Operational Optimization of Energy Systems

25 years of experience

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Outline

- Use Case
- Past Developments
- Optimization of Operation
- Demand Forecasting
- Outlook

Use Case

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- Operational Optimization of an energy supply system
  - System automation and planning purposes
  - Objective: minimizing operational costs
- Local energy provider
  - Supply area: medium-sized city, approx. 200.000 inhabitants
  - 40% of buildings connected to district heating network
  - Length of district heating network approx. 300 km
- Supply system
  - CHP units, heat plants, heat accumulators, steam generator, auxiliary coolers
  - Minor share of renewable energies

Past Developments - Use Case

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- First algorithm applied on a mainframe
- Fixed-order of operations
- Supporting the operation of the heat accumulator
- No consideration of electricity supply

- Combined method of dynamic programming and linear optimization
- First long-term optimizations up to one year

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- Combined optimization of heat and power supply
- First advanced demand forecasting algorithm

- Formulation as a mixed integer linear problem
- Reduction of the time step size
- Introduction of a graphic user interface

- Model improvements and adjustments
- Refinement of the demand forecasting algorithm
- Integration of electricity trading and balancing power
- Interface to external software

Operational Optimization

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- Objective:
  - Minimizing operational costs
  - Including fuel, starting processes, CHP cogeneration bonus, power trading, system usage charges, CO_2 certificates
- Constraints:
  - Balance equations for heat, power and steam
  - Technical boundaries, logical constraints
- Mixed integer linear optimization
- Optimization environment: GAMS + CPLEX
- User interface: FORTRAN and C++

$$\min_x c^T x \quad \text{subject to}$$

$$A_\mathrm{E} x = b_\mathrm{E}, \quad A_\mathrm{I} x \leq b_\mathrm{I}, \quad x_\mathrm{L} \leq x \leq x_\mathrm{U}$$

$$x = (x_1, \ldots, x_n)^T, x_j \ldots \text{integer or continuous}$$

System size

per time step:

- approx. 200 continuous variables
- approx. 30 integers variables
- approx. 250 constraints

(before reduction by the solver)

Operational Optimization - Process

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Long-term optimization

- Long-term contracts
- Period: several month - one year

data input

Strategic scenario analysis

1. Data collection
   - Measurements
   - Demand forecasts
   - Electricity prices
   - Generator availabilities

2. Optimization
   - Period: one day - two weeks
   - Step size: 15 minutes

fixed bounds

Control

1. Data update
   - Measurements
   - Demand forecasts

2. Optimization
   - Period: 8 hours
   - Step size: 15 minutes

3. Downscaling
   - One minute values

iteration every 15 min.

control

Supply system

Management database

external input

monitoring

System operator

Operational Optimization - Example

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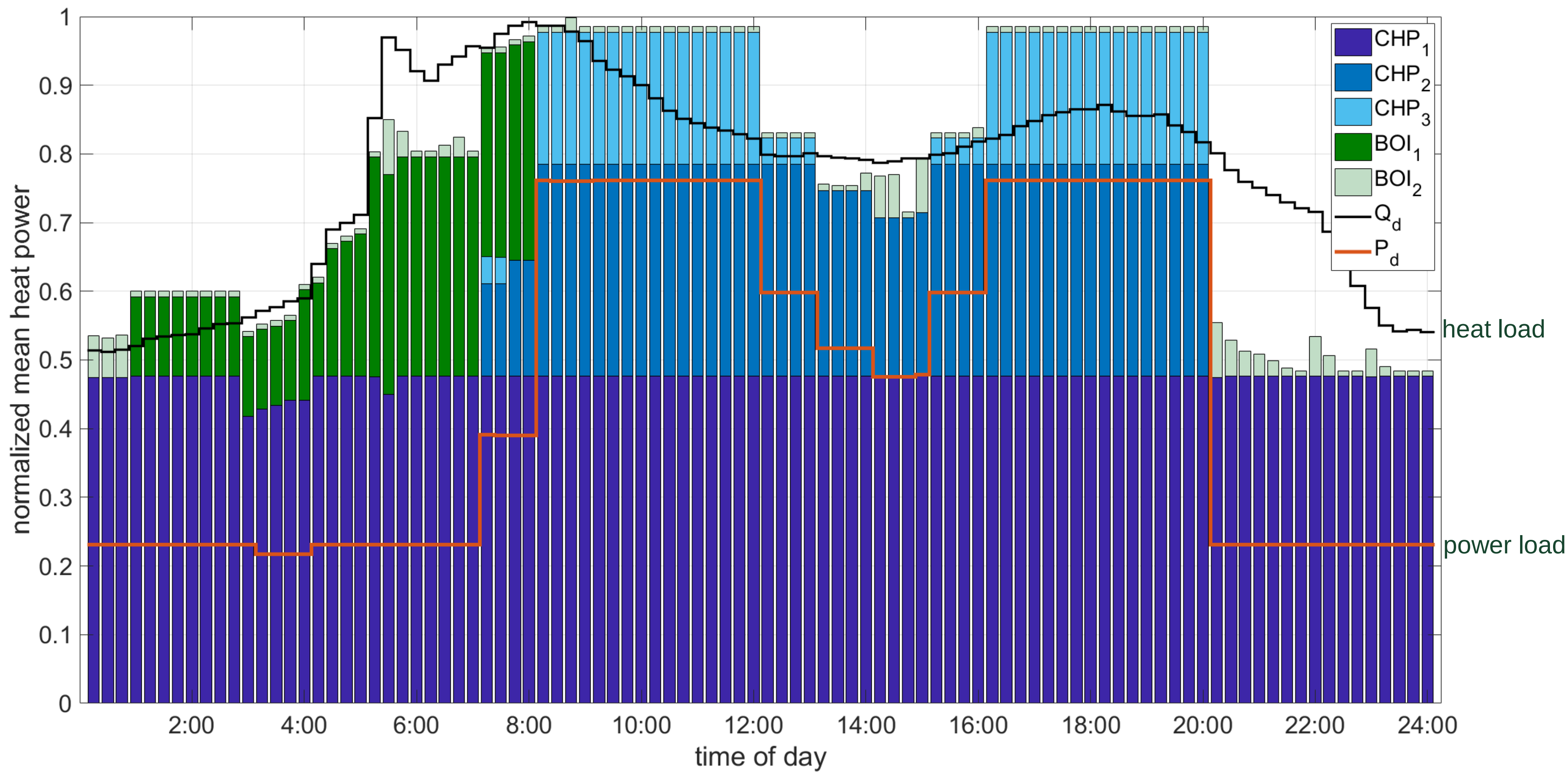
Heat balance, optimization period of 24 hours



Operational Optimization - Example

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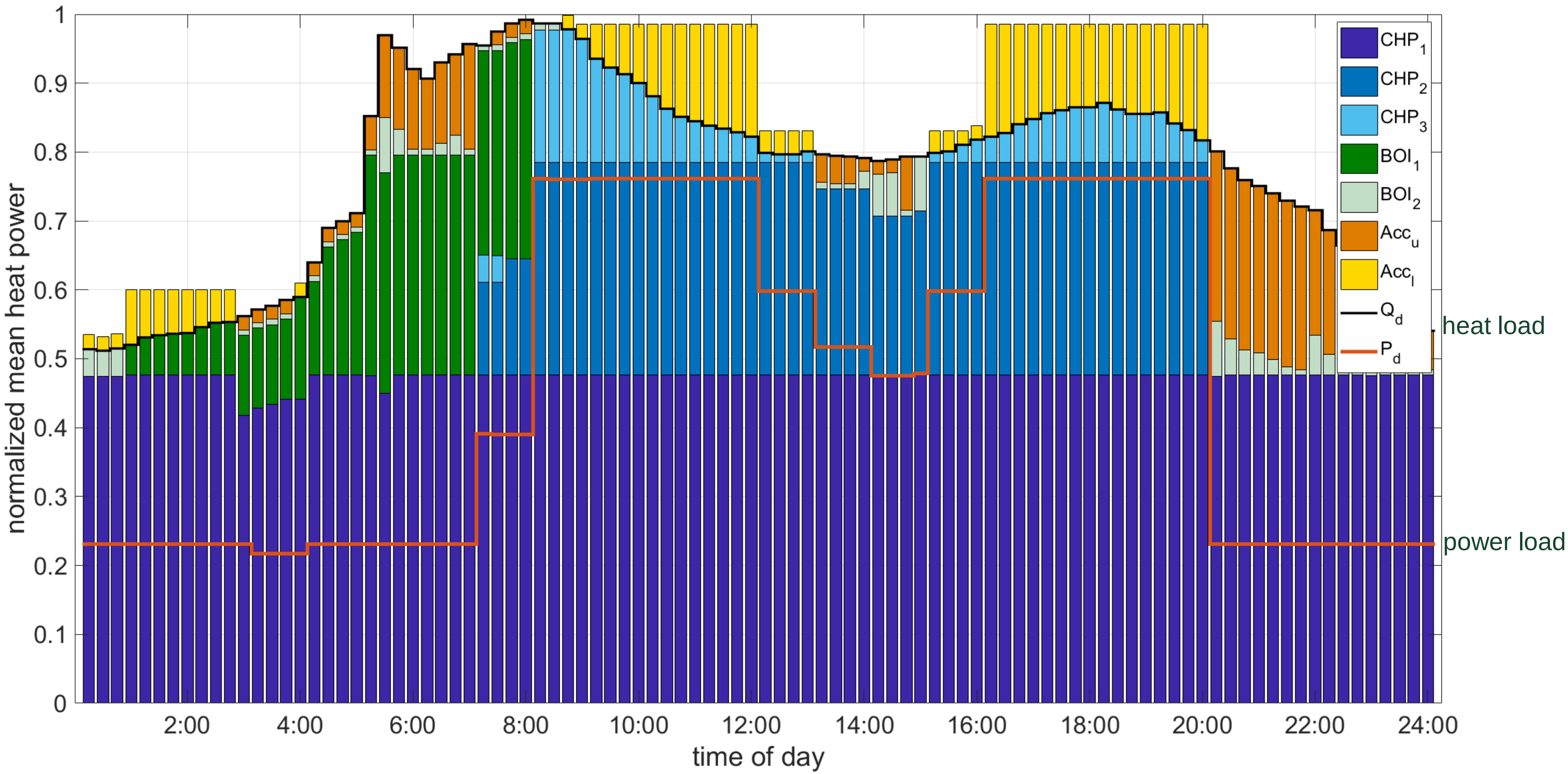

Demand Forecasting - Method

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- Forecasting of local heat and electricity demand
- Method is based on multiple linear regression and time series analysis
- Multiple linear regression (heat case):
  - Model includes 36 explanatory variables
  - Weather data, date dependent binaries, transformations
  - Categorization by timeframes of 15 minutes

$$\dot{Q}_{f,\tau} = k_1 + \sum_{i=2}^{n} k_i X_{i,\tau}$$

- Time series analysis of the residual:
  - Second order autoregressive model
  - Seasonal first order autoregressive model with seasonality of seven days
  - First order autoregressive model to connect categorized time frames

$$R_\tau^t = a_1 R_\tau^{t-1} + a_2 R_\tau^{t-2} + s_1 R_\tau^{t-7} - a_1 s_1 R_\tau^{t-8} - a_2 s_1 R_\tau^{t-9} + c_1 R_{\tau-1}^t$$

Demand Forecasting - Example

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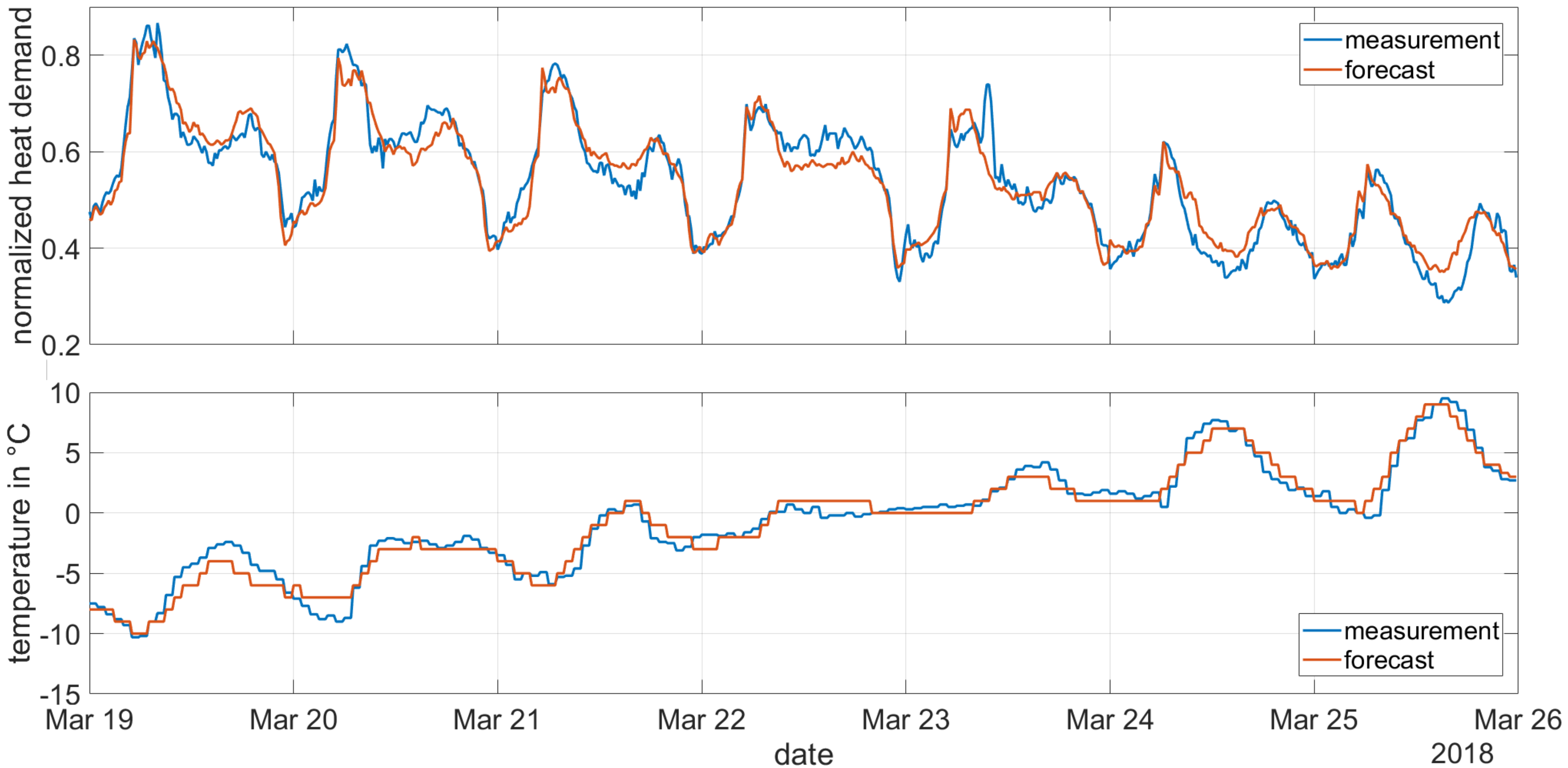
Comparison between actual and daily forecasted heat demand, sample week



(temperature forecast provided by German Meteorological Service (DWD))

Demand Forecasting - Example

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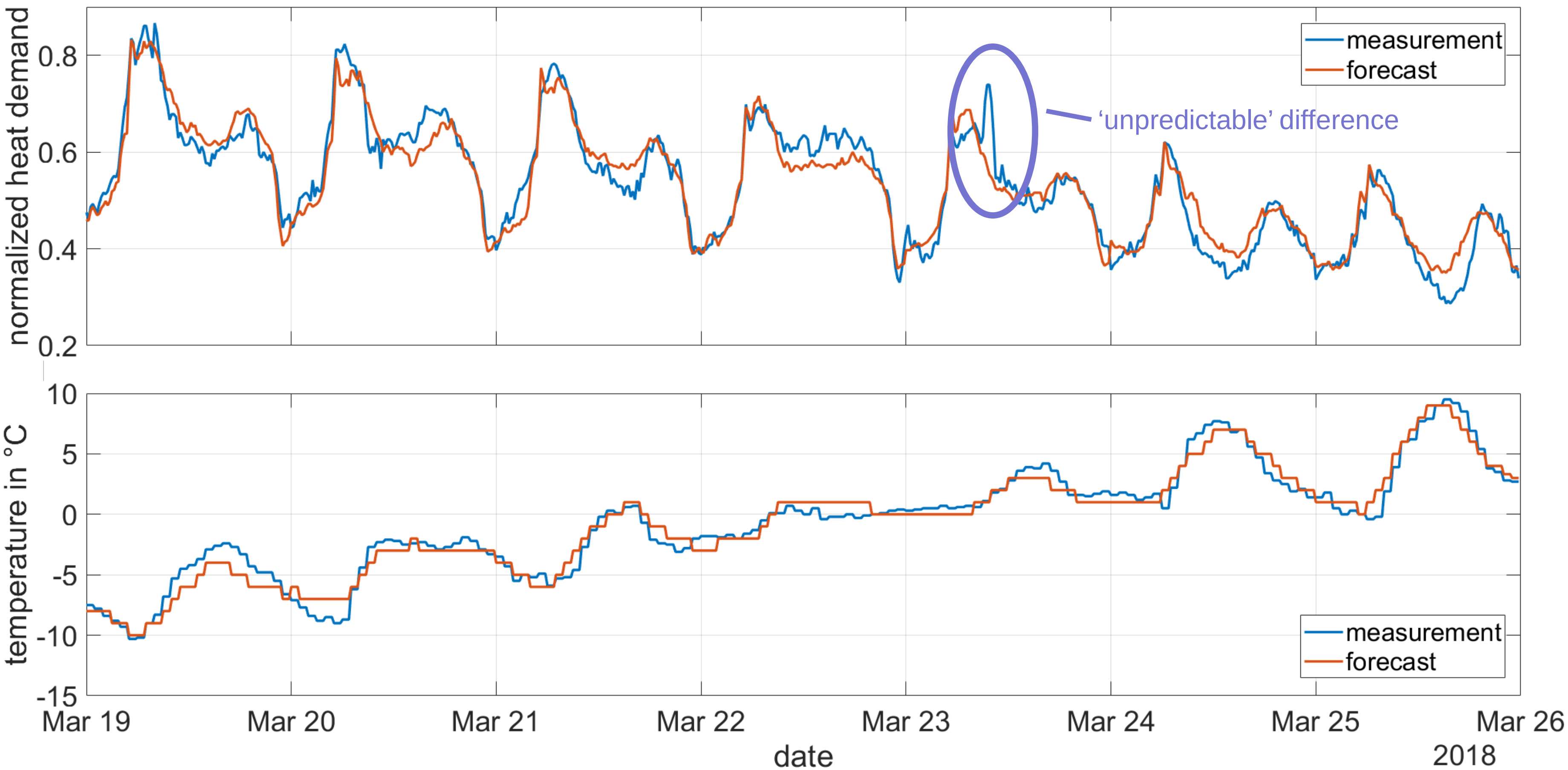

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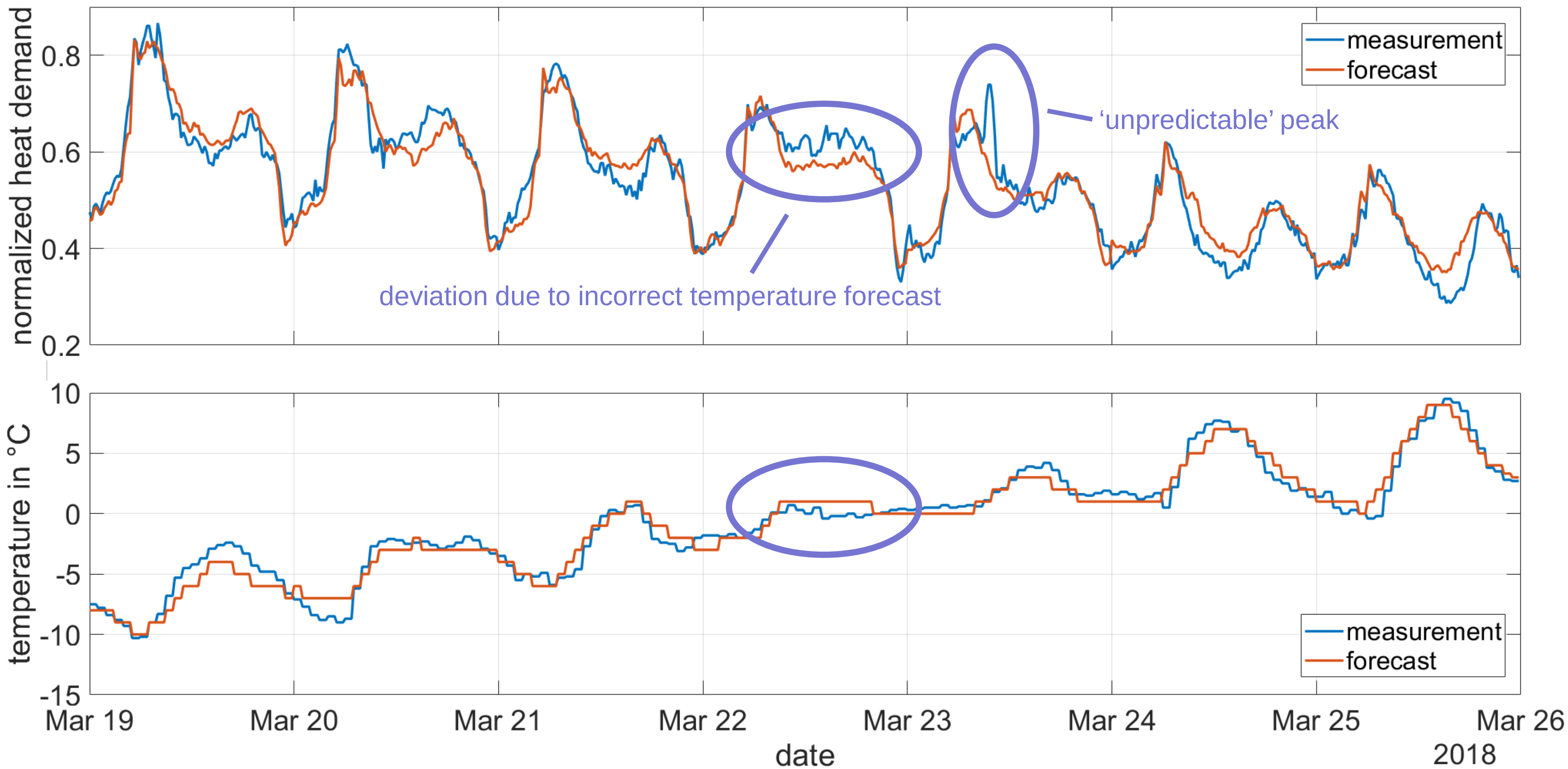

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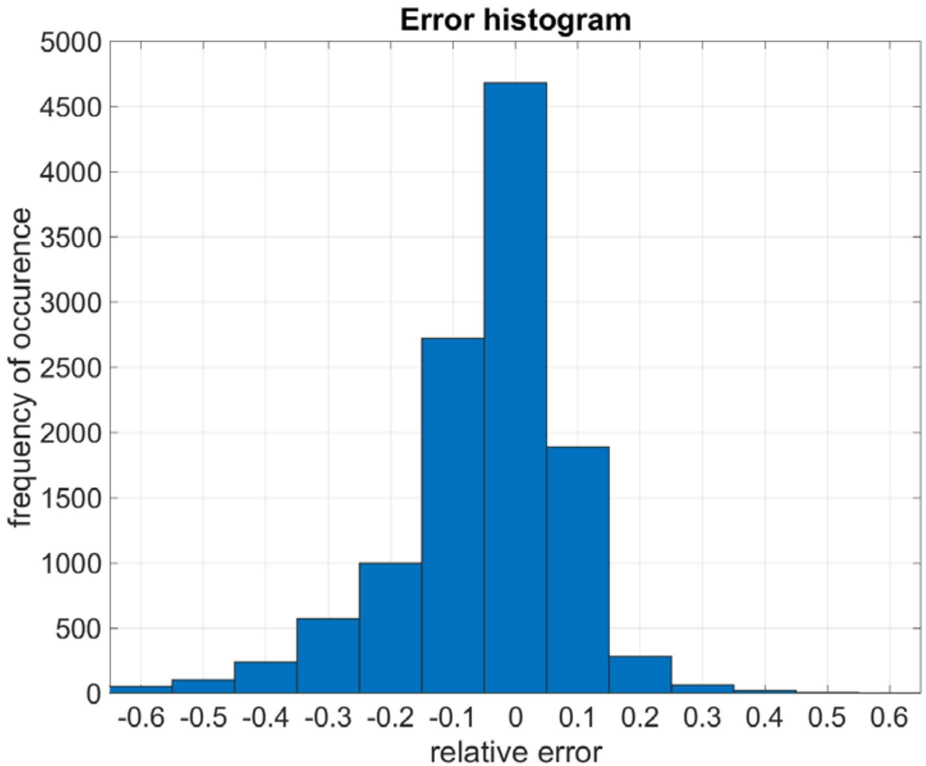

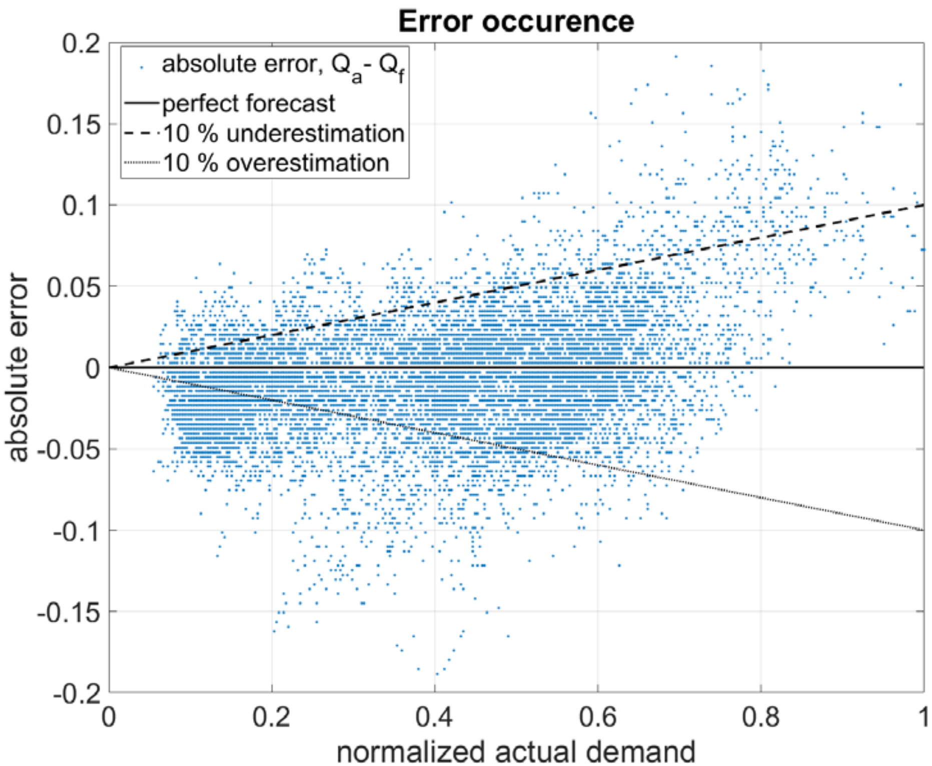

Observed period:

11.01. – 15.05.2018, 11.616 data points

75 % of data: $err_{rel} < 12$ %
95 % of data: $err_{rel} < 31$ %
max. $err_{rel} = 116$ %

period	time step	MAE	R^2
19.3. – 26.03.	15 min.	0.028	0.914
11.01. – 05.15.	15 min.	0.029	0.963

MAE … mean absolute error
R^2 … coeff. of determination

Outlook

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- Consideration of uncertainties
  - Balancing power, demand data, prices
- Model improvements
  - Network related constraints
  - Advanced models for the heat accumulator
- Smaller scale applications, e.g., small districts, single-family houses
- Design of energy supply systems
  - Based on operational optimization
- Alternative objectives or multi-objective optimization
  - CO_2 – emissions, self-sufficiency, home consumption, lifecycles

Thank you for your attention!

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