The Impact of Forecast Uncertainties on the Model Predictive Control of a Domestic PV Battery Heat Pump Heat Storage System

Ronny Gelleschus, Thilo Bocklisch
Chair of Energy Storage Systems

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Agenda

1. Motivation
2. Methods
3. Simulation design and results
4. Conclusions and Outlook

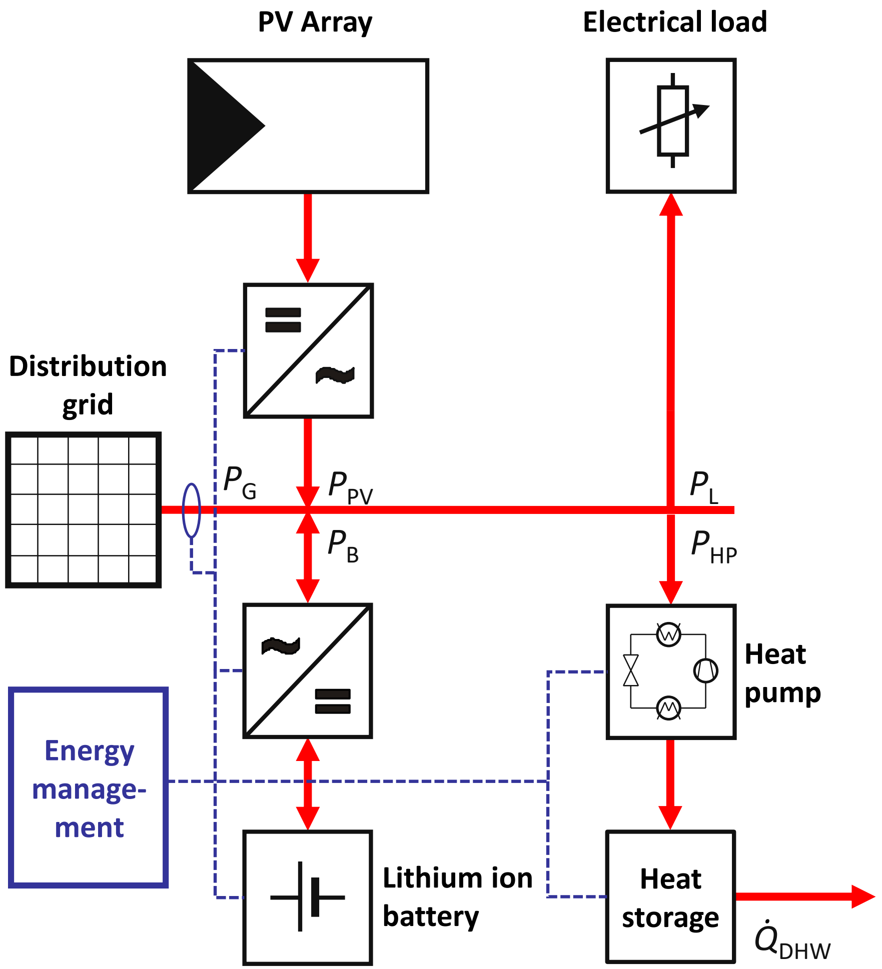
1. Motivation

1. Motivation
System

- Grid-connected single-family house
- PV plant for self-consumption
- heat pump for DHW supply
- lithium-ion battery for improved self-sufficiency

→ two degrees of freedom that need to be managed

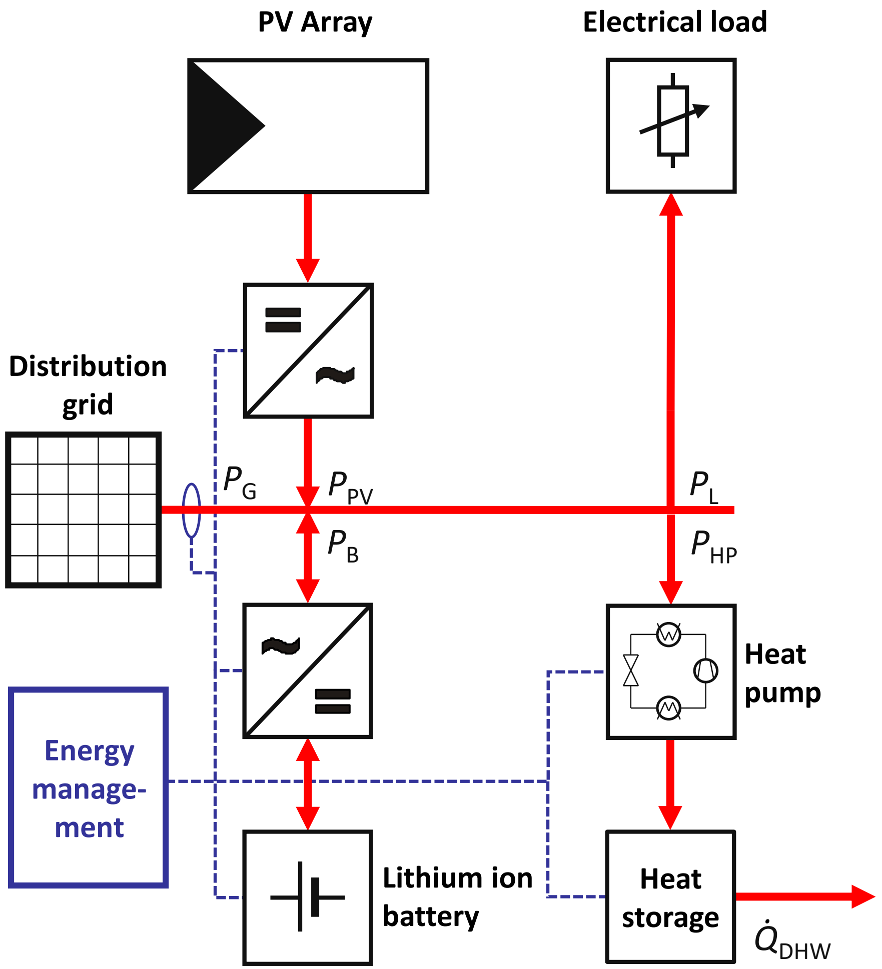
- Peak Shaving:
  - study was conceptualized and begun when PV curtailment was still in effect in Germany
  - still makes sense: battery ageing



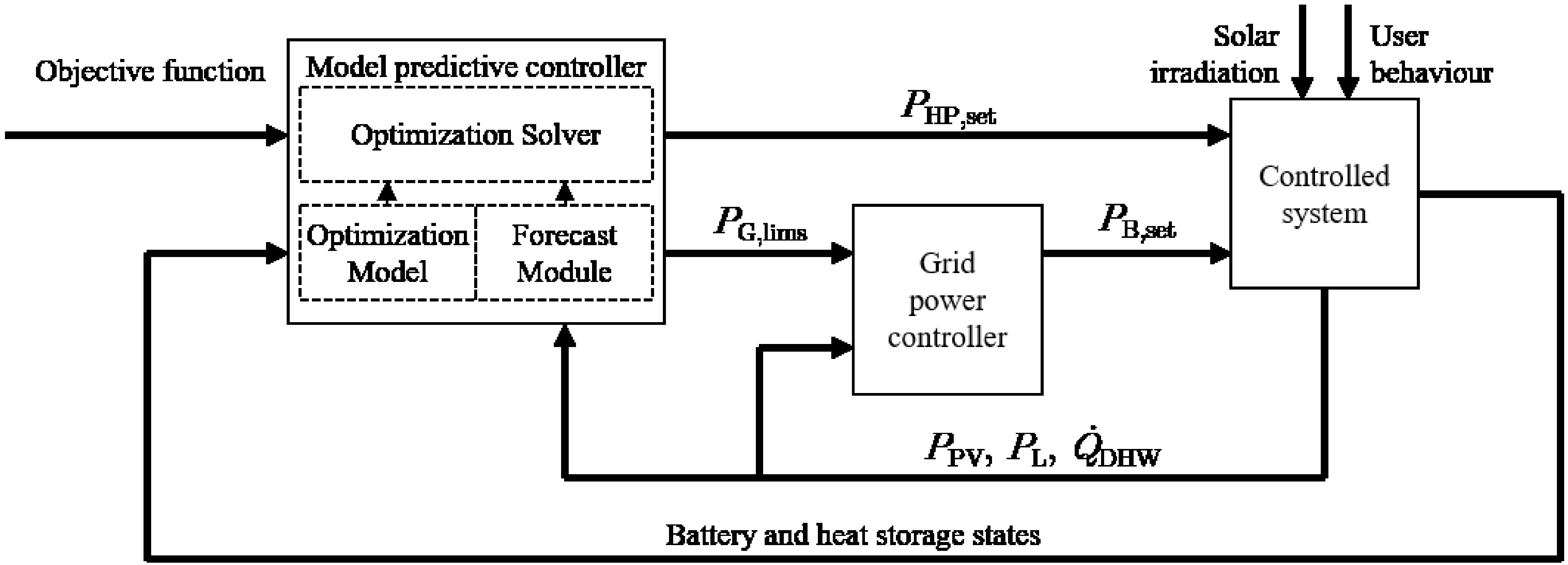
1. Motivation
Multi-Use

- three main objectives
  - high security of DHW supply
  - minimize operation cost
  - maximize components‘ lifetimes (especially battery)

- Solution: model predictive control (MPC)
  1. forecast external variables and system behaviour over time horizon
  2. optimize decision taking into account forecasts
  3. apply only first part (e.g. 15 min) of decision and re-optimize afterwards



1. Motivation
Model predictive control



2. Methods

2. Methods
Overview

How to measure energy management performance?

What characteristics of forecast errors might be important for energy management performance?

How to measure impacts on energy management performance?

How to ensure high reliability of the results?

2. Methods
How to measure energy management performance?

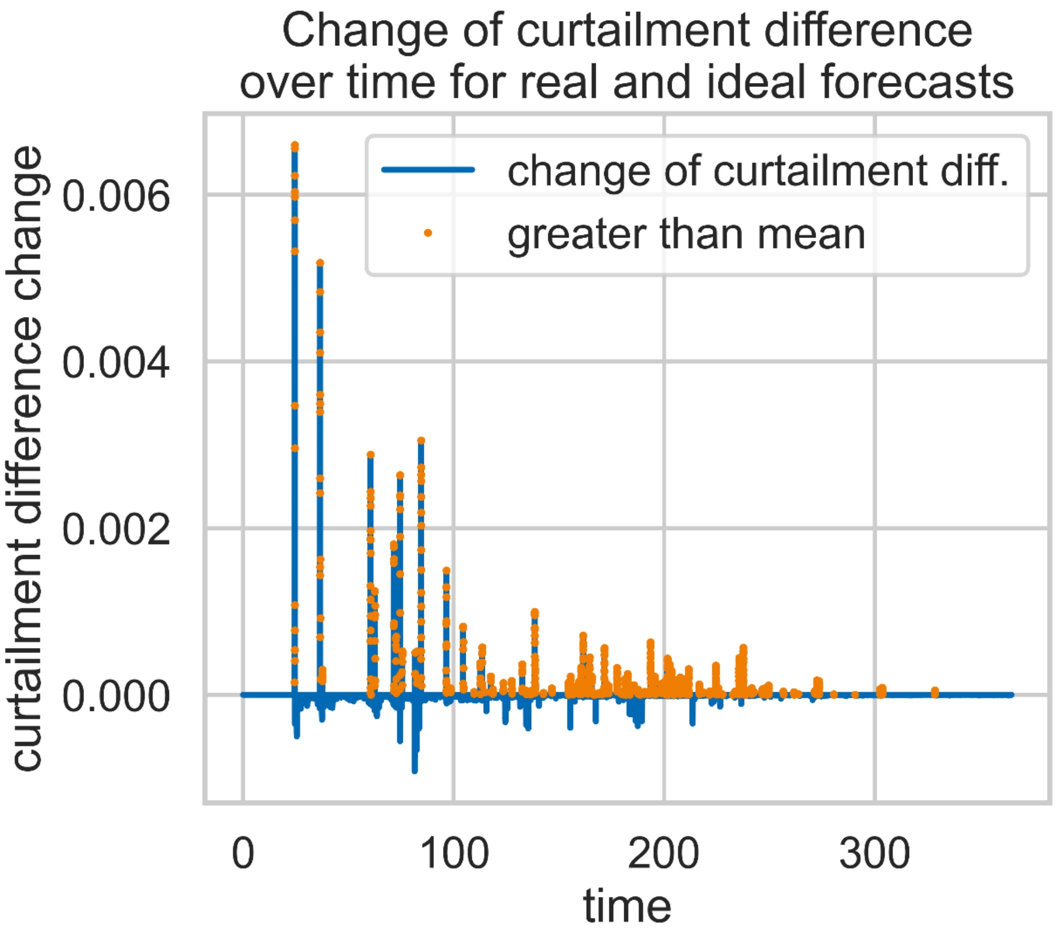
Performance criteria

that are impacted by forecast errors

- cost
- PV curtailment
- degree of self-sufficiency
- quality of DHW supply
- …

How to model them?

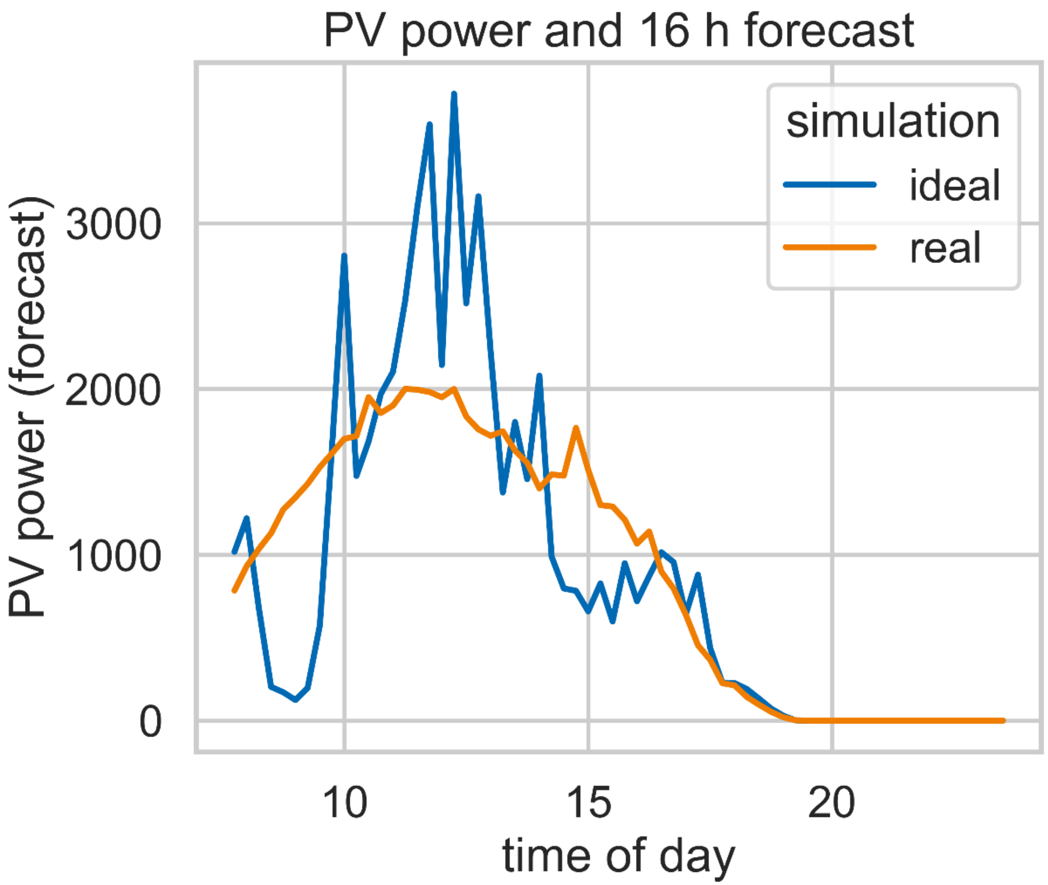
- highly nonlinear relationship and more influences than just forecast errors
- difference to ideal values when using ideal forecasts → better, but difference accumulates
- change of difference → events → model occurence instead of extent



2. Methods
What characteristics of forecast errors might be important for EM perf.?

Power time-series forecasts are very complex

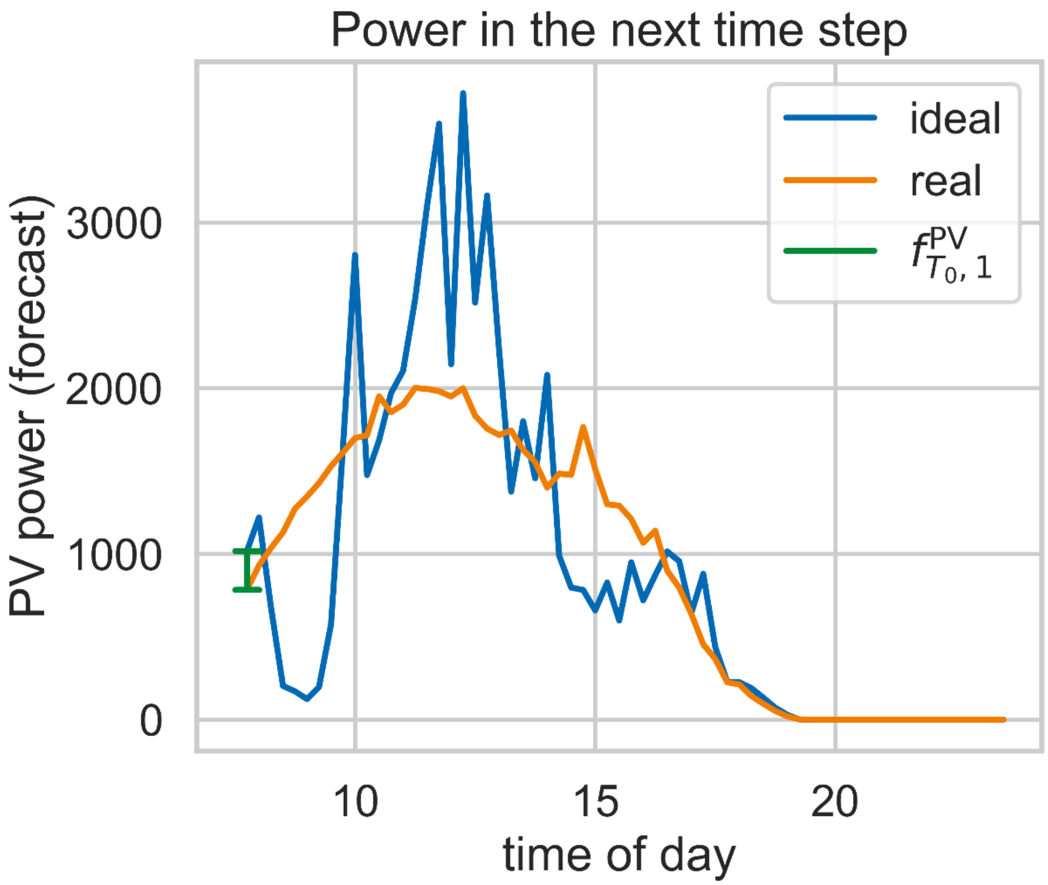
- three physical variables to forecast
  - PV power
  - electric load power
  - DHW „load“ (enthalpy flow, equivalent to power)
- time horizon of 16 h in 15-minute intervals
- all of this every 15 minutes
- errors in the past may have influence on the future

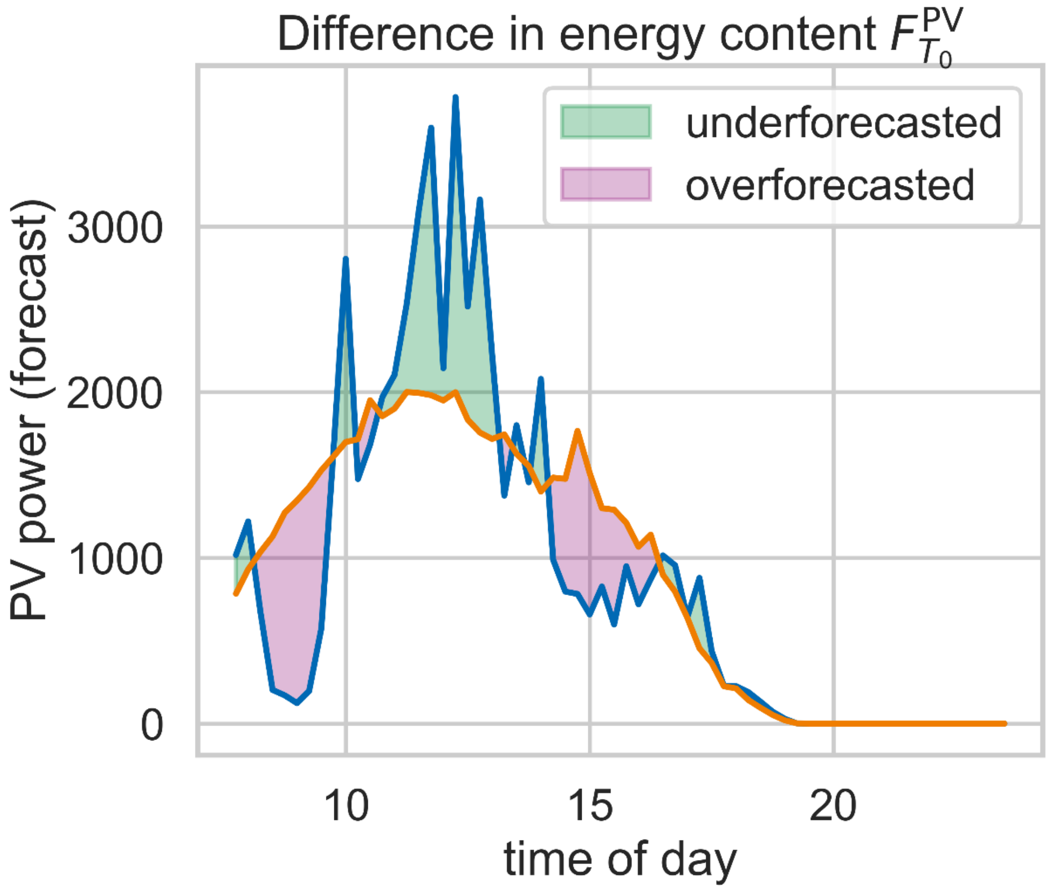


Solution: feature engineering

- extraction of characteristics of forecast errors that could have an influence
- here: manual feature engineering for interpretable features

2. Methods
What characteristics of forecast errors might be important for EM perf.?





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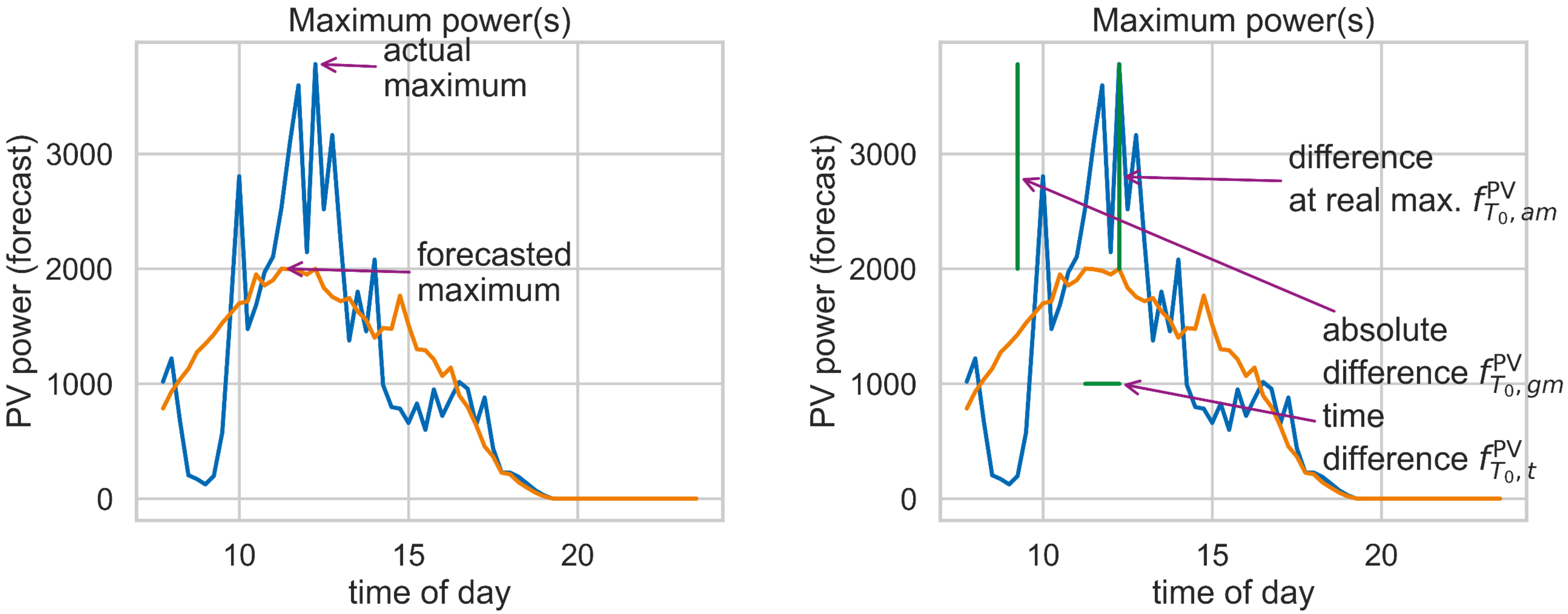
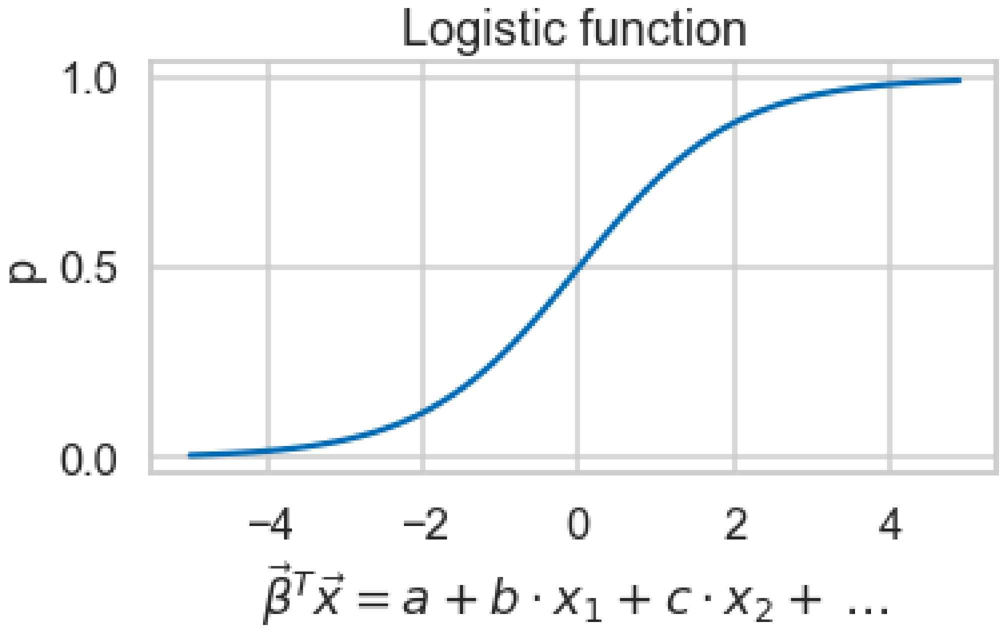


2. Methods
How to measure impacts on energy management performance?

- correlation is not sufficient due to correlation among influences
- regression isolates individual contributions
- logistic regression: $\frac{\ln p}{1-\ln p} = a + b \cdot x_1 + c \cdot x_2 + \cdots$



→ **How much does p change due to changes in one influence?**

→ Semi-standardized change in probability

$$SS_{x_1}^{\Delta p} = p\left(x_1 = \overline{x}_1 + \frac{\sigma_1}{2}, x_j = \overline{x}_j\right) - p\left(x_1 = \overline{x}_1 - \frac{\sigma_1}{2}, x_j = \overline{x}_j\right)$$

2. Methods

How to ensure high reliability of the results?

Questions on possible problems

- Is the relationship identified by the model adequate or is it just outputting some random noise?
- Are the results reproducible?
- How sensitive are the results?

Solutions

→ „Pseudo-R^2 values“, here „coefficient of discrimination“ measure model adequacy

→ Carry out study for multiple households instead of just one

→ Vary the energy management strategy to see if the results change

→ Vary the reference point for the semi-standardized change in probability (not shown here)

3. Simulation design and results

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Simulation design

Load: 20 households from HTW Berlin dataset

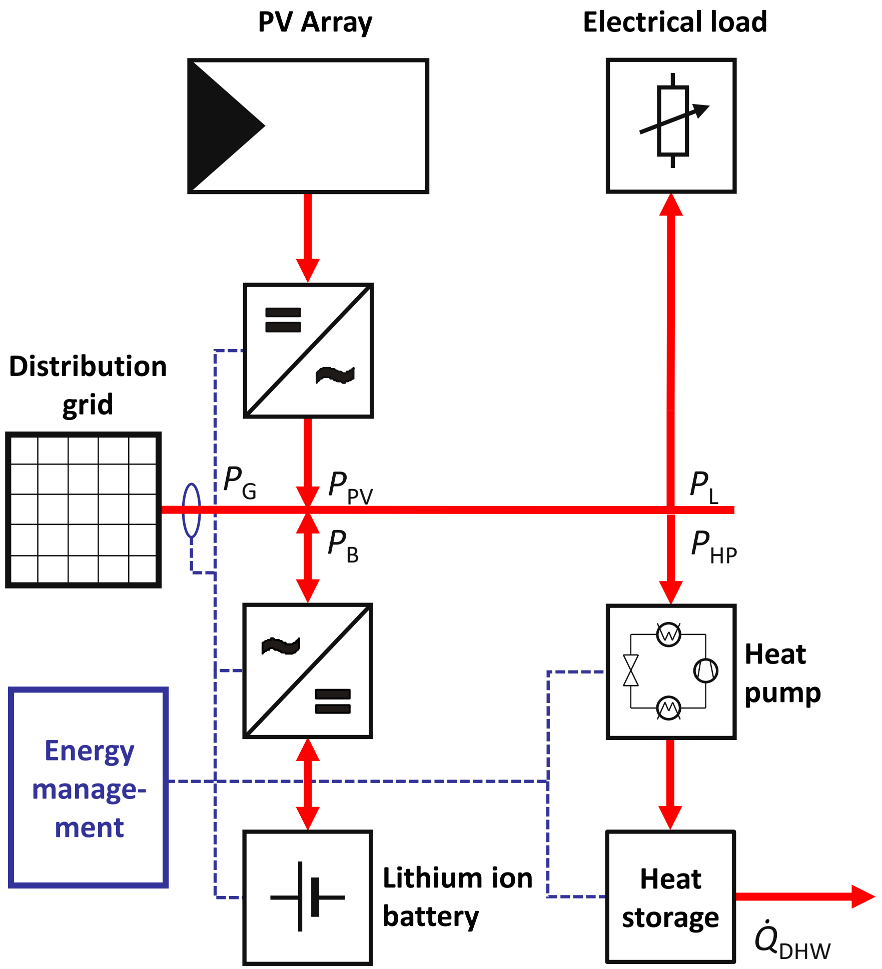
PV: one timeseries scaled to 1.5 times load energy

DHW: created probabilistically using DHWcalc

Battery: either around 5 or around 10 kWh, depending on PV size

Heat pump: 750 W electric power

Heat storage with electric heater: 300 l / 1500 W



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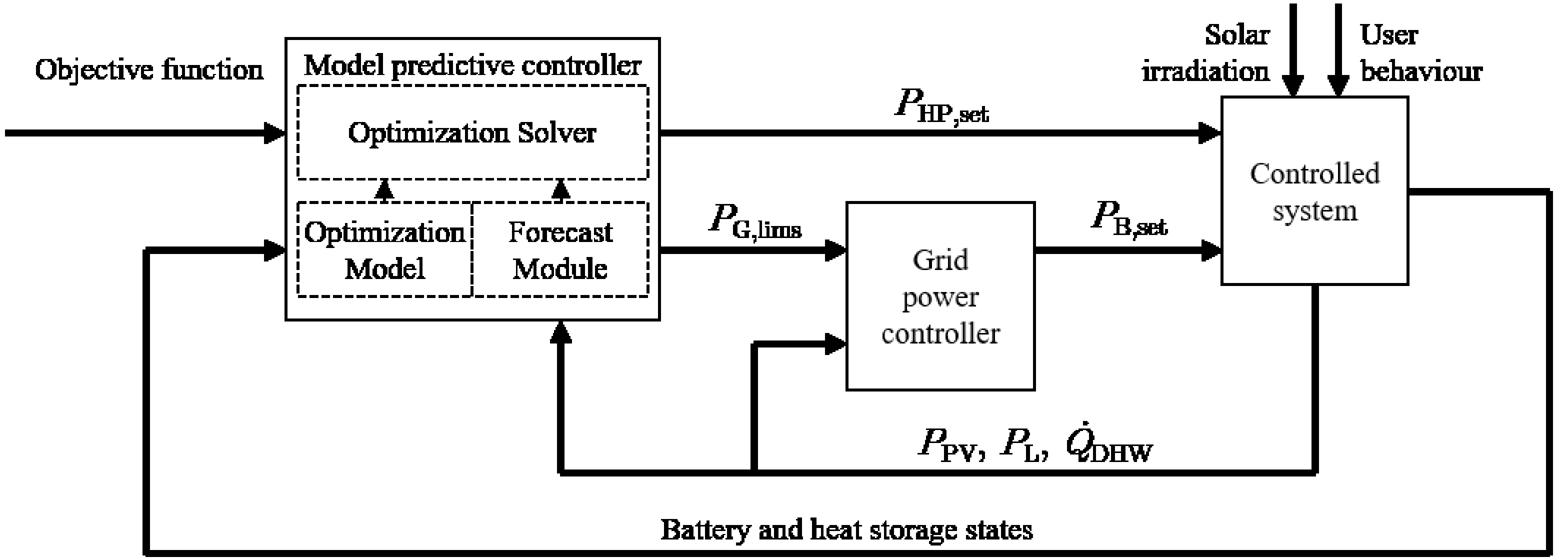
Simulation design



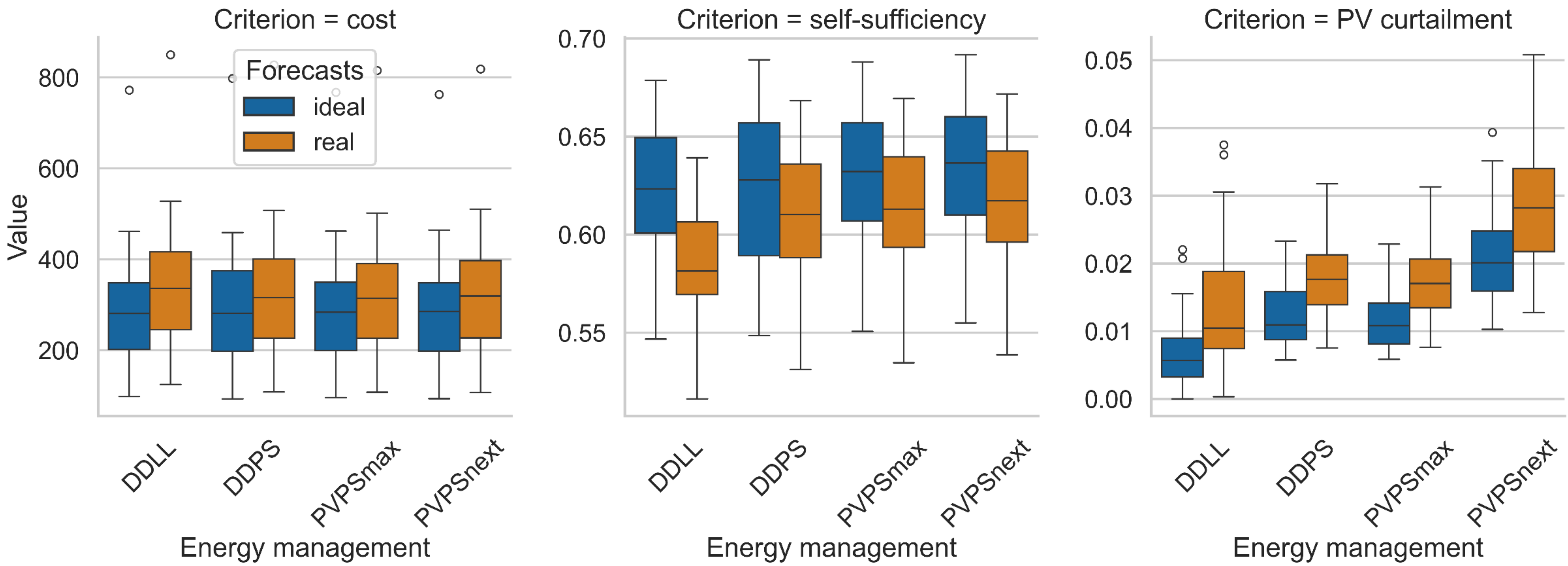
Feed-in peak shaving

- lower limit always 0
- upper limit either
  - grid feed-in limit from optimization: „PVPSmax“
  - grid feed-in at first time step from optimization (usually lower): „PVPSnext“

Double-sided peak shaving

- only peak shaving: grid feed-in and buy limits from optimization: „DDPS“
- also with load levelling : grid feed-in and buy limits are both set to first time step‘s grid power from the optimization: „DDLL“

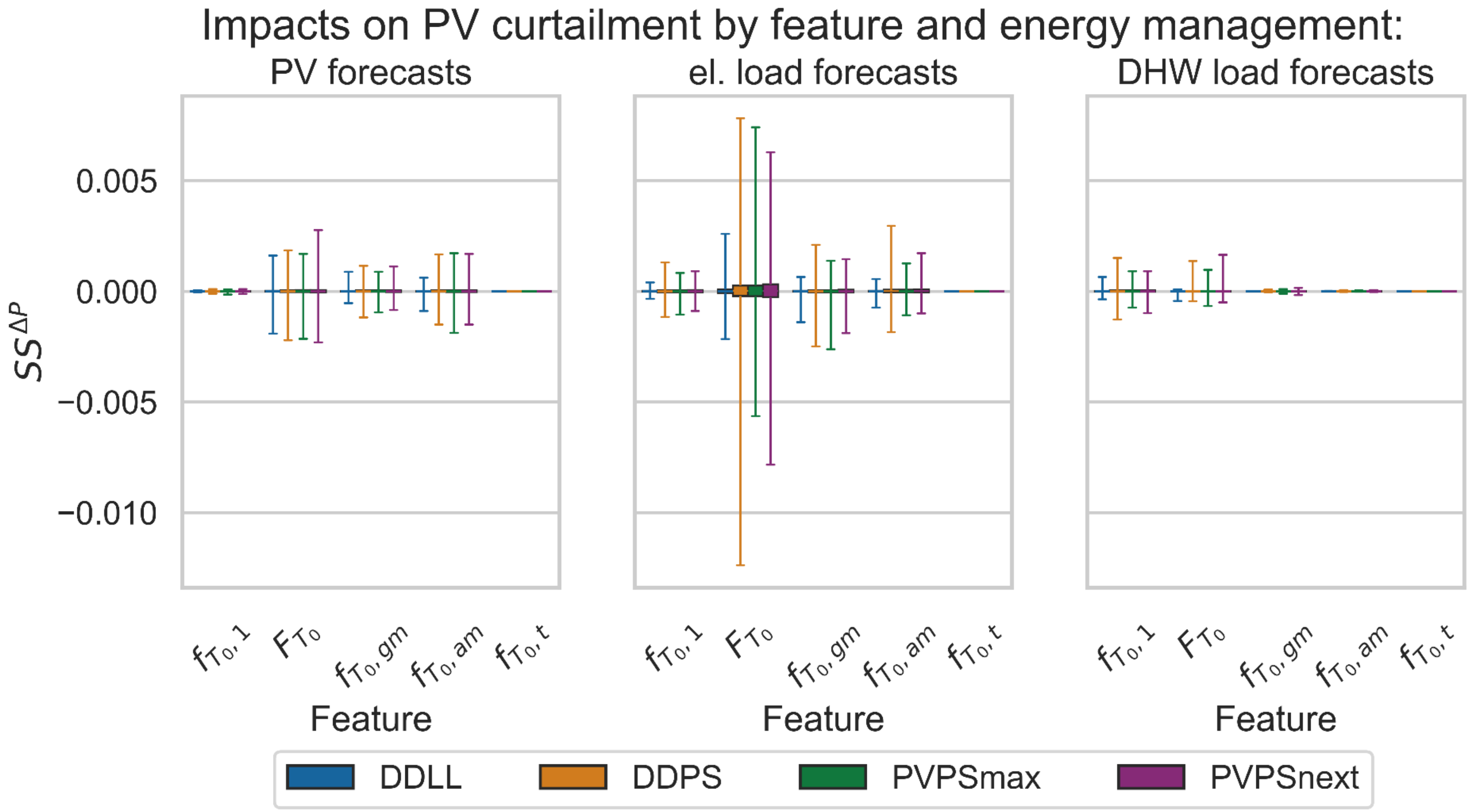
3. Simulation design and results
Simulation results



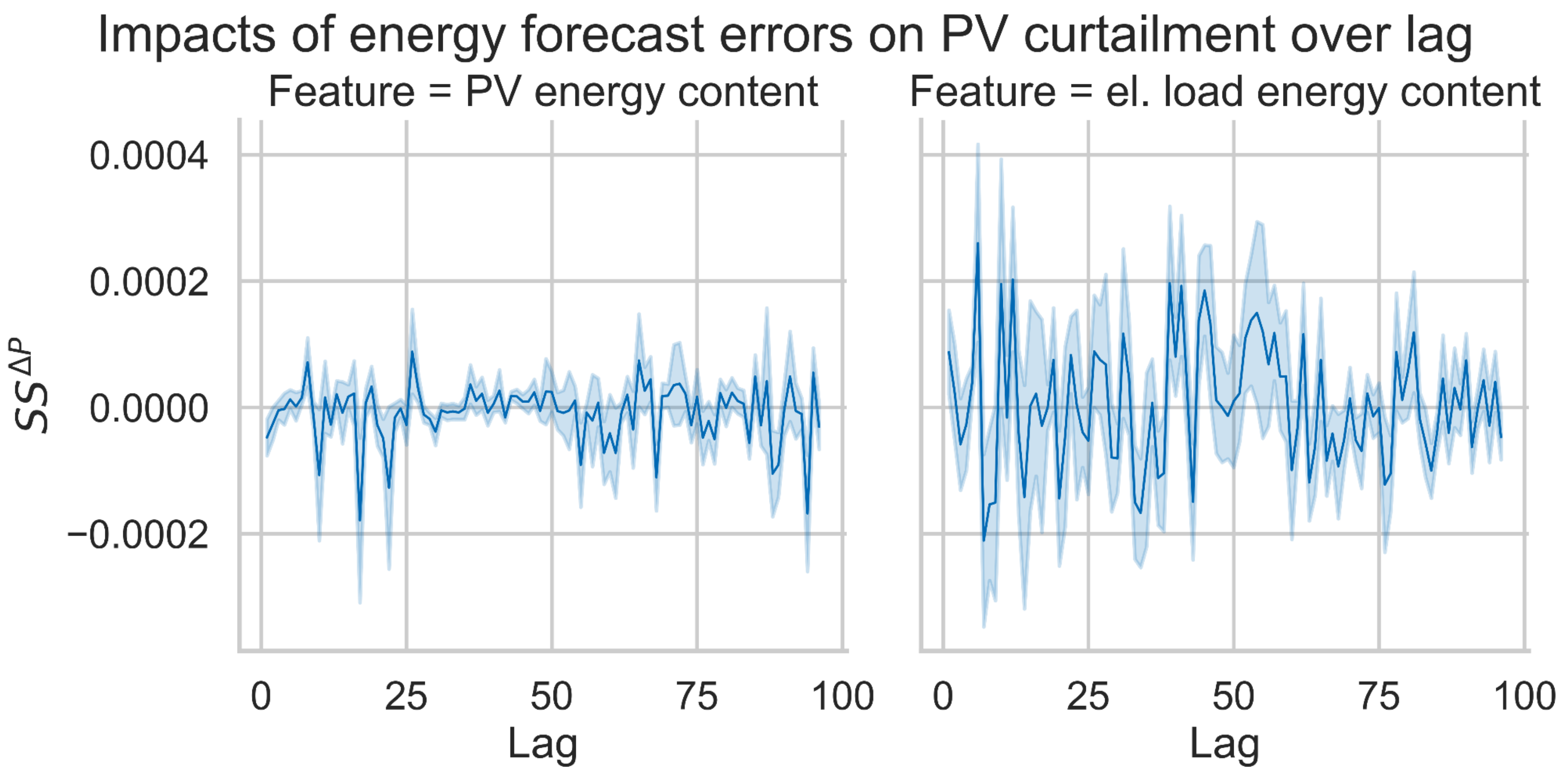
3. Simulation design and results
Spread of impacts

Legend: forecast error features

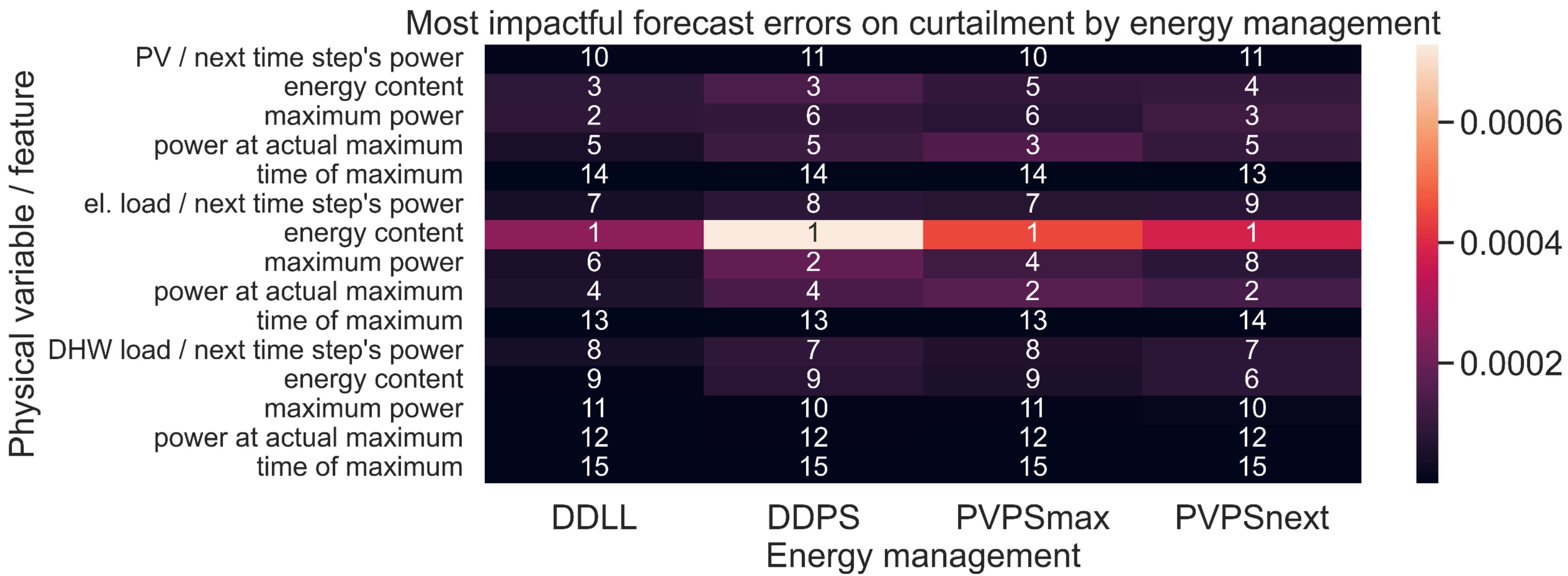
$f_{T_0,1}$	next time step's power
F_{T_0}	energy content
$f_{T_0,\mathrm{gm}}$	maximum power
$f_{T_0,\mathrm{am}}$	power at the actual maximum
$f_{T_0,t}$	time of maximum



3. Simulation design and results
Selected impacts over lag



3. Simulation design and results
Most influential forecast error features



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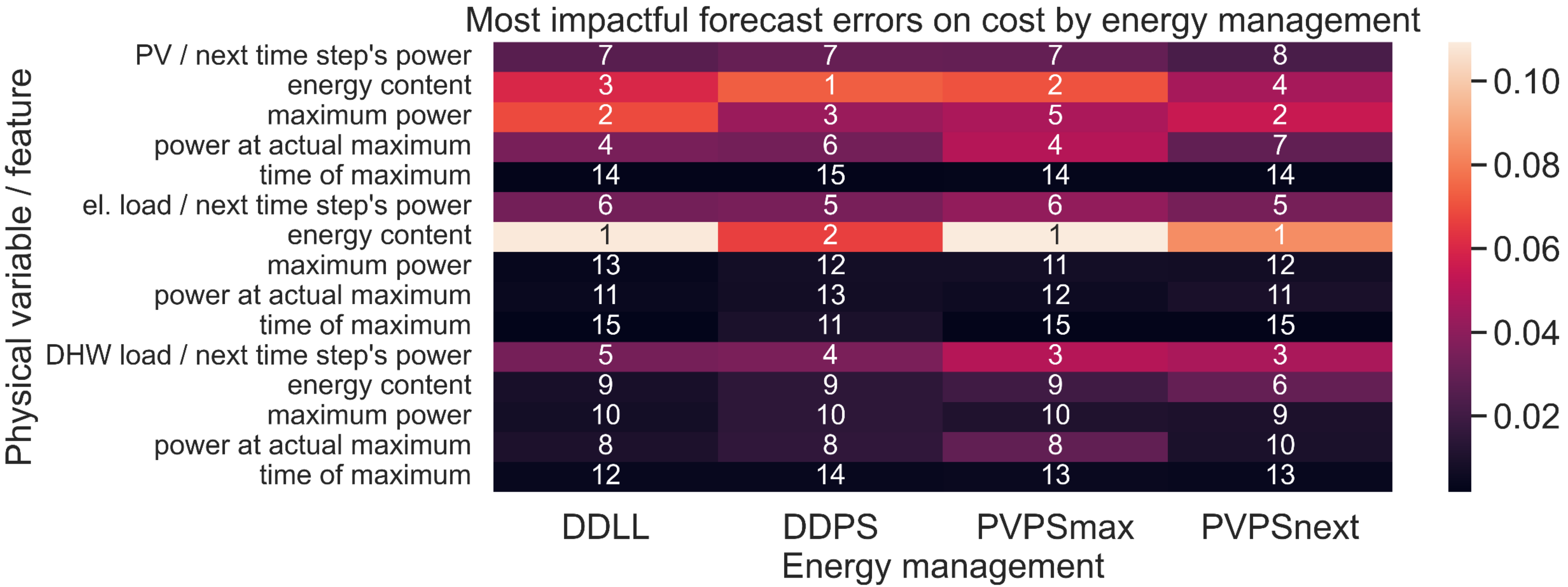

4. Conclusions and outlook

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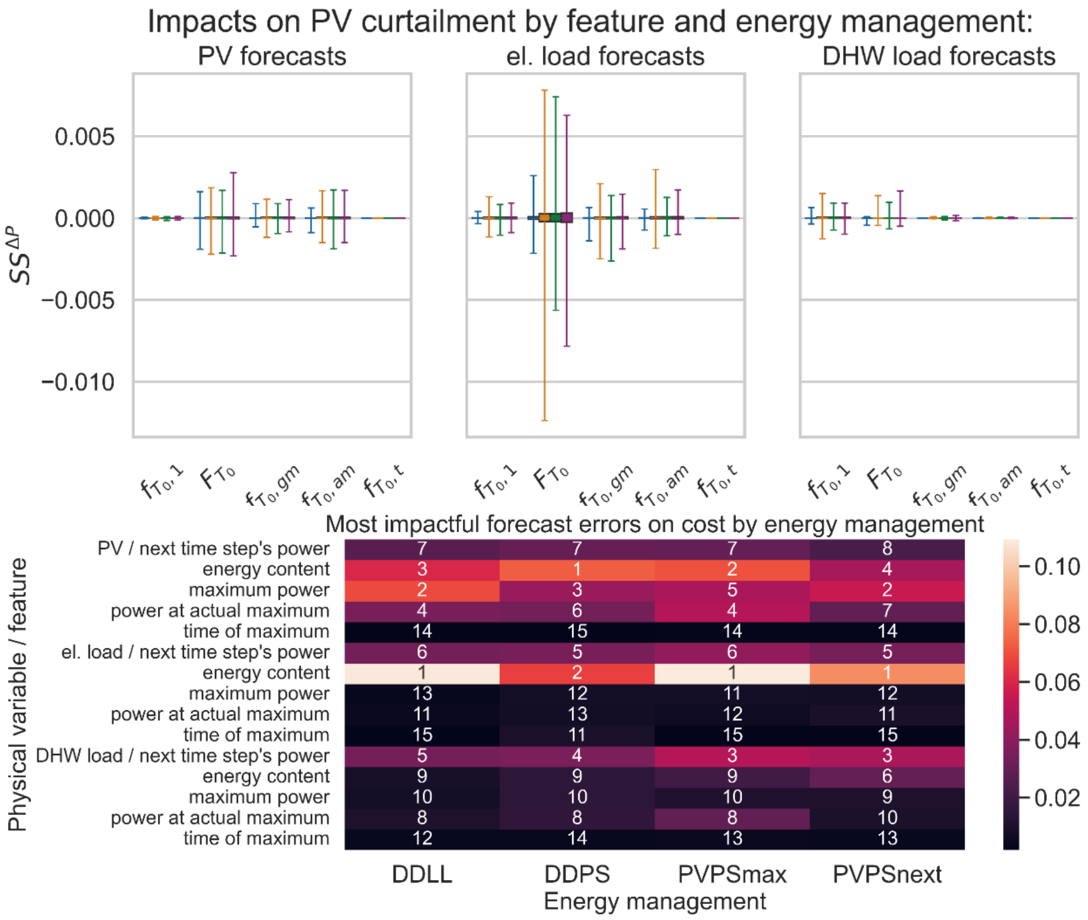
Conclusions

- reliable identification of important influences needed rather complex array of methods

- results:
– individual PV or electrical load powers not very important (even for next time step)
– energy content forecasts are what matters most

- most important limit of these results:
– other energy storage applications



4. Conclusions and outlook
Outlook

Forecasts

- evaluate methods with respect to important features, espescially energy content
- modelling uncertainty

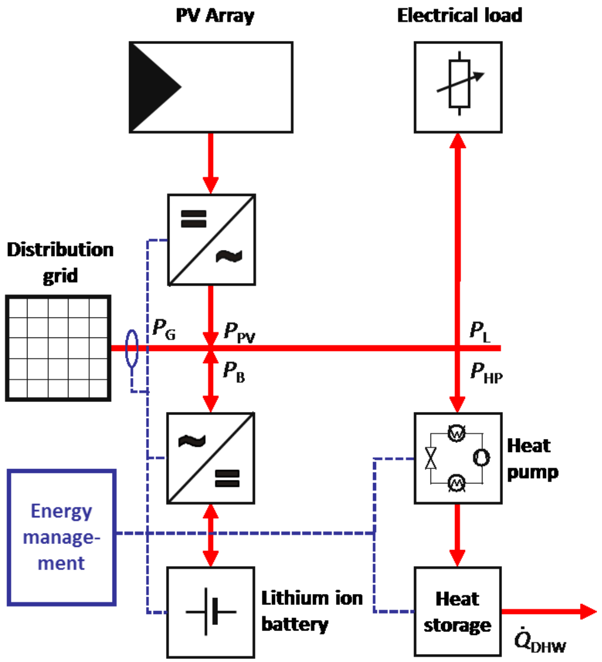
Optimization

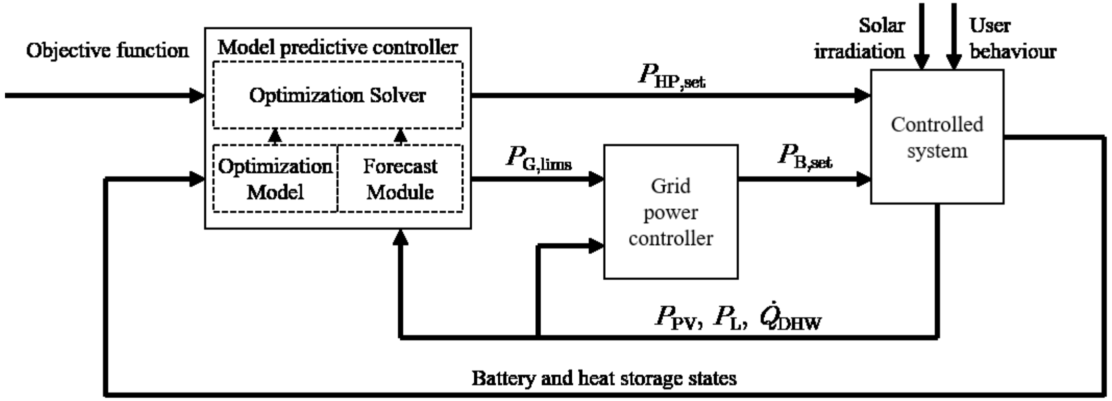
- adequately take into account information about uncertainty

Energy management evaluation

- implement forecasts and optimizations into MPC
- see if performance improved

Transfer findings to other applications and into practice





Thank you!

Dipl.-Ing. Ronny Gelleschus

(main author)

ronny.gelleschus@tu-dresden.de

+49 351 463 40332

Prof. Dr.-Ing. Thilo Bocklisch

thilo.bocklisch@tu-dresden.de

+49 351 463 40270