Model reduction is applied if necessary.

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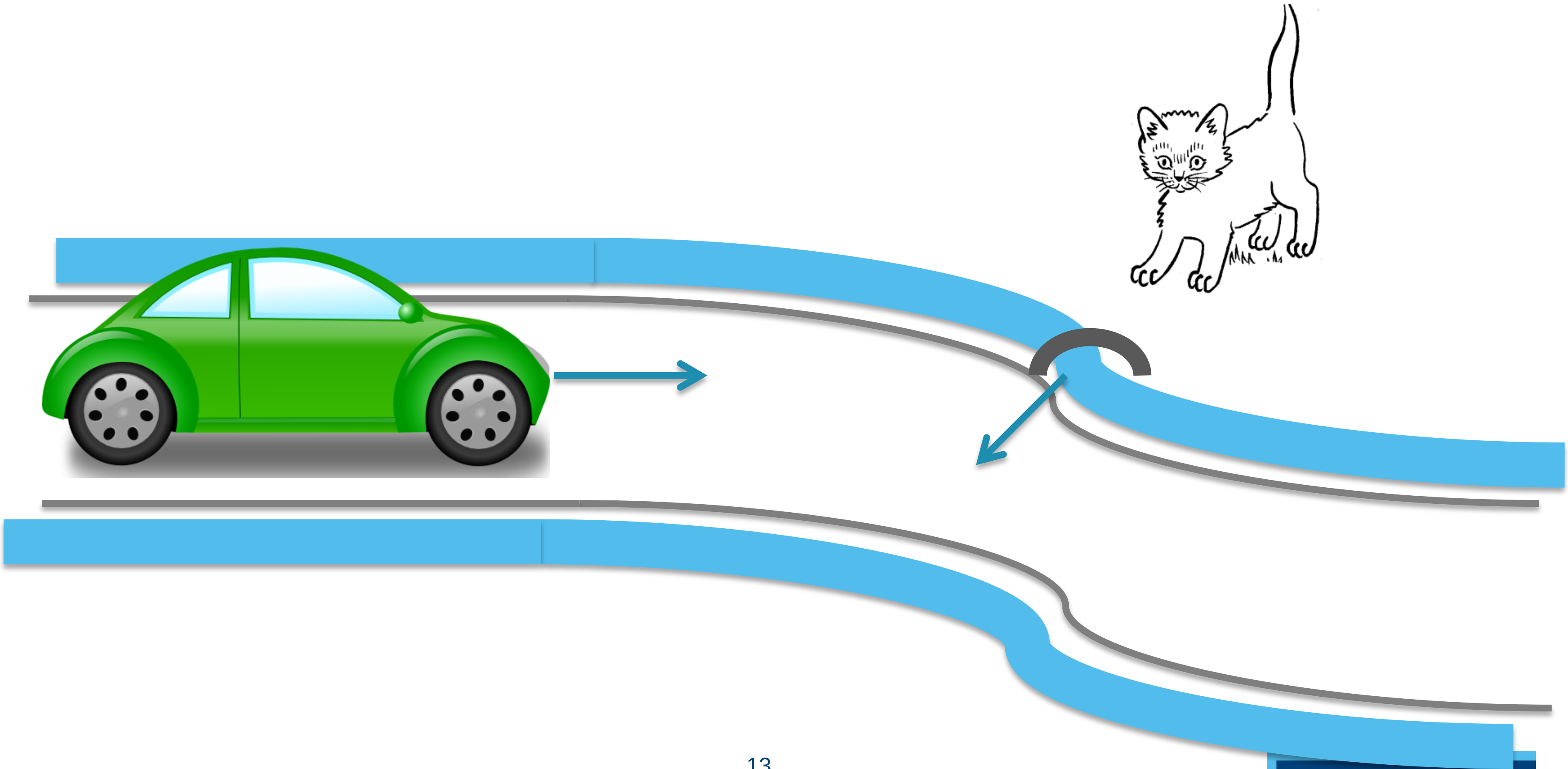
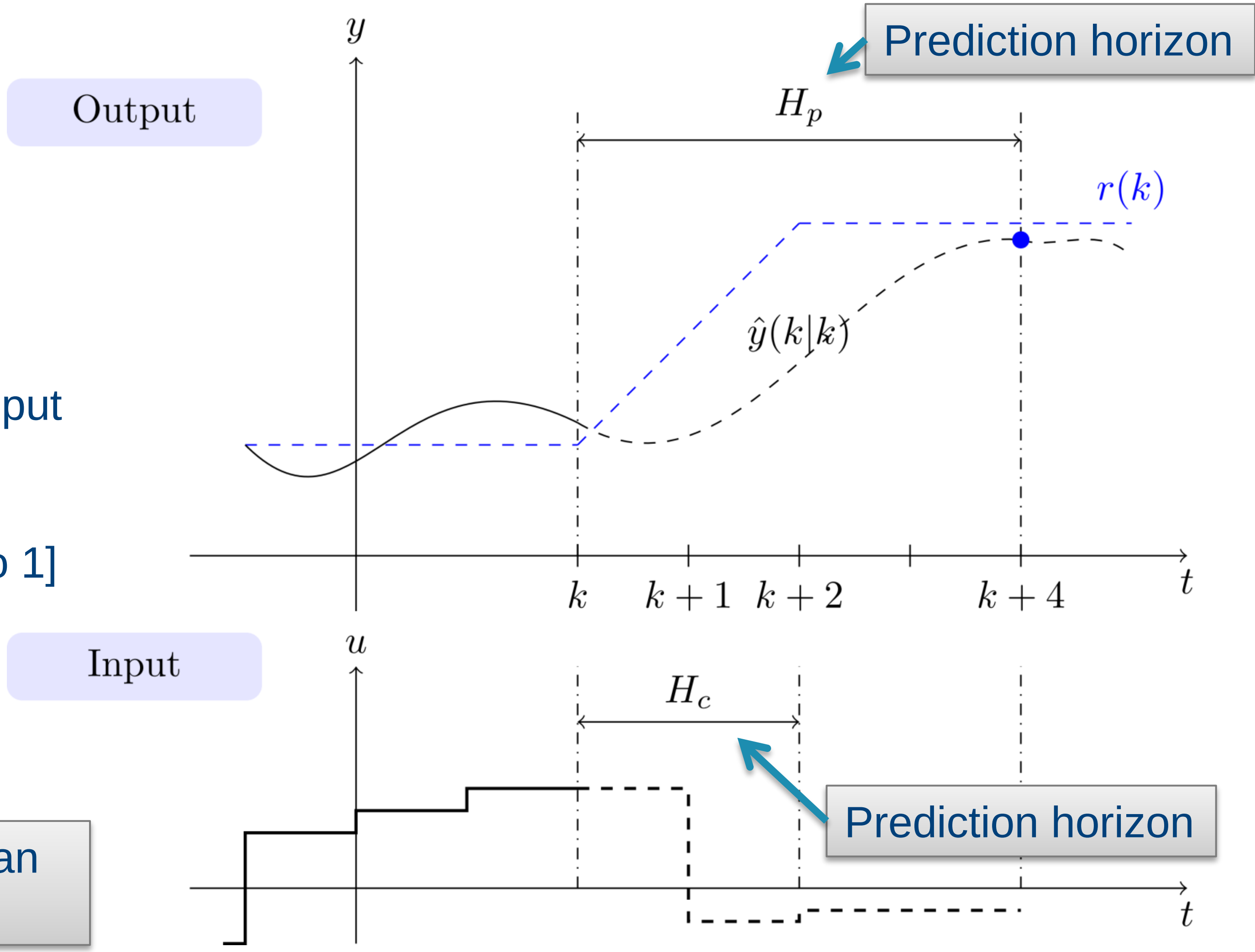
Model predictive control: the idea



Model predictive control in this work

1. Determine current status system
2. Select desired trajectory
3. Calculate optimal input sequence
4. Apply first input
5. [wait and go back to 1]



In- and outputs can be bounded

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MPC design

- Cost function

Stay close to output reference

Stay close to change on input reference

$$J = \sum_{i=1}^{H_p} \|\hat{\mathbf{y}}(k+i|k) - \mathbf{y}_{\mathrm{ref}}(k+i|k)\|^2_{W_y}$$

$$+ \sum_{j=0}^{H_c-1} \|\Delta\mathbf{u}(k+j|k) - \Delta\mathbf{u}_{\mathrm{ref}}(k+j|k)\|^2_{W_u} .$$

- Linear state-space model
- Bounds on the inputs

  → results in a Quadratic Problem

  → to be solved each time step

Implementation

Online solution methods

QP solvers

- Hildreth QP algorithm
- qpOASES
- CVXGEN

MPC + QP solver based on code generation

- CVXGEN MPC

Built-in MPC + QP solver on CompactRIO

- LabVIEW MPC

PLC

PAC

Devices characteristics

Programmable Automation Controller

- Less powerfull PC
- In- and outputs
- Typical 64 – 1 Gb of memory
- 10^7 – 10^9 FLOPS

Programmable logic controller

- Robust industrial controller
- Lots of in/outputs
- Typical max 8 Mb of memory
- 10^6 – 10^7 FLOPS

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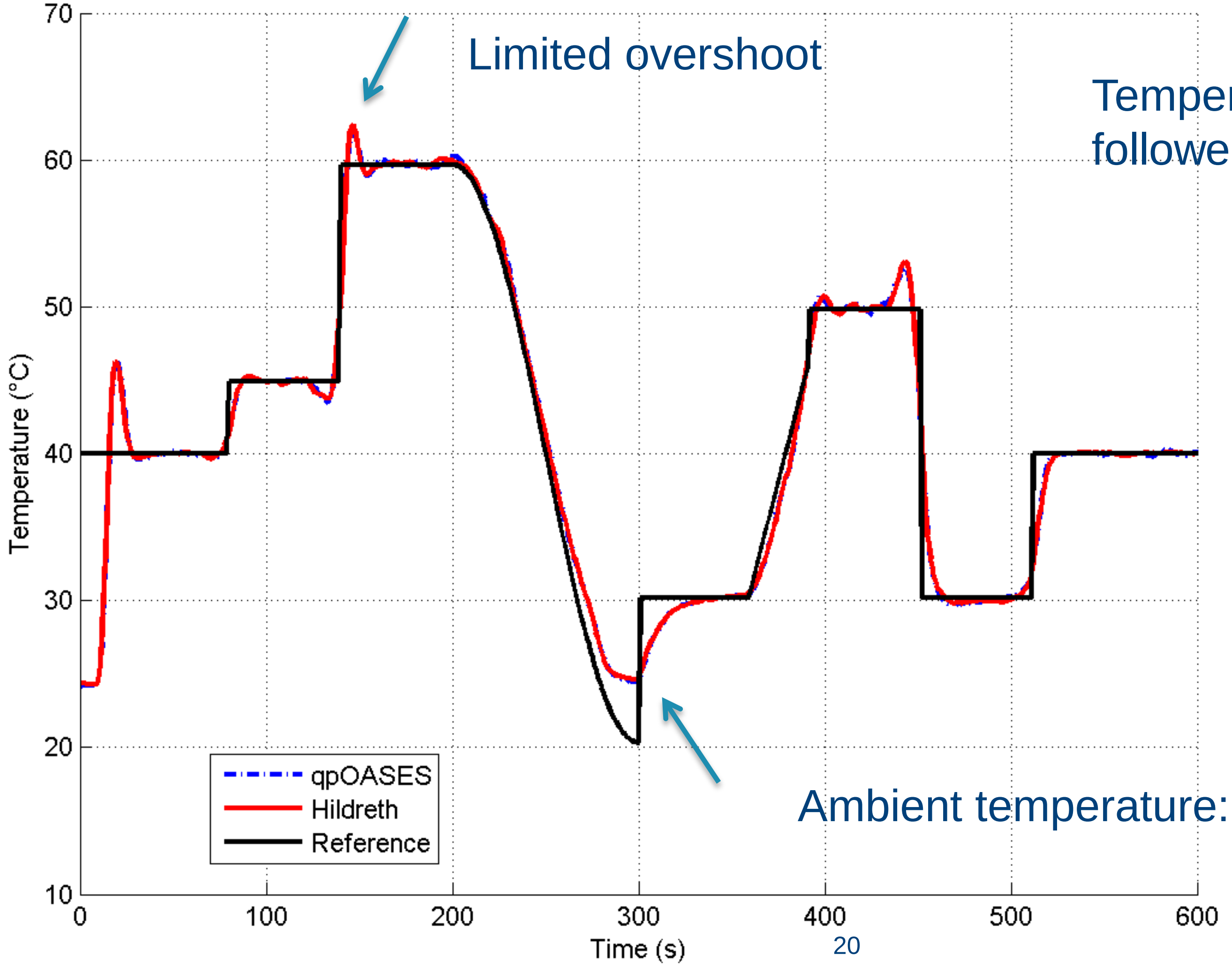
Case I: Air heating set-up

- Identification results:
  - 2 input – 1 output model based on transfer functions

$$T_{\mathrm{n}} = \begin{bmatrix} \frac{-0.98(\pm 0.03)}{1+5.17(\pm 0.39)s} e^{-1.34(\pm 0.22)s} & \frac{0.83(\pm 0.03)}{1+7.16(\pm 0.51)s} e^{-1.53(\pm 0.25)s} \end{bmatrix} \begin{bmatrix} u_{\mathrm{Fan,n}} \\ u_{\mathrm{Power,n}} \end{bmatrix}$$

  - Converted to a state-space model (4 states)
- MPC settings:
  - Control horizon: 7
  - Prediction Horizon: 22
  - Cost function weight matrices:
    - Diagonal elements: 1
    - Off-diagonal elements: 0

Case I: MPC on PLC: output

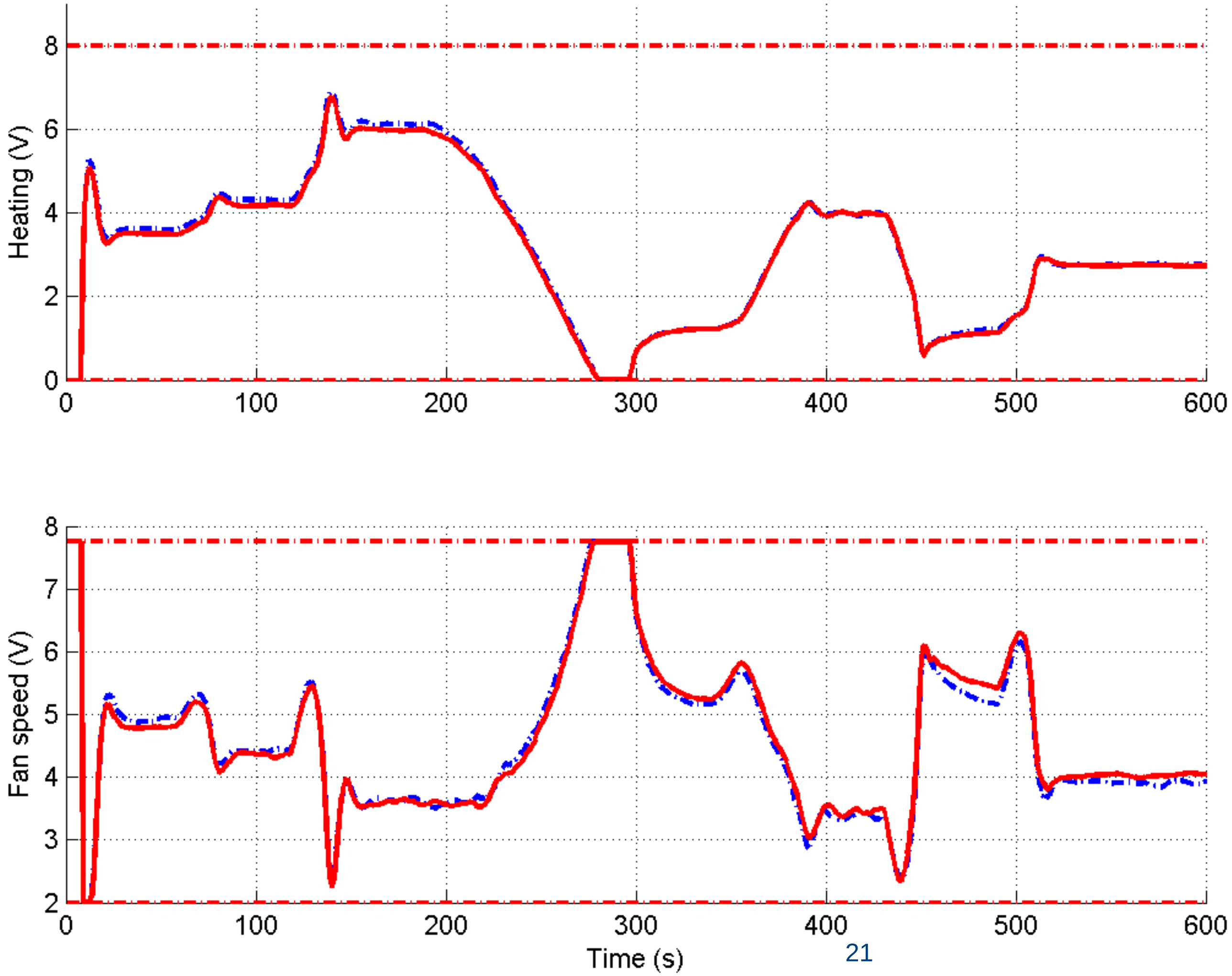


Limited overshoot

Temperature reference followed accurately

Ambient temperature: 26°C

Case I: MPC on PLC: inputs

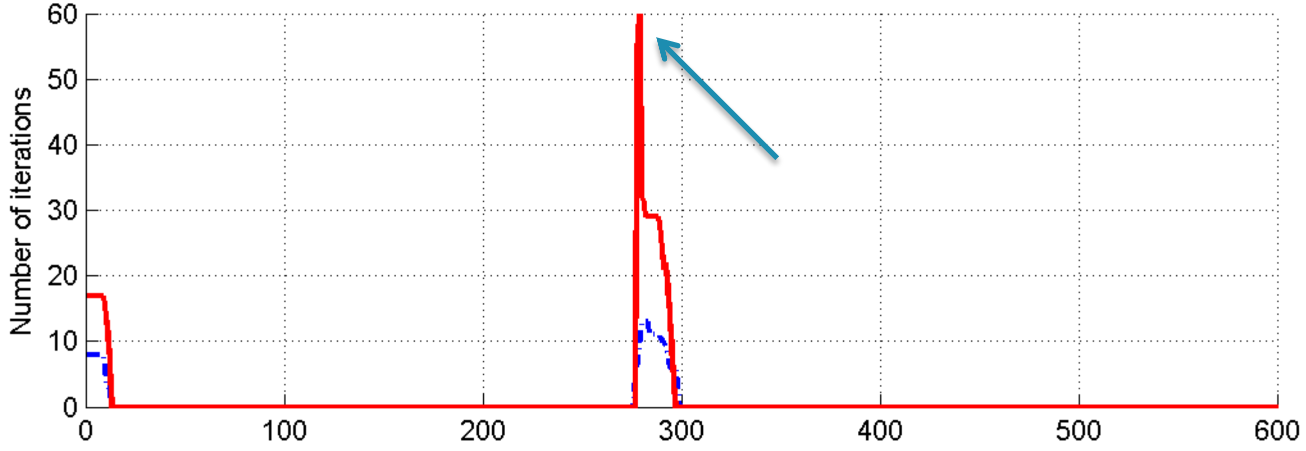


No constraints violated

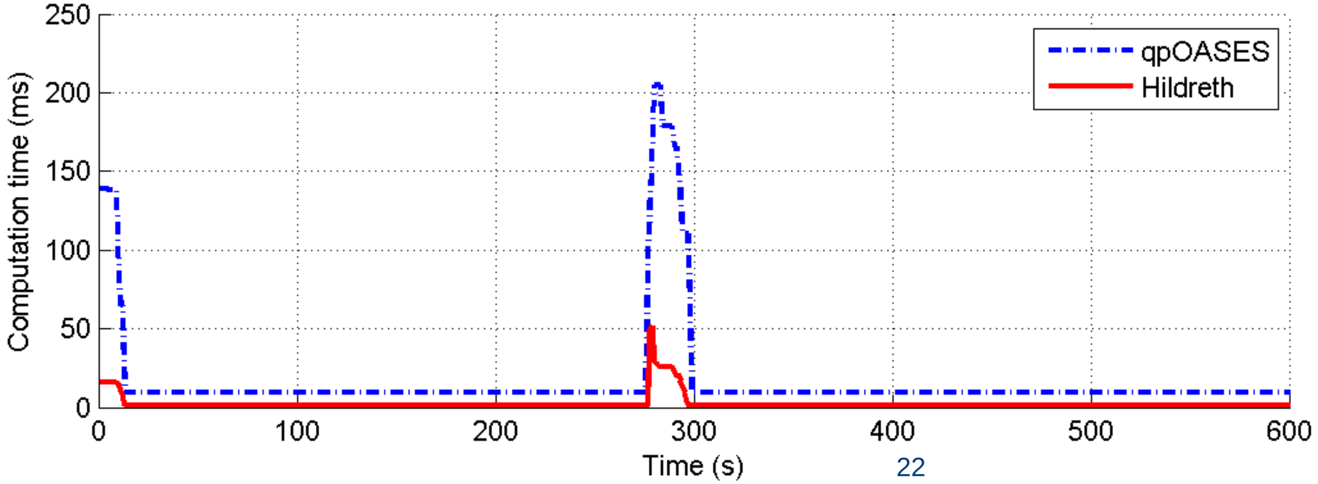
The different experiments are close to each other.

Differences caused by slightly different environmental conditions.

Case I: calculation time/iterations



Maximum number of iterations lower than allowed for qpOASES, but reached for Hildreth.



Calculation time for Hildreth lower compared to qpOASES.

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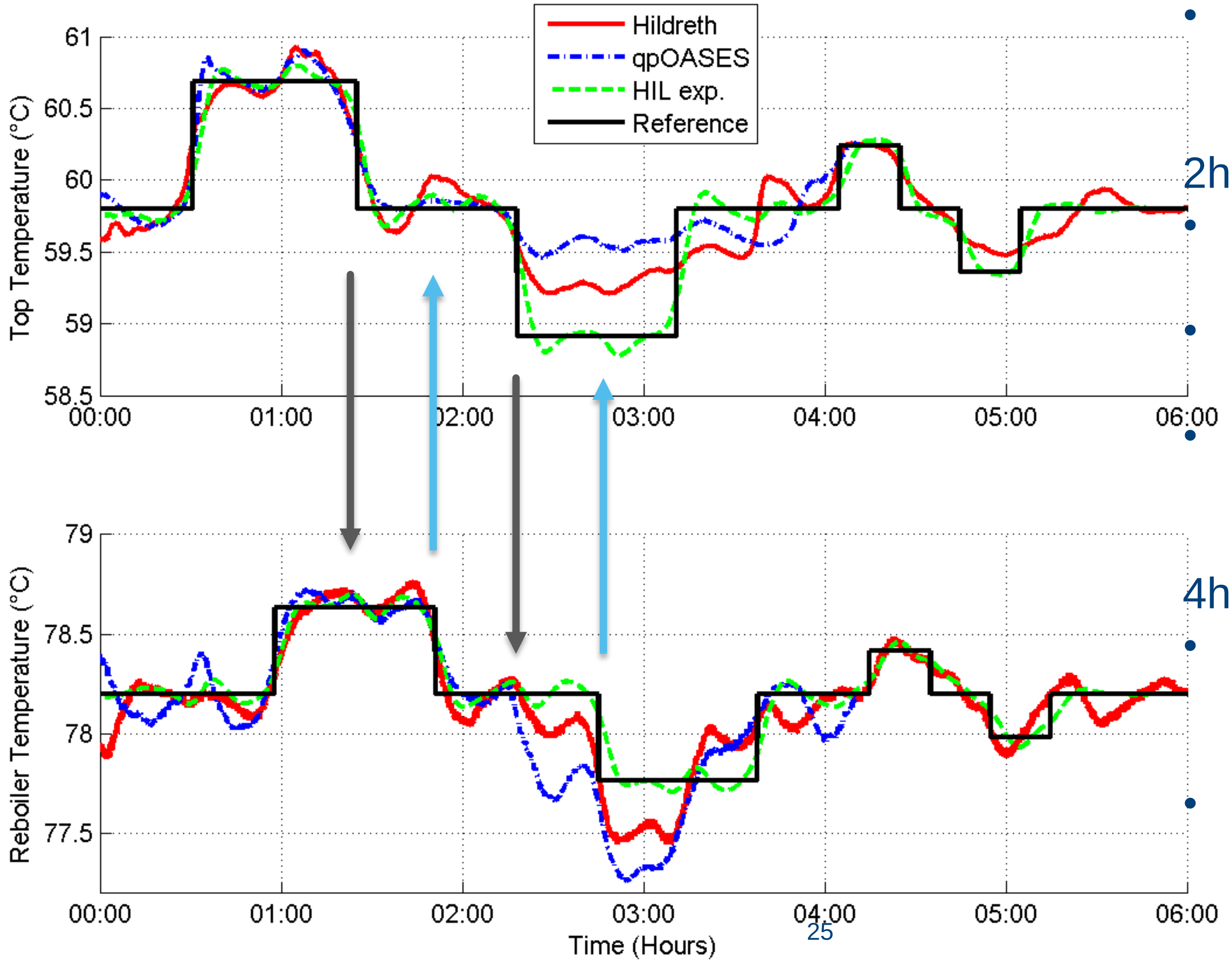
Case II: pilot-scale distillation column

- Model identification:
  - 4 input – 2 output model

$$\begin{bmatrix} Tt \\ Tb \end{bmatrix} = \begin{bmatrix} \frac{-2.26}{(1+2565s)(1+135s)} & \frac{0.53}{1+735s} & \frac{3.74}{(1+1803s)(1+78s)} & \frac{-3.45}{(1+2698s)(1+72s)} e^{-53.3s} \\ \frac{-1.87}{(1+890s)(1+169s)} & \frac{0.62}{1+1465s} e^{-307s} & \frac{5.21}{(1+2864s)} e^{-43s} & \frac{-2.36}{(1+1275s)(1+525s)} \end{bmatrix} \begin{bmatrix} \mathrm{Fv} \\ \mathrm{Qv} \\ \mathrm{Qr} \\ \mathrm{Fr} \end{bmatrix}$$

  - Converted to a (reduced) state-space model (13 states)
- MPC settings:
  - Control horizon: 10
  - Prediction Horizon: 50
  - Diagonal elements in cost function weight matrices:
    - Punish temperature deviations more at top than bottom
    - Encourage the use of flow rates

Case II: MPC on PAC



First 2 hours:

- Small deviations from HIL experiment
- Only temperature increases

2h to 4h

- Large deviations from HIL experiment
- Top temperature does not decrease enough.
- Reboiler temperature decreases too much.

4h to 6h

- Repeated sequence of first 4 hours, but faster & smaller steps
- HIL experiment followed more closely

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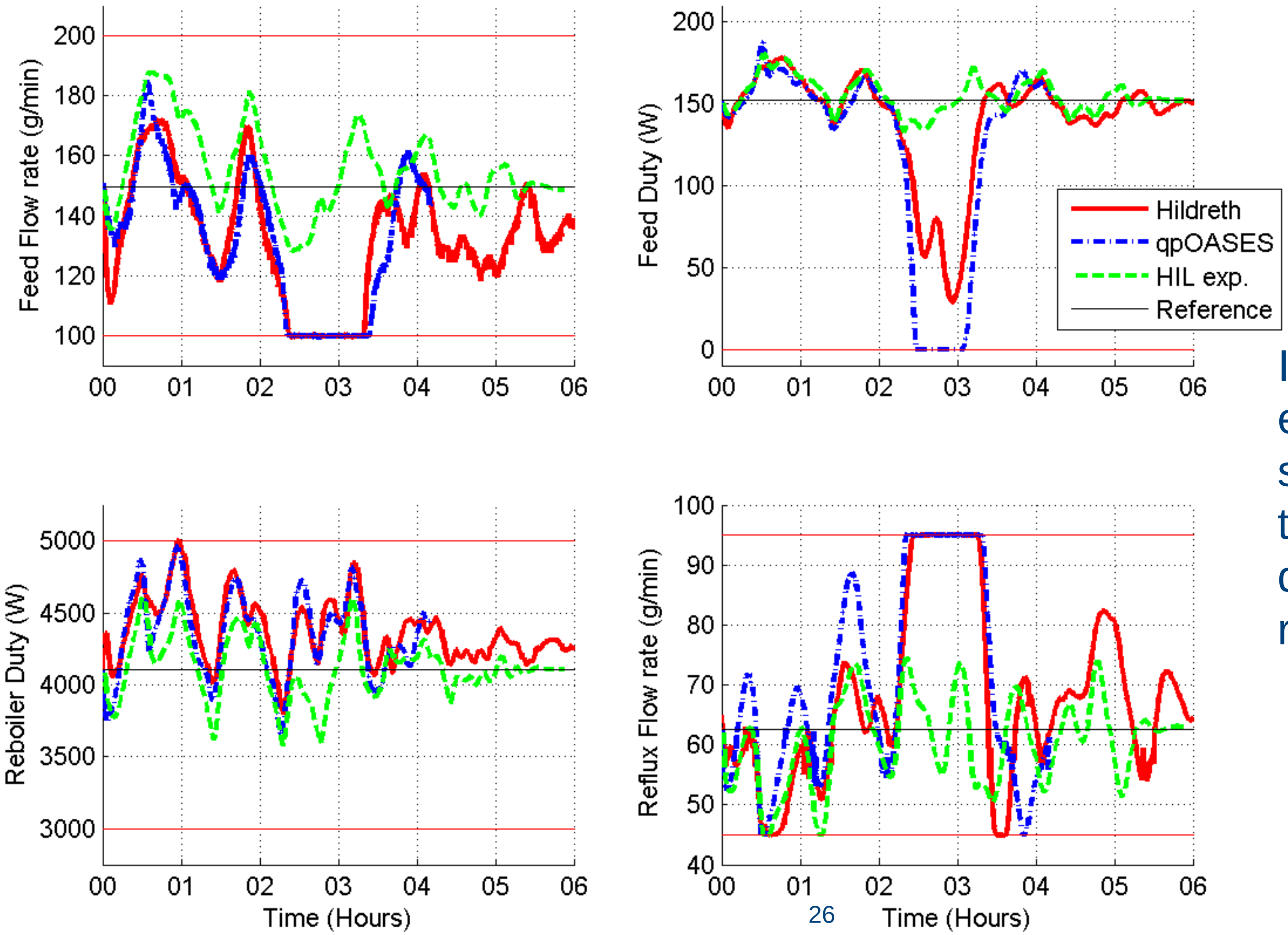
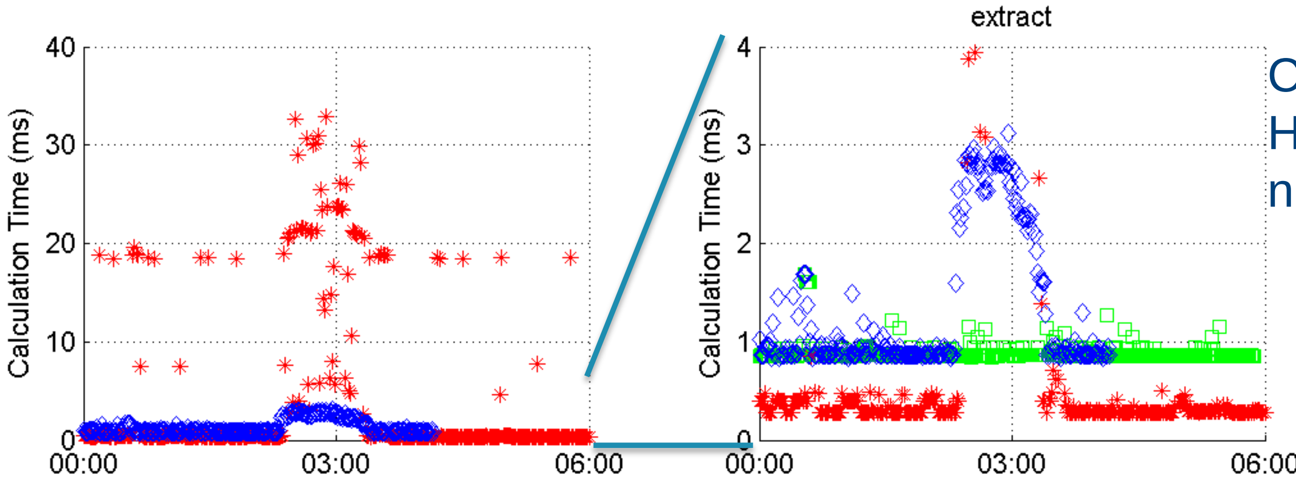
Case II: MPC on PAC

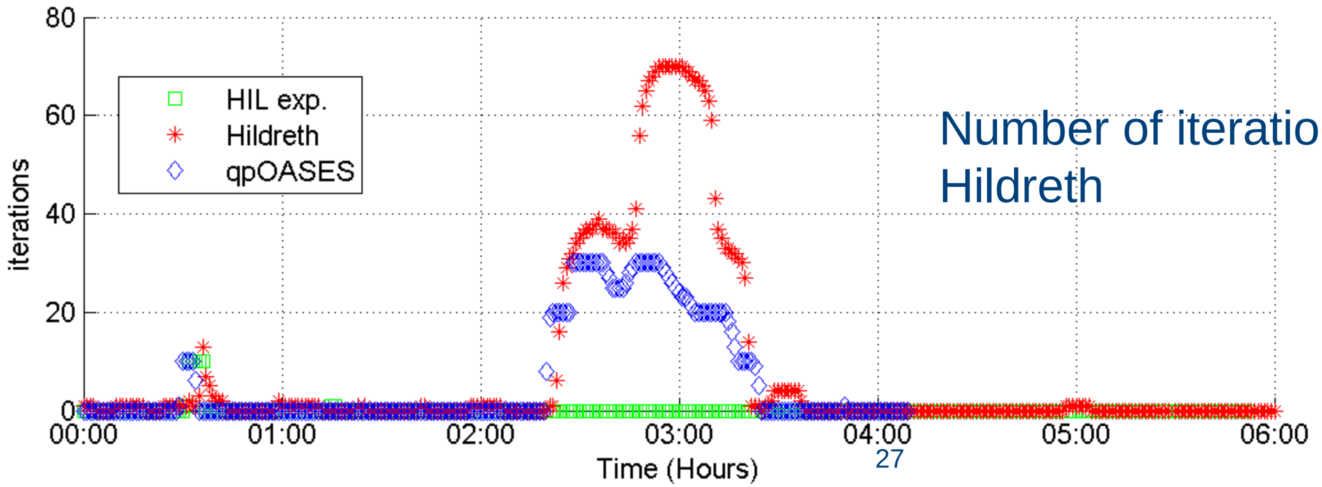


Input bounds hit for experiments on the set-up. This causes the temperatures to deviate from the reference.

Case II: calculation time/iterations



Calculation time lower for Hildreth, except for large number of iterations



Number of iterations higher for Hildreth

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Discussion

- Implementation of model predictive controllers on commonly used industrial devices has been investigated.
  - PAC: successful and promising for practical industrial use in industry.
    - Easy-to-use software
    - Fast, flexible hardware
  - PLC: possible, however only suitable for niche market
    - Reason: state-of-the-art QP solvers not programmed in a typical PLC language.
    - Too slow devices for this type of controllers

Conclusions

- Online MPC has been implemented on a PLC for two case studies:
  - Air heating set-up
  - Pilot-scale distillation column
- Successful completing of the loop to set up a controller including problem definition, model identification, MPC design and implementation on industrial hardware.
- Evaluation of performance for several industrial control devices with decreasing computational power
  - (PC →) PAC → PLC

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Thank you for listening