



Fraunhofer UMSICHT/aviate Luftaufnahme

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How Forecast Errors affect Optimal Scheduling and Control
of Local Cross Energy Systems

Outline

1. Introduction
2. Study Case & Framework
3. Tools
4. Results
5. Conclusion & Outlook



Quelle: MEV-Verlag

Introduction

Baseline

a) Growing electricity demand

- Coalition Agreement 2021: „680-750 kWh in 2030“
(+20% to +33% compared with 565 TWh in 2021)

b) Increasing share of renewables

- Coalition Agreement 2021: „80% by 2030“
(41.1% in 2021)

[„Mehr Fortschritt Wagen“](#)

Coalition agreement between SPD, BÜNDNIS 90/DIE GRÜNEN and FDP

[Data of Electricity Consumption | Federal Environmental Agency \(UBA\)](#)

Solution?

- More battery storage
- Expansion of transmission grid
- Expansion of distribution grid

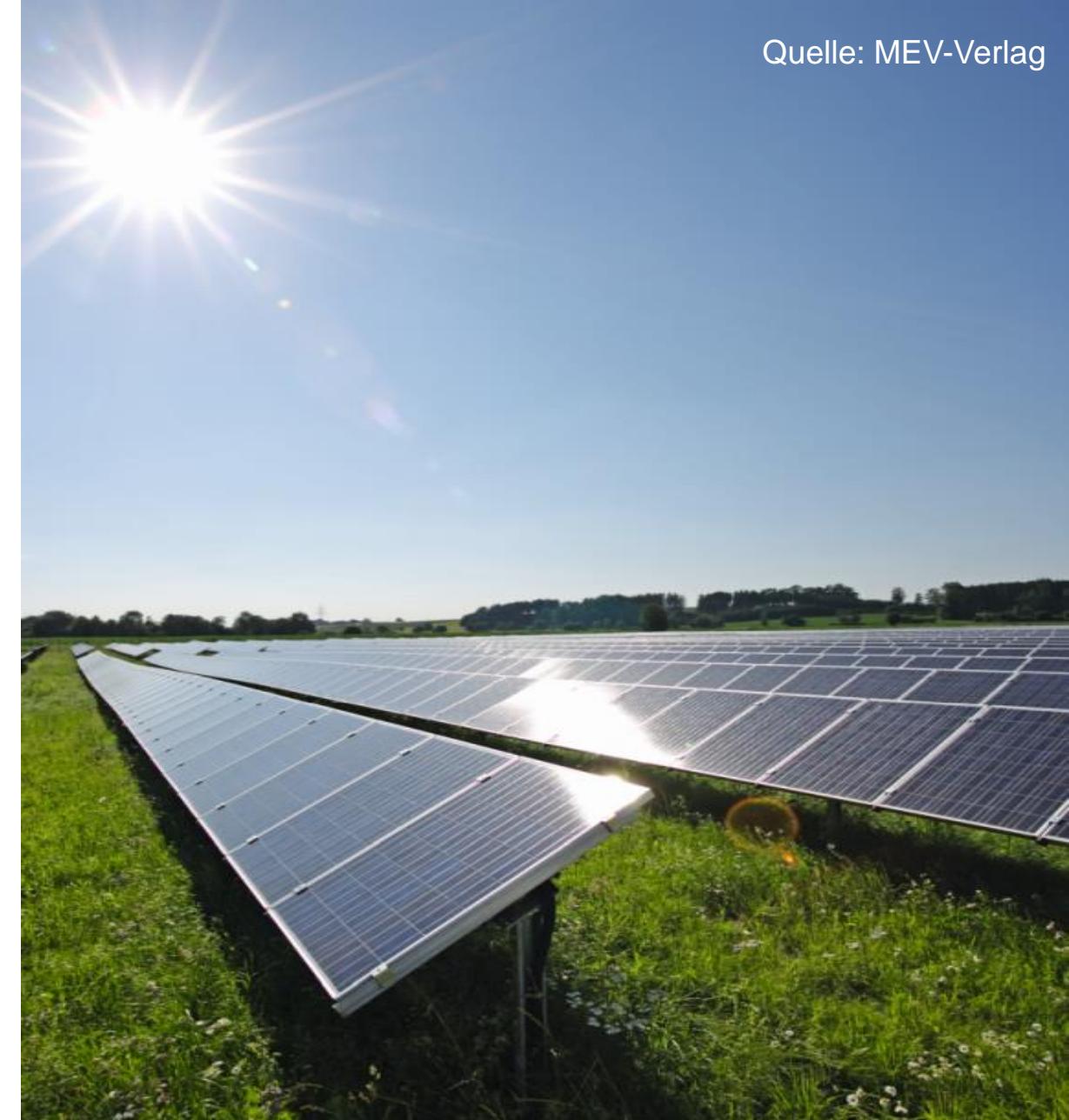


Introduction Requirements

Information flow from high level to low level

- Varying electricity prices
- Varying grid prices
- Incentives for an efficient use of existing resources

Optimal Scheduling and Control



Introduction

Optimal Scheduling and Control

Optimal Scheduling = Operational Optimization

- Create a model of the existing energy system
- Input expected electricity prices
- Input expected demands
- Input expected on-site generation

- Get operation schedule with minimal possible costs

And Control ?

- Deviations in heating and cooling sector may make interventions during control necessary



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Study Case

Energy System at Hand

Augusta Hospital Hattingen

- Medium size hospital (~300 beds)
- Energy consumption 2020:
 - Gas: 8,300 MWh
 - Electricity: 1,100 MWh
- Generation units:
 - Gas boiler: 2x 1,250 kWth
 - CHP: 500 kWth, 330 kWel
 - Thermal Storage: 14 qm
 - (Compression Chiller: 500 kW)
- Measurements:
 - 1 min resolution
 - Full data set for 13 months
 - Outside temperature from DWD in Essen-Bredeney

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



Study Case

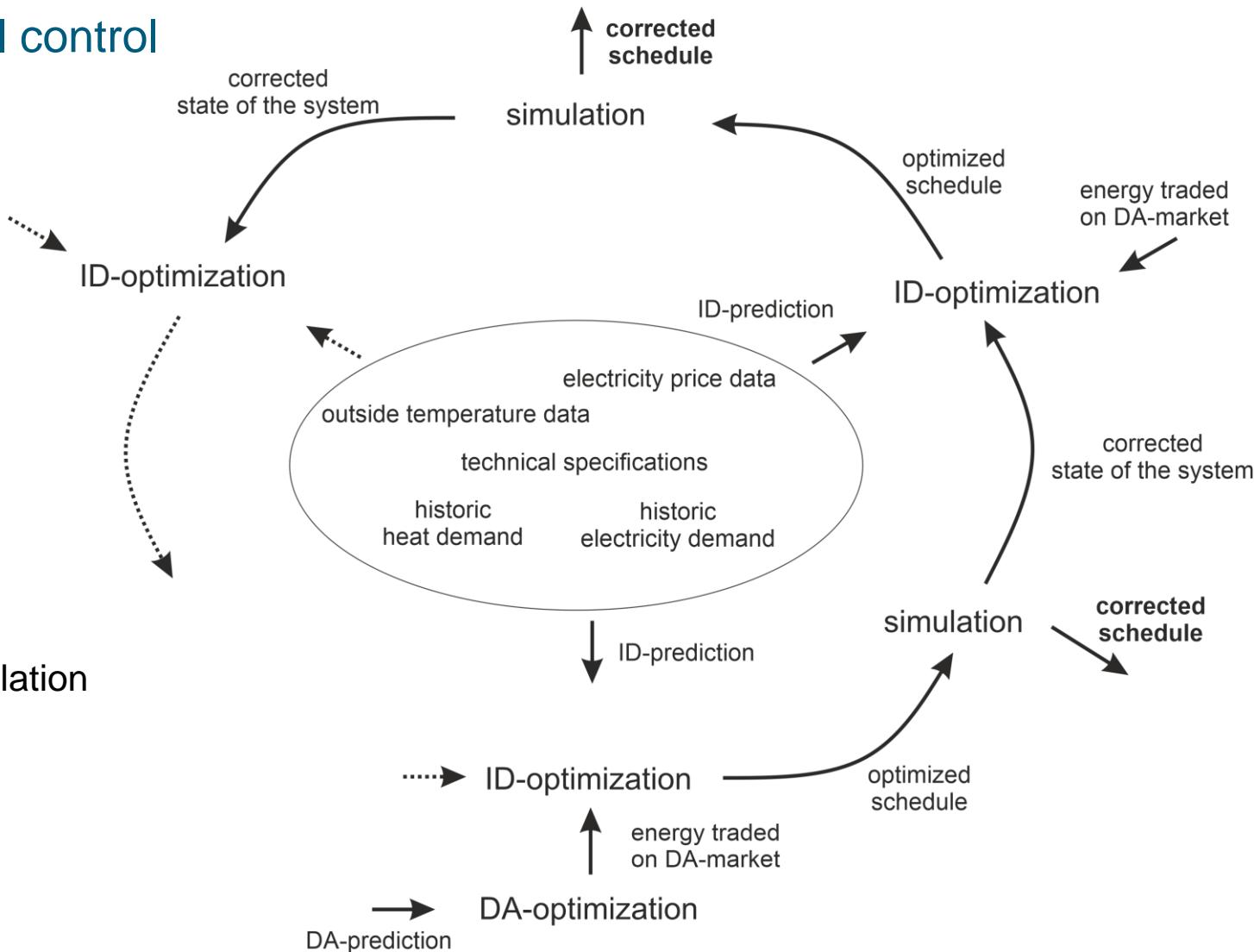
Towards stock-price oriented, cost-optimal control

Markets to participate in:

- Day-ahead Market: 12 am
- **Intraday Auction: 3 pm**
- Continuous Intraday Market (OTC): t-5min

Framework:

- Ideal price predictions (no taxes, no fees)
- Ideal electricity demand predictions
- Ideal outside temperature predictions
- Identical system behavior in optimization and simulation
- **Real predictions on heat demand**



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Prediction Models

What is needed?

Intraday-Auction:

Closure 3 pm, Delivery Period from t+9h until t+33h

Continuous-Intraday-Market:

Closure t-5min, Delivery Period from t until t+24h

Look ahead for optimization of 12 hours

→ **Prediction horizon from 15 min to 45 hours
in 15 min resolution (45 times 4 values)**

Prediction Methods

Persistence Forecast:

Shift historic values by fixed number of hours

ARIMA/SARIMA Forecast:

Rule based forecast using values from previous season

Machine Learning Forecasts:

self-learning on defined set of historic training data

(Decision trees, support vector machines, deep or **shallow ANNs**, ensemble methods, pre-training, transfer learning...)

Prediction Model Building

Creating ANN predictions

Single-Model-Prediction (Multivariate):

Complicated model, many hours not needed

Iterative-Prediction (Univariate):

Easy to train, poor performance

Multi-Model-Prediction (Uni- or Multivariate):

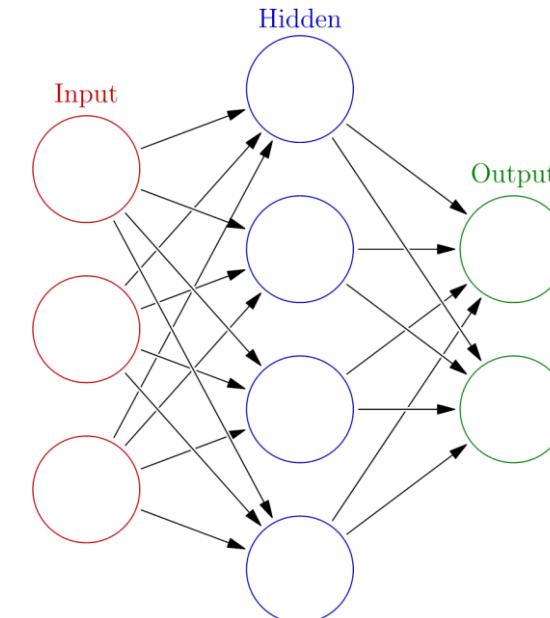
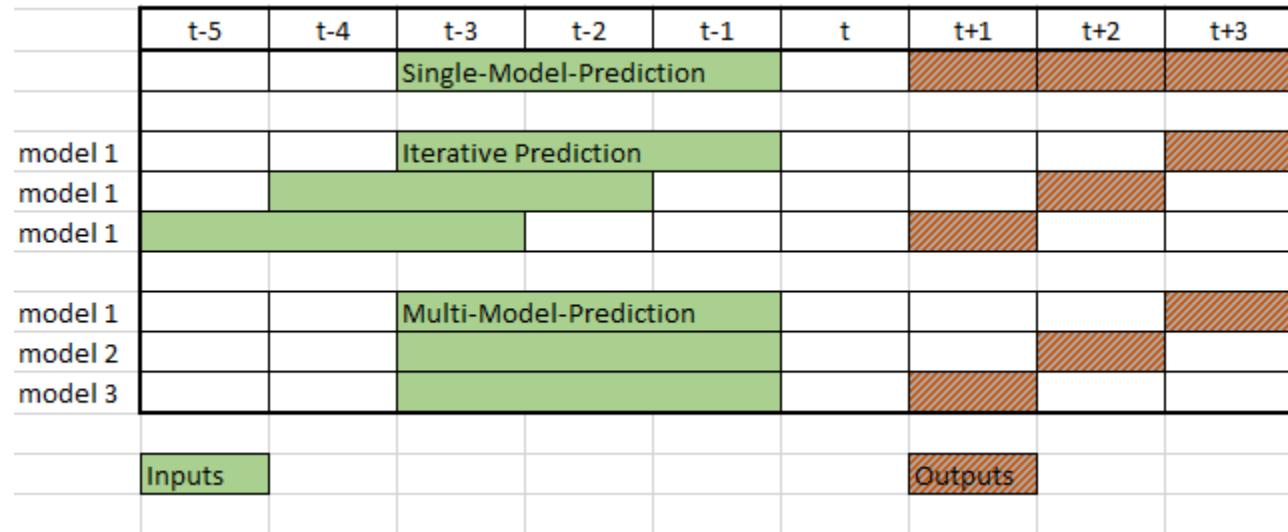
Many models with different horizons

→ **45 Prediction Models, one for each hour**

Benchmark

Persistence Forecast

(+48 hours or +24 hours where applicable)

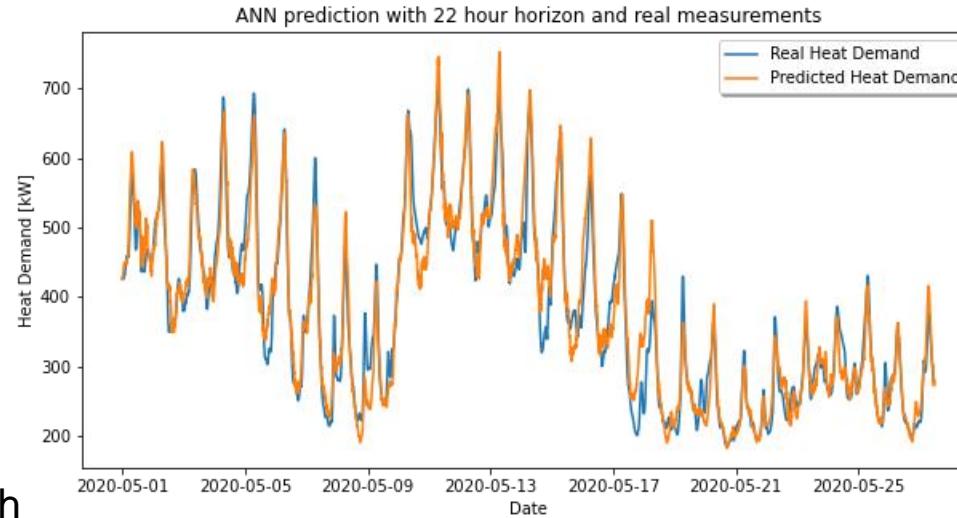


[Colored neural network - Wikimedia Commons](#)

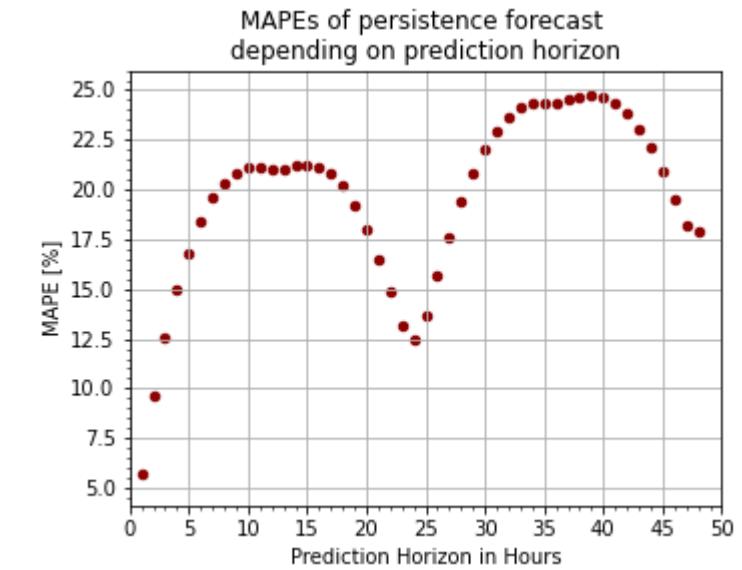
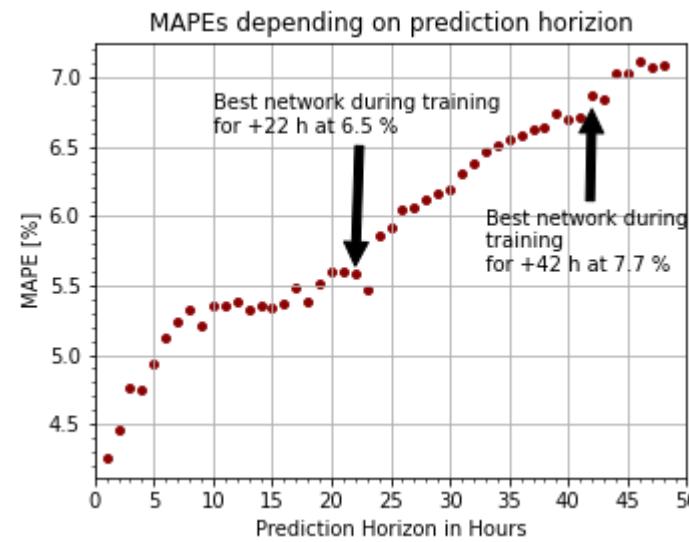
Prediction Model Building

Results

- 7 months of training data (both summer and winter)
- Intensive tuning of inputs, input representation, network structure...
- Decent performance (below 10 % MAPE)
- Persistence forecast only comparable for horizon +1h



Keras



Operational Optimization

MILP model based on oemof and solved with gurobi

Energy flow model, no temperatures

Framework:

- Minimal loads: boiler 30%, chp: 50%
- Minimal run time: boiler 1 min, chp: 15 min
- CHP: varying power-to-heat ratio, varying efficiency
- Storage temps: $55^{\circ}\text{C} < T < 85^{\circ}\text{C}$
- Rolling horizon overlap: 12 hours
- Gas price: fixed



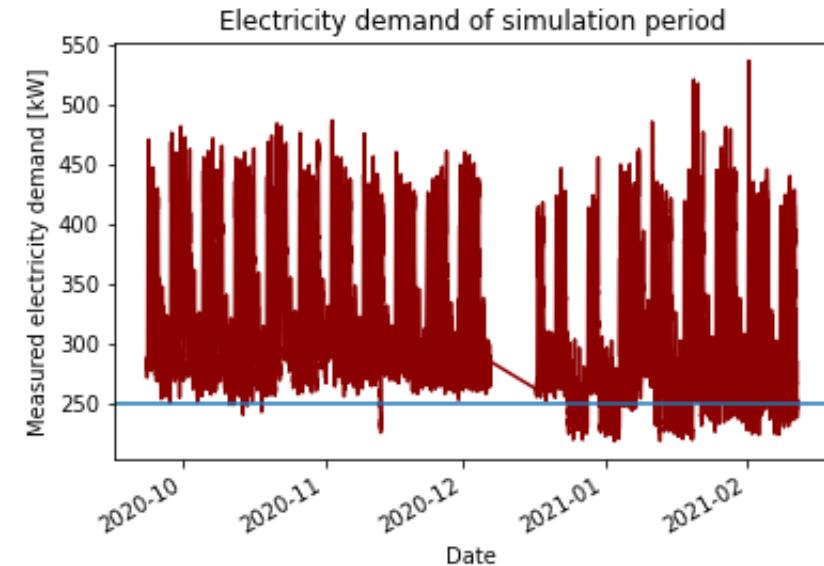
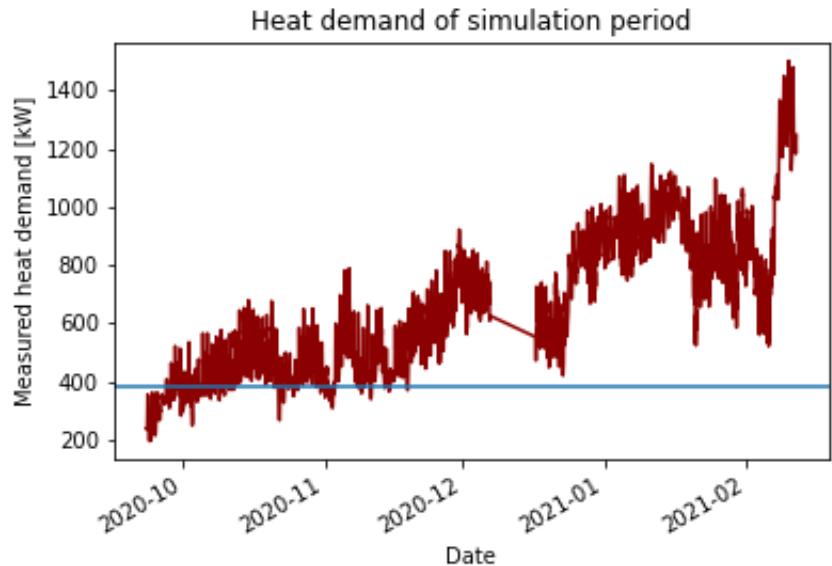
oemof ['ø:mɔ:f]
open energy modeling framework



GUROBI
OPTIMIZATION

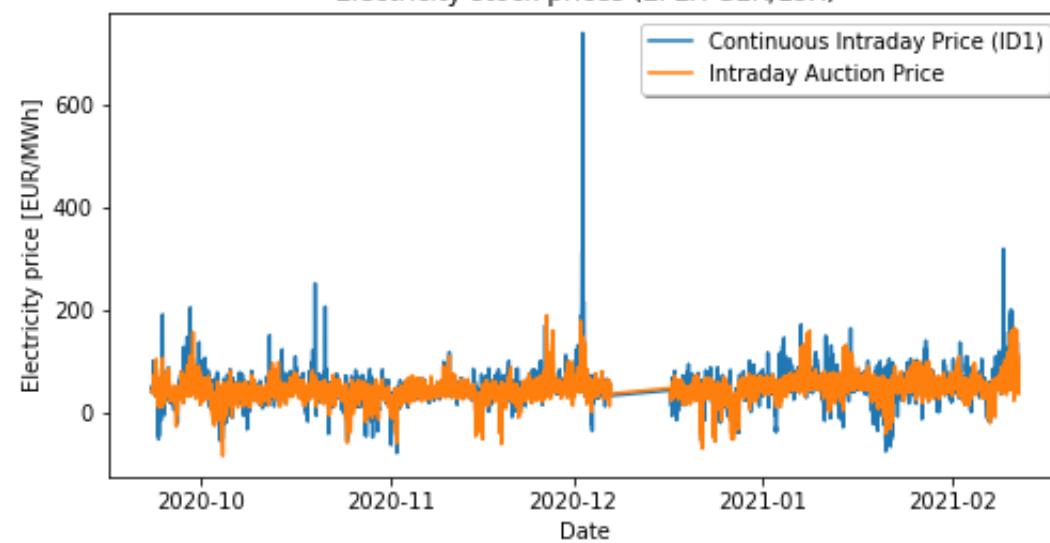
Simulation of Operation

- Identical technical behavior
- Test different operation strategies
 - How to predict?
 - How to intervene?
 - How to schedule?
- Sept 2020 to Feb 2021



Intervention Strategy

- Satisfy energy demands
- Prevent technical failures
- Minimize effects on electricity sector
 - Avoid balance energy
 - Avoid contractual penalties
- Safety margin: 40 kWth



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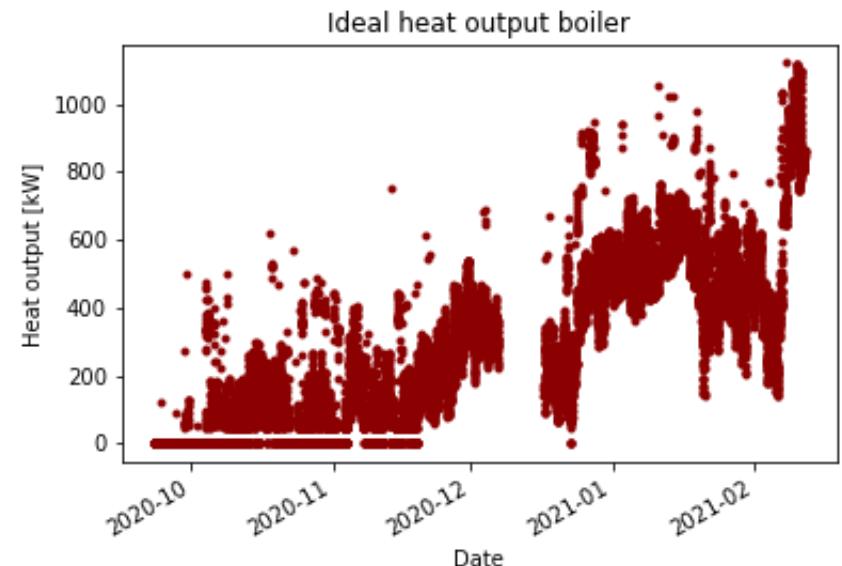
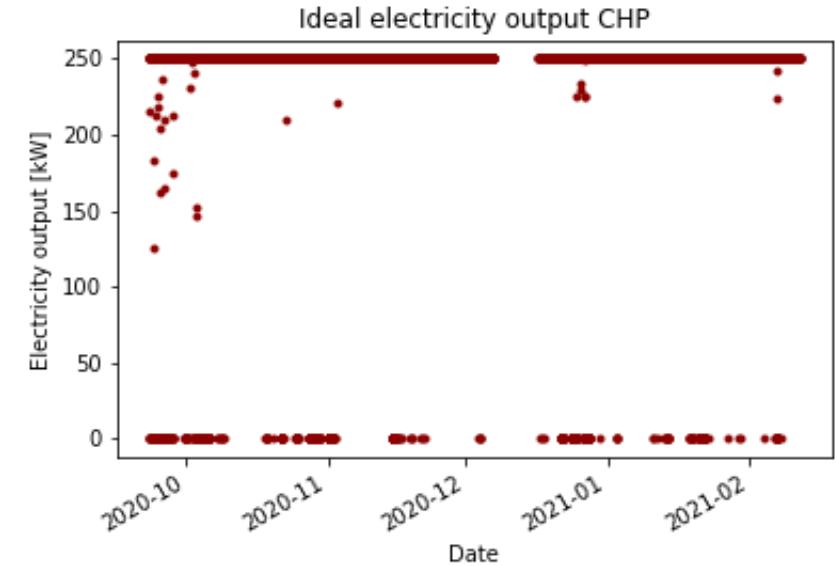
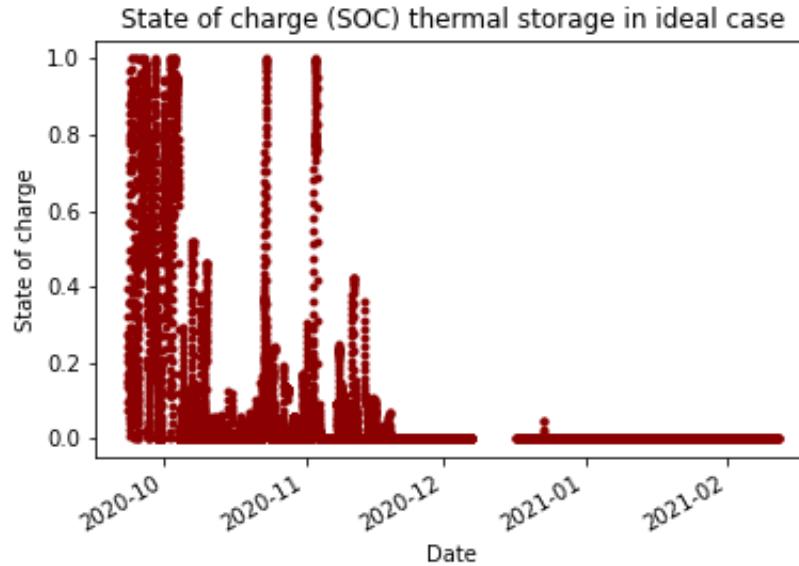
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Results

Fundamentals

Ideal Scenario (perfect foresight):

- No deviations during simulation, no interventions
- Single intraday optimization
- Interventions: 0
- Gas consumption: 3,100 MWh
- Electricity generation: 755 MWh
- Electricity import: 242 MWh
- Electricity export: 3 MWh
- Balance energy: 0 MWh

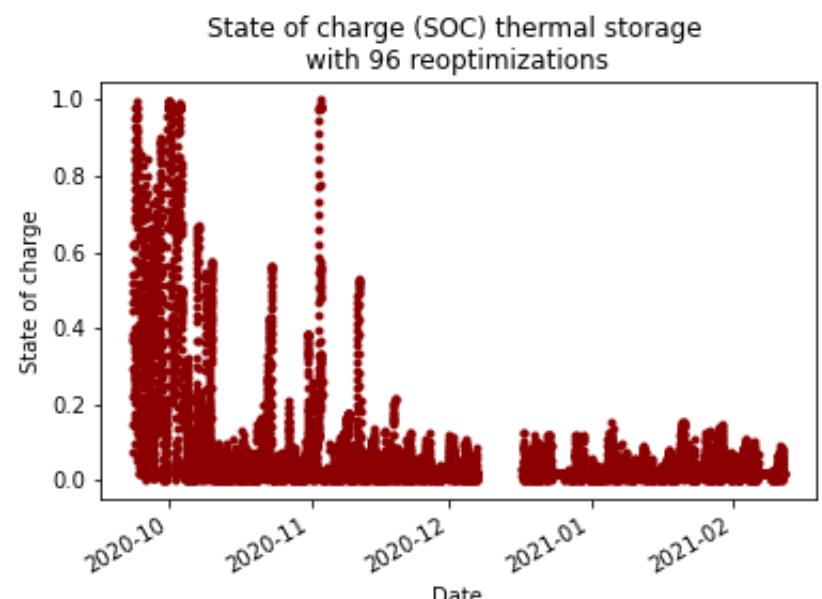
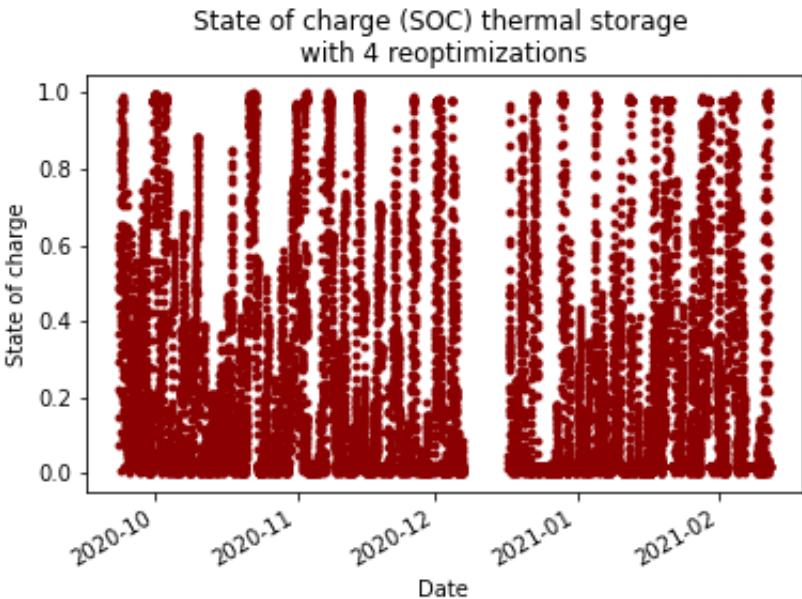
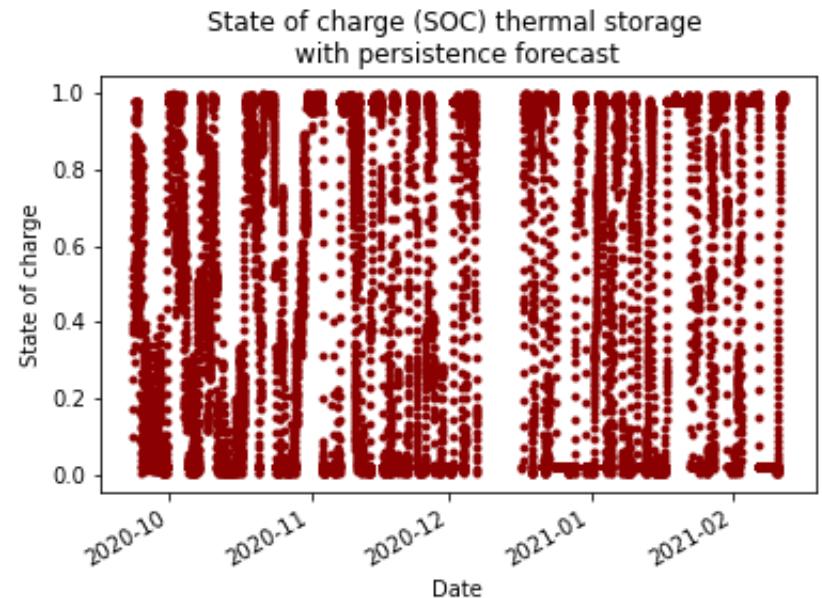
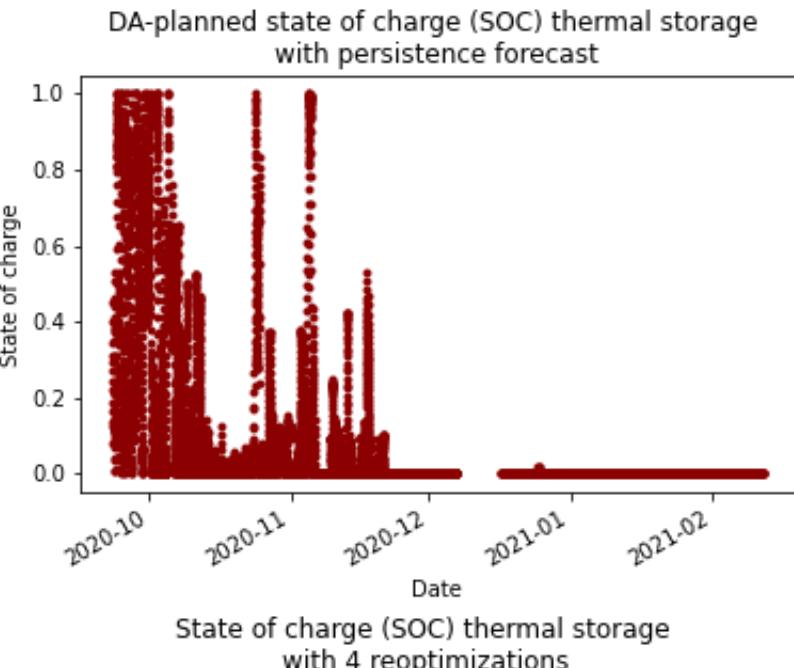


Results

Storage Behavior

Persistence Forecast:

- MAPE +48 h: 12.5 %
- MAPE +24 h: 9.8 %
- ME +48 h: - 17 kW
- ME +24 h: - 8 kW



Results

Interventions

Persistence Forecast:

- MAPE +48 h: 12.5 %
- MAPE +24 h: 9.8 %
- ME +48 h: - 17 kW
- ME +24 h: - 8 kW
- Total number of timesteps: 12,670

Number of ID-optimizations	Number of interventions	Positive balance energy [MWh]
0	6420	3.4
1	6037	2.9
2	5609	2.7
4	4022	1.8
6	3884	1.6
12	3960	1.3
24	4207	1.2
96	5509	1.0

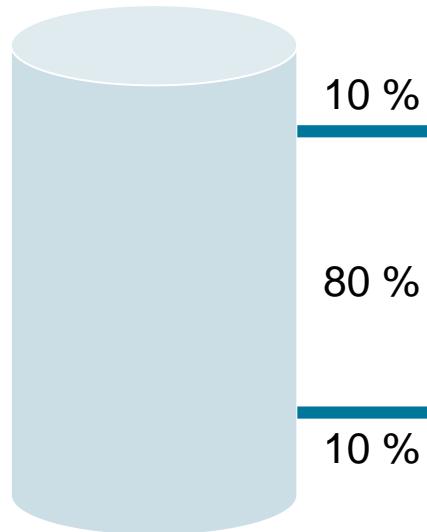
Number of ID-optimizations	Boiler Heat Output DA-opti [kW]	Boiler heat output ID-opti [kW]	Boiler heat output sim [kW]
6	267.9	257.0	286.3
96	267.9	239.5	285.8

Results

Interventions

ANN Multi-Model-Forecast:

- MAPE DA: 7.2 %
- ME DA: 12.9 kW



Number of ID-optimizations	Number of interventions	MAPE of ID-forecast [%]
0	3641	-
1	2498	6.1
2	2470	5.73
4	2498	5.66
6	2709	5.3
12	2746	5.1
24	2787	5.0

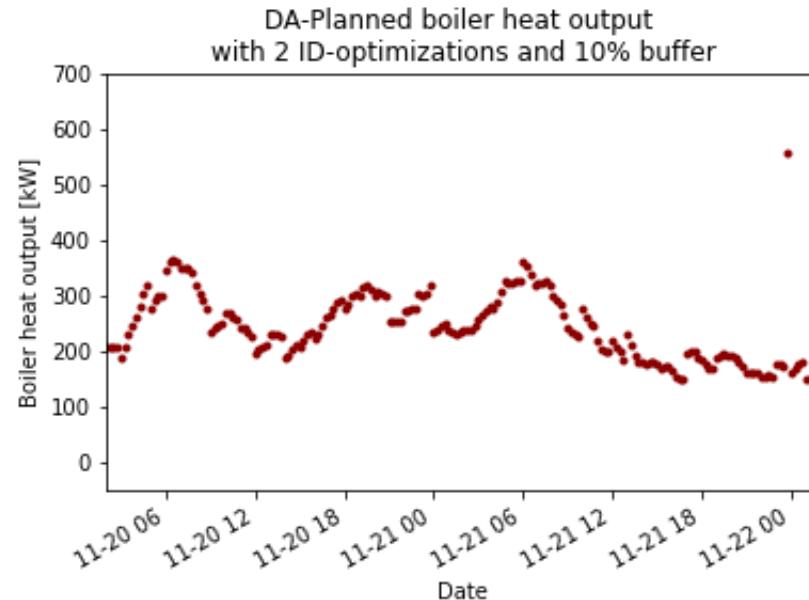
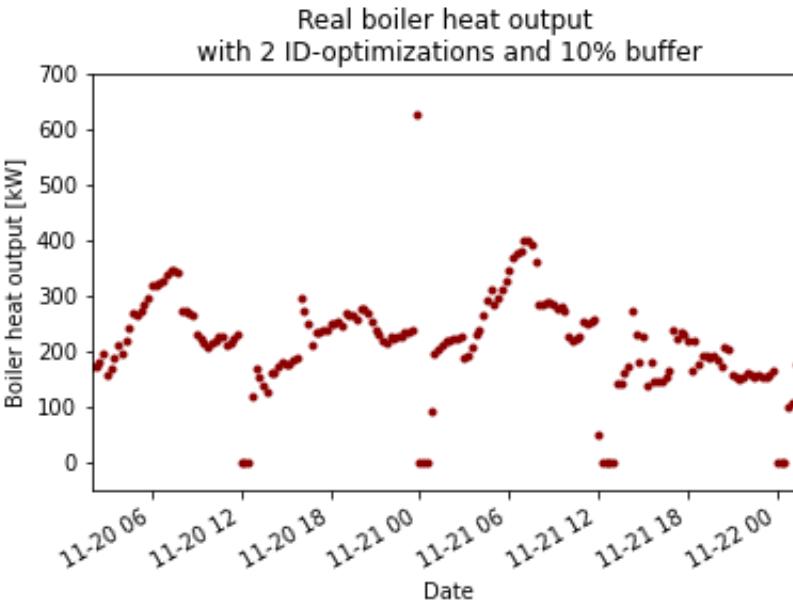
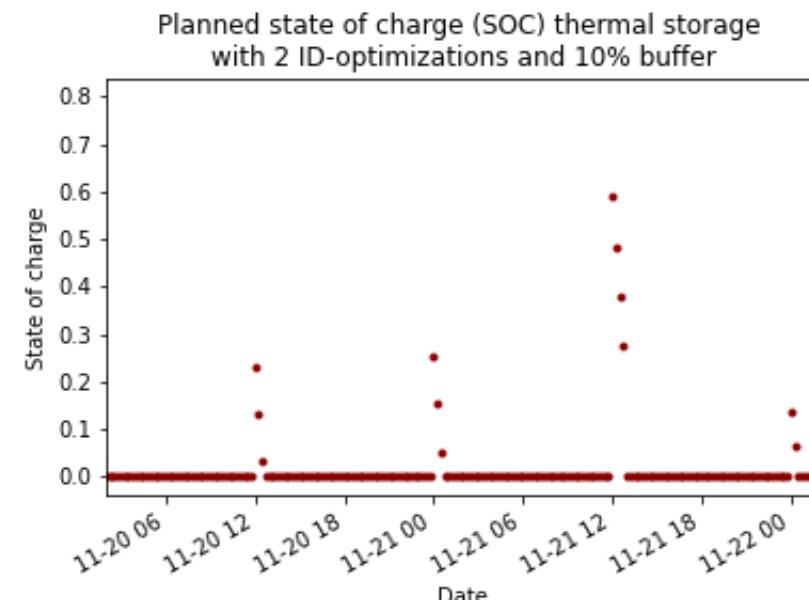
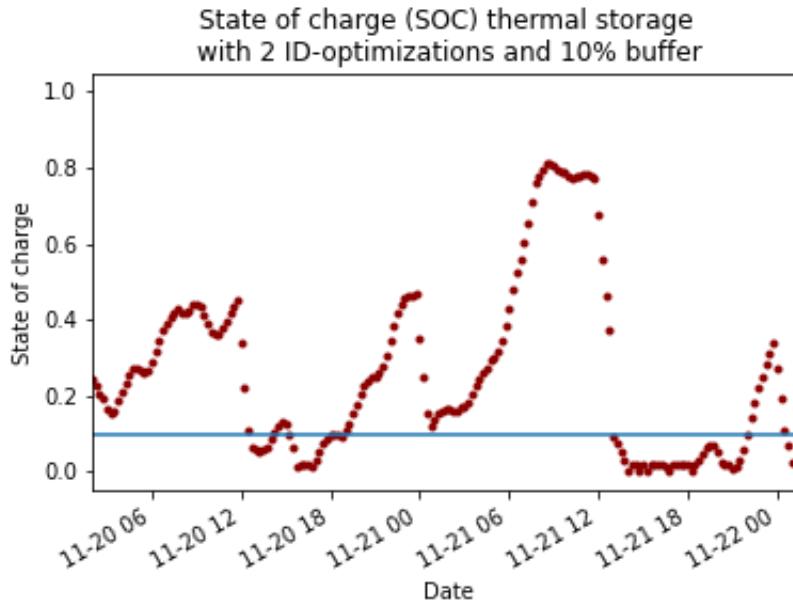
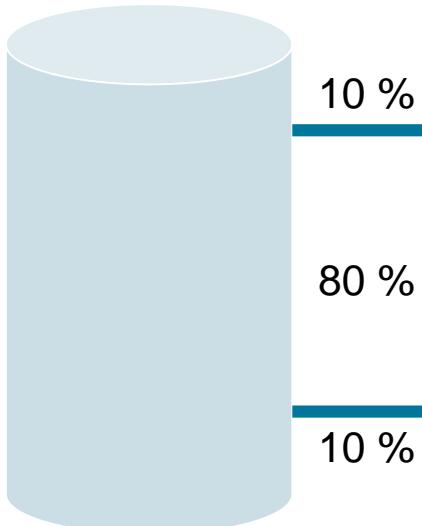
Buffer size [%]	Number of interventions
0	2470
10	2157

Results

Interventions

ANN Multi-Model-Forecast:

- MAPE DA: 7.2 %
- ME DA: 12.9 kW

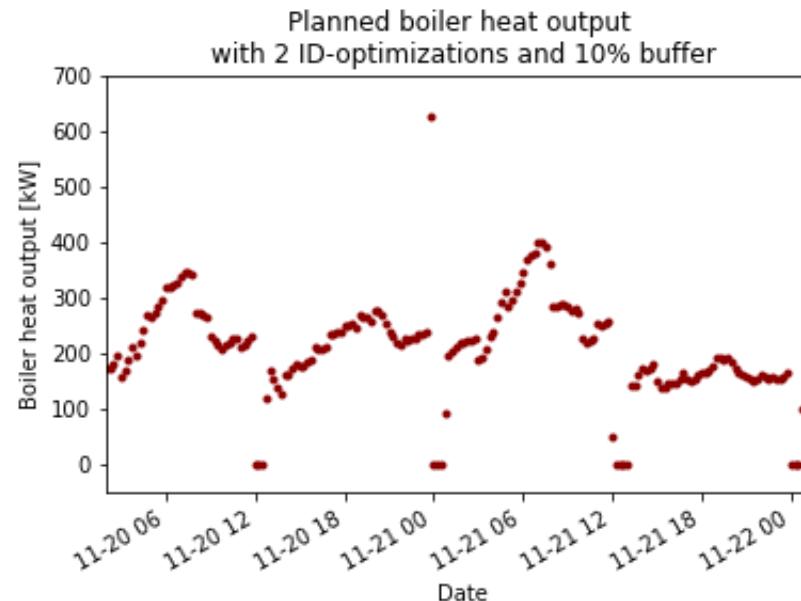
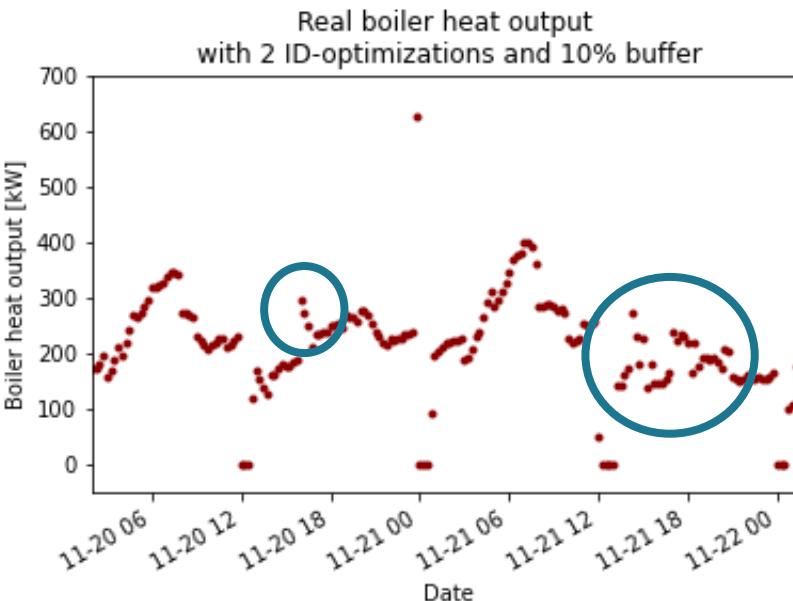
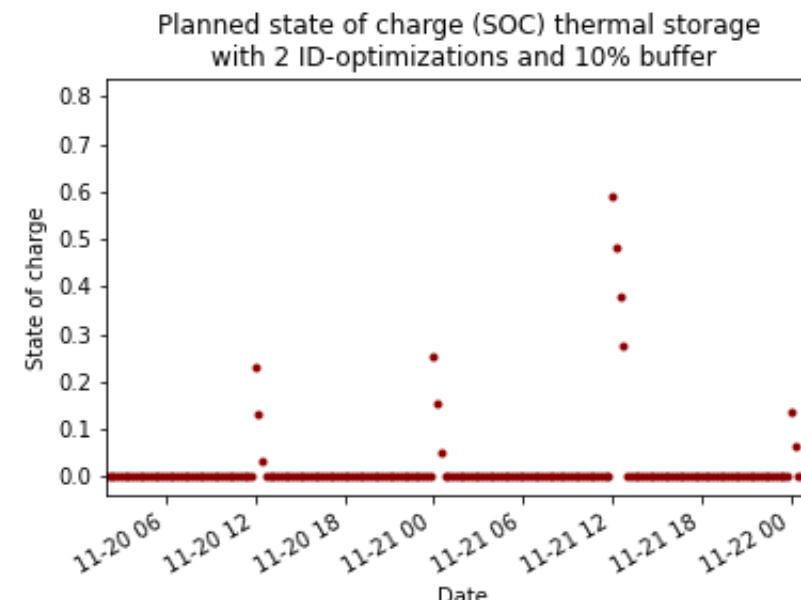
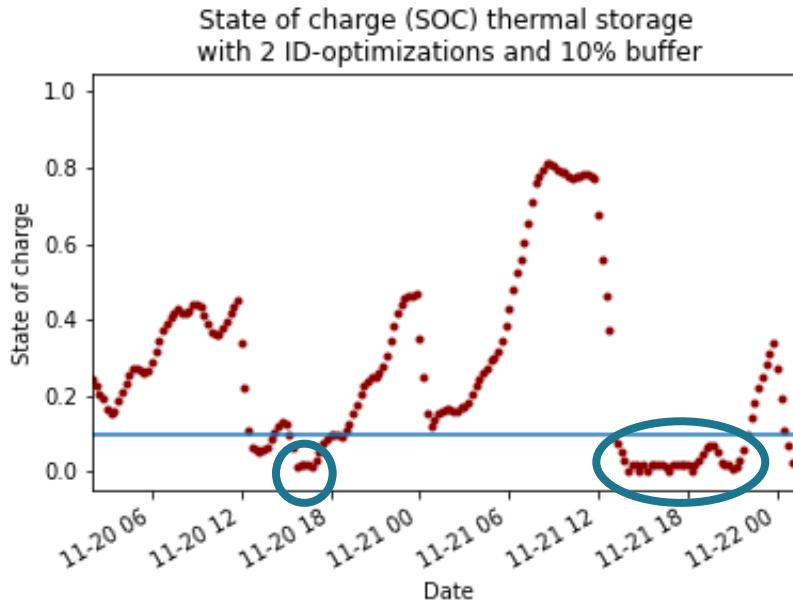
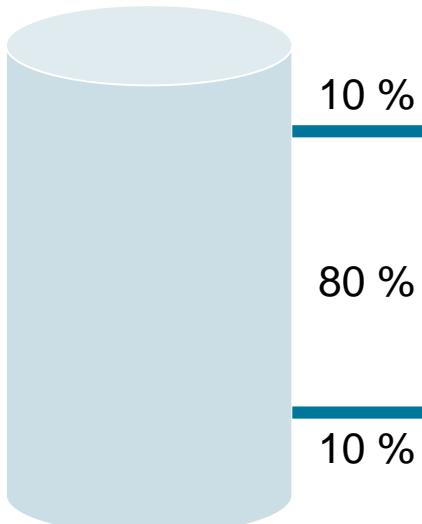


Results

Interventions

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Conclusion & Outlook

- Decent prediction accuracies outperforming benchmark
- Economic effects depend strongly on circumstances especially available markets
- Prediction errors cause adaptions to optimal schedule
- Number of adaptions decreases with increasing prediction accuracy
- Maximizing number of intraday optimizations does not minimize schedule adaptions
- Optimization adds an asymmetry to the system even if prediction errors are symmetric
- “Optimal schedule” from optimization may not be optimal for control
- Dynamic error handling strategies (event based optimization, energy system adaptions...)
- Application of tool to real world energy system

Kontakt

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Thank you for your
attention, interest
and questions
