Supported by:

Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag

FORECASTING MULTIPLE ATTRIBUTES CONSIDERING UNCERTAINTIES IN A COUPLED ENERGY SYSTEMS MODEL

CFE-CMStatistics, 16th of December 2023, Berlin

Ulrich FREY[1], A. Achraf EL GHAZI[1], Evelyn SPERBER[1], Fabia MIORELLI[1], Christoph SCHIMECZEK[1], Stephanie STUMPF[2], Anil KAYA[2], Steffen REBENNACK[2]

[1] Deutsches Zentrum für Luft- und Raumfahrt, [2] Karlsruher Institut für Technologie

Karlsruher Institut für Technologie

DLR

Project: EN4U, FKZ 03EI1029A

OVERVIEW

Motivation: Massive uncertainties

- Recent geopolitical disruptions increase uncertainties & change prosumer reactions

→Energy systems pathways highly uncertain

→ Assumptions (e.g. fuel prices) might be off

→Prosumer reactions largely unknown

  - Buy an electric vehicle?
  - Buy PV + storage?
  - Buy a heat pump?

Research questions

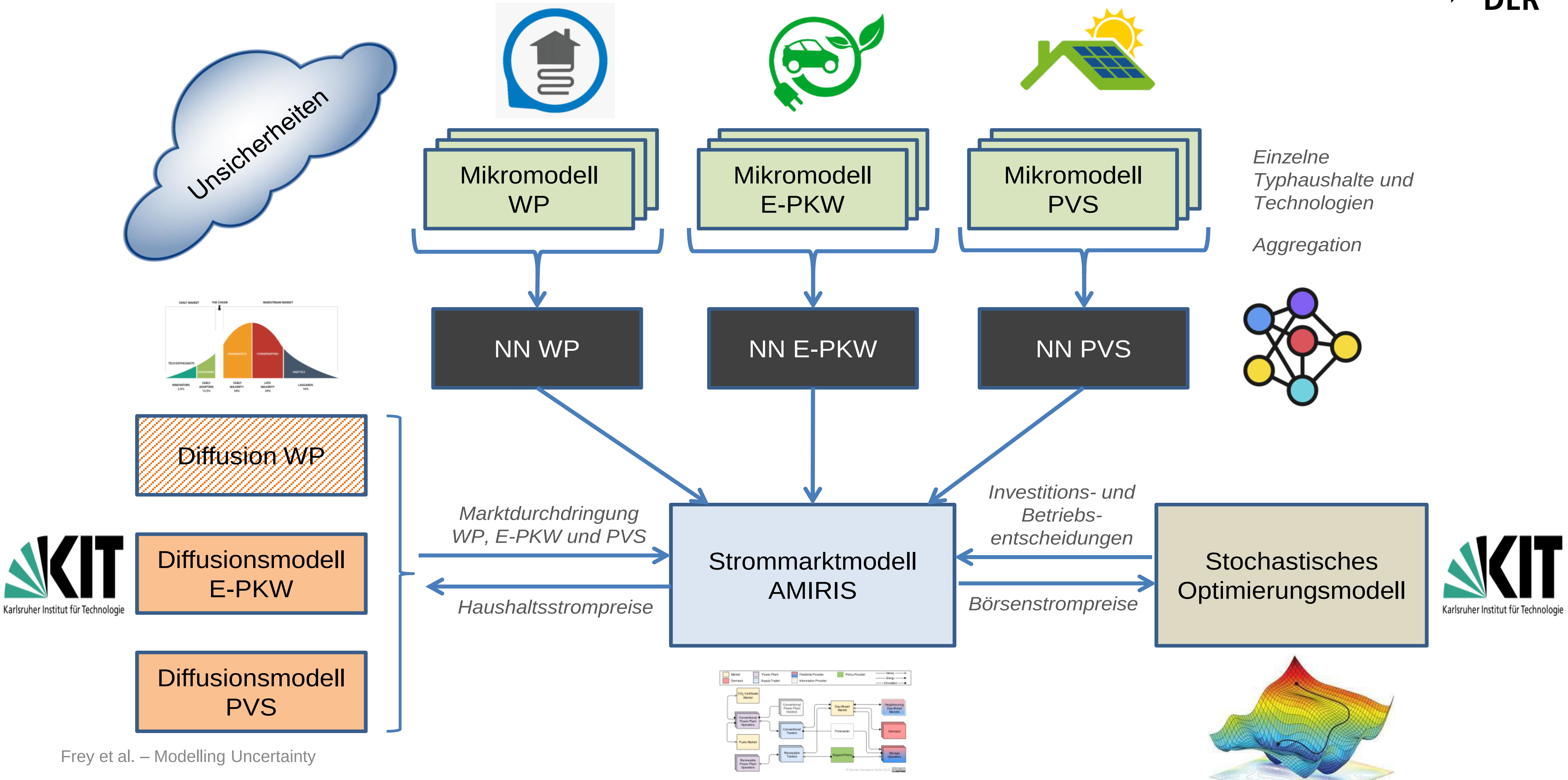
- How to represent prosumer investment decisions under uncertainty?
- How to abstract individual decisions of prosumers so they can be integrated in energy systems models?

Idea

- Model **individual** decisions:
  - Simulate actual optimal operation of PVS, HP, EV
  - **Diffusion model** of household investment decisions (PVS, HP, EV)
- Large energy system models:
  - Feed these models into an **agent-based simulation** of electricity markets, AMIRIS
  - Couple AMIRIS with a **stochastic optimization model** for the supply side

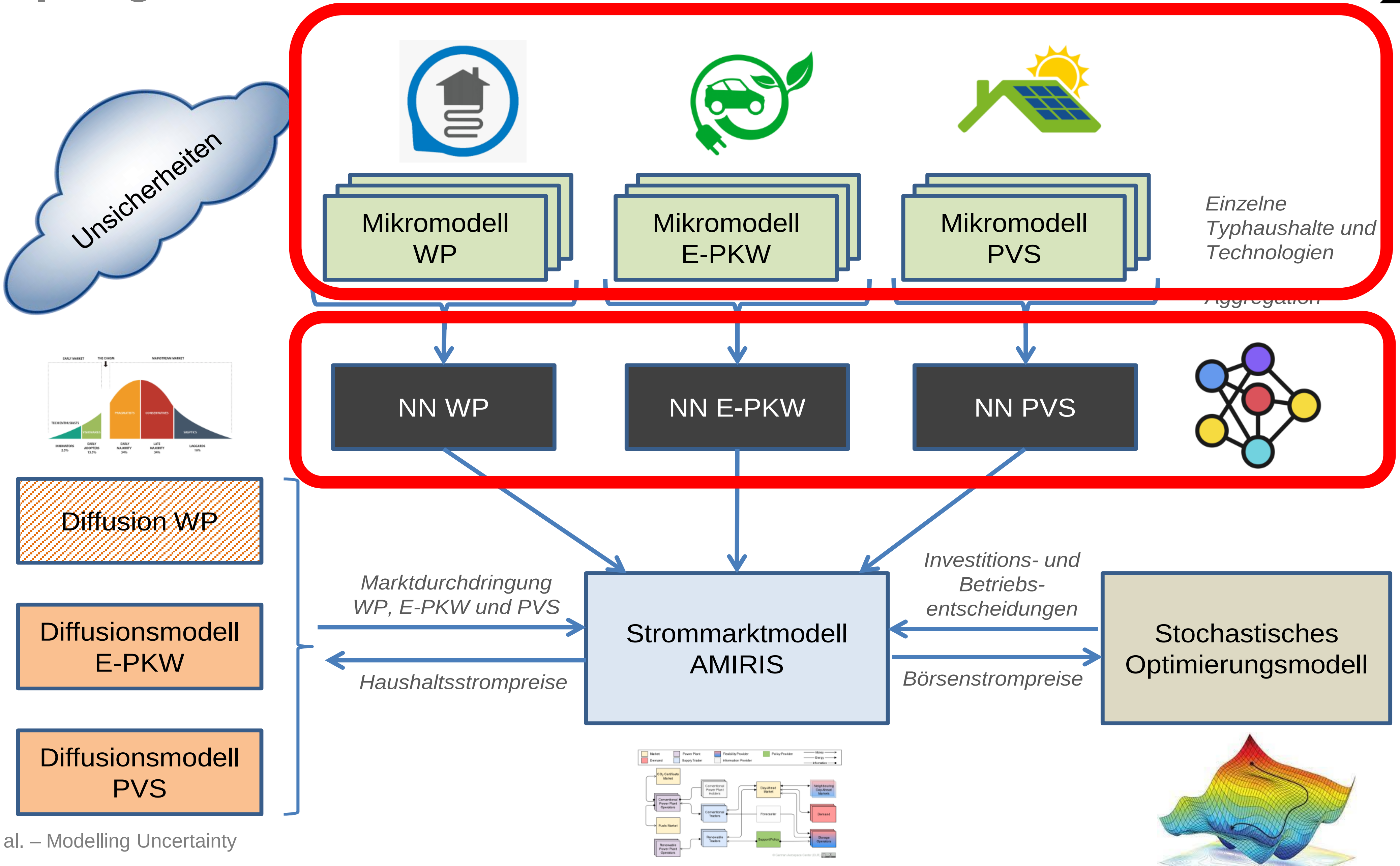
→ **Ability** to model uncertainties between all these components of the energy system comprehensively

Model Setup


Unsicherheiten
Mikromodell WP
Mikromodell E-PKW
Mikromodell PVS
Einzelne Typhaushalte und Technologien
Aggregation
NN WP
NN E-PKW
NN PVS
Diffusion WP
Diffusionsmodell E-PKW
Diffusionsmodell PVS
Karlsruher Institut für Technologie
Marktdurchdringung WP, E-PKW und PVS
Haushaltsstrompreise
Strommarktmodell AMIRIS
Investitions- und Betriebs-entscheidungen
Börsenstrompreise
Stochastisches Optimierungsmodell
Karlsruher Institut für Technologie

MODELING INDIVIDUAL DECISIONS

Coupling models



How to model individual household decisions?

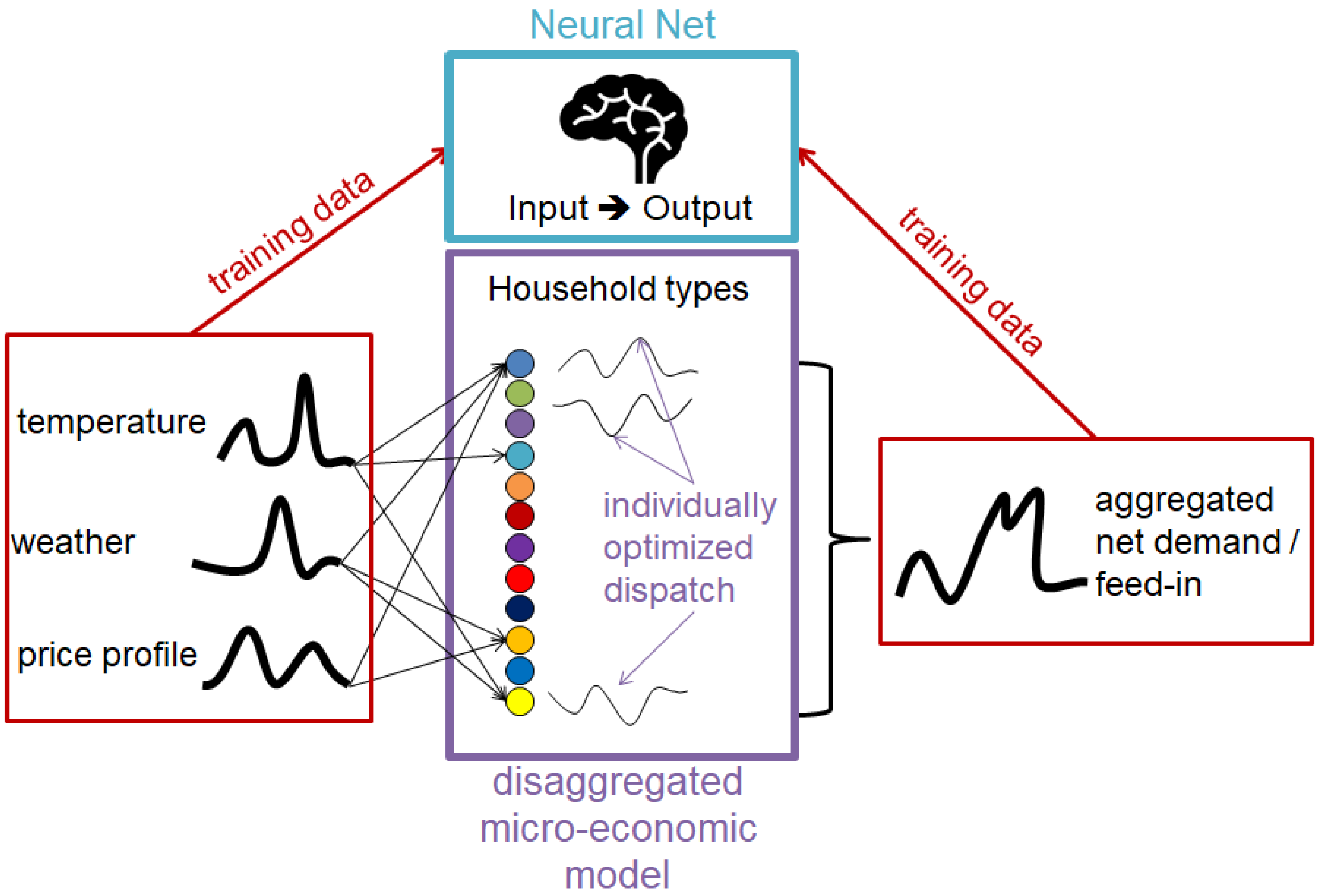
Problem

- Many different households
- High computational effort per optimization

➔ Dispatch optimization of all household types not possible within AMIRIS simulation

Idea

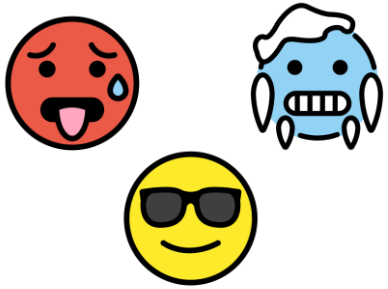
- Individual household **dispatch** optimization done for multiple input variations (weather,…)
- Aggregate household results
- Train Neural Net to predict household aggregated behavior based on given input variations

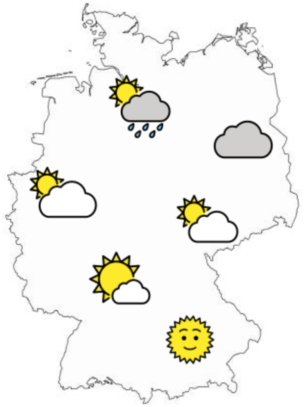


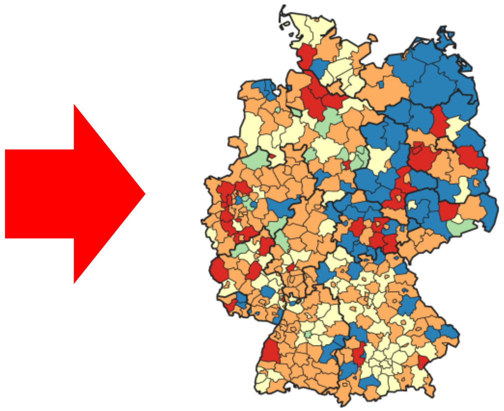
Input variation for heat pump model

- Exploring various household’s decisions

18 building types	3 user comfort types	2 heat pump types	6 weather locations	Total demand







Annual Electricity Demand

- High **computational effort** per optimization → Produce training data via input variations
- Train **Neural Nets** to predict household **aggregated** behavior i → dynamic reaction possible in AMIRIS

FORECASTING WITH ML

Introducing Focapy – A new Python package

What is it?

- Provides Time Series forecasting
- Covers the whole workflow from data preparation to automatic plot generation
- Built around Darts 3.8
- GPU use possible

Felix Nitsch (2023). Focapy: Timeseries forecasting in Python. https://doi.org/10.5281/zenodo.7792750

README.md

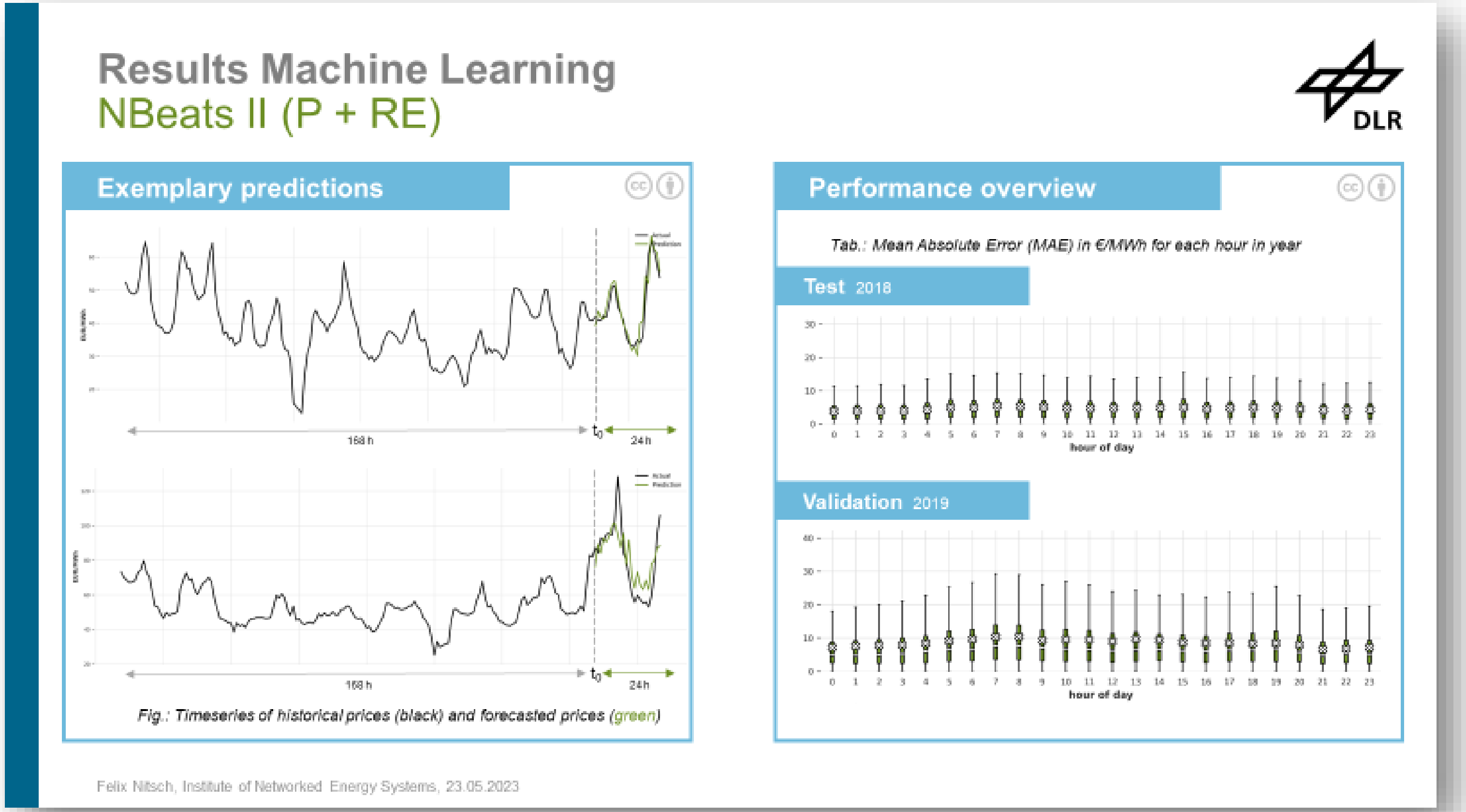
pipeline status coverage report DOI 10.5281/zenodo.7792750 License Apache 2.0 code style black

focapy - Timeseries Forecasting in Python

`focapy` is a package built to conduct timeseries forecasts. It is built around the framework `darts`.

https://gitlab.com/focapy

Comparison of Machine Learning Architectures



The competitors:

- NaiveSeasonal
- ExponentialSmoothing
- ARIMA
- LinearRegressionModel
- LightGBMModel
- RandomForest
- NBEATS
- RNN
- TFT

And the winner for the aggregated demand of typical households is…

TFT = Temporal Fusion Transformers

RESULTS

Results of diffusion model

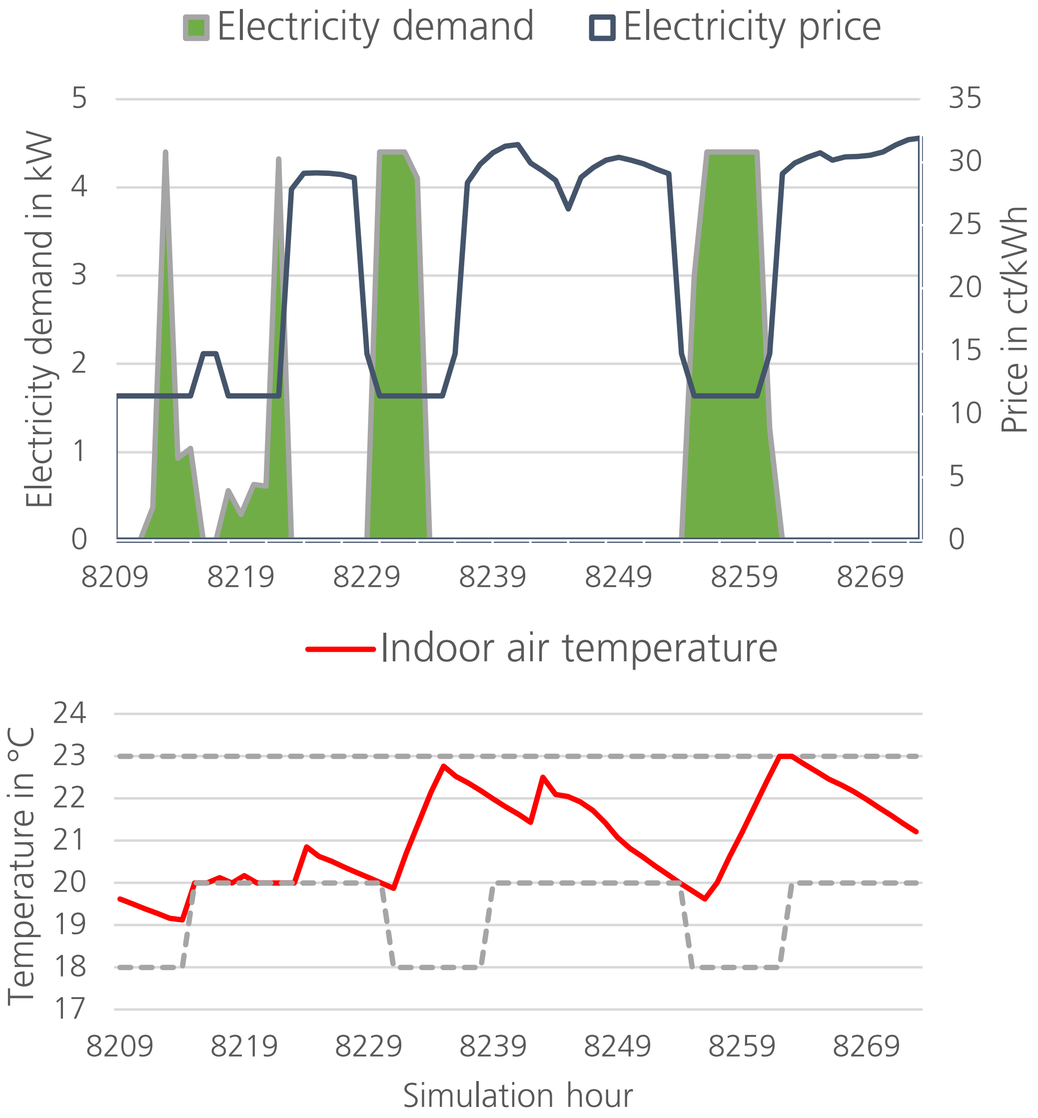
- There are four different subgroups of renewable technology patterns:

 (84.5%)  (5.4%)  (7.05%)  (3.0%)

- **Interested households** tend to install multiple electric technologies together
- A household’s technology profile is mainly influenced by **age** and **education**
- Household income did not significantly predict class membership
- Small percentage of EE-adopters: just 3 out of 20 types of households

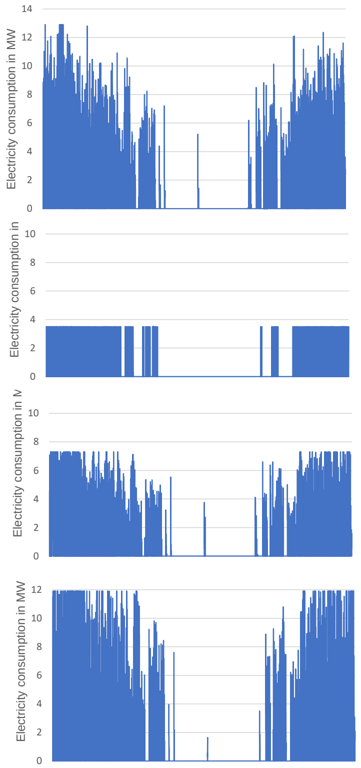
Heat pump model

- **GAMS optimization model:**
  - Minimizes operating cost of residential heat pumps
  - Flexibility by varying temperature within boundaries
  - Electricity demand calculated bottom-up by reduced-order thermodynamic models of building archetypes[1)]

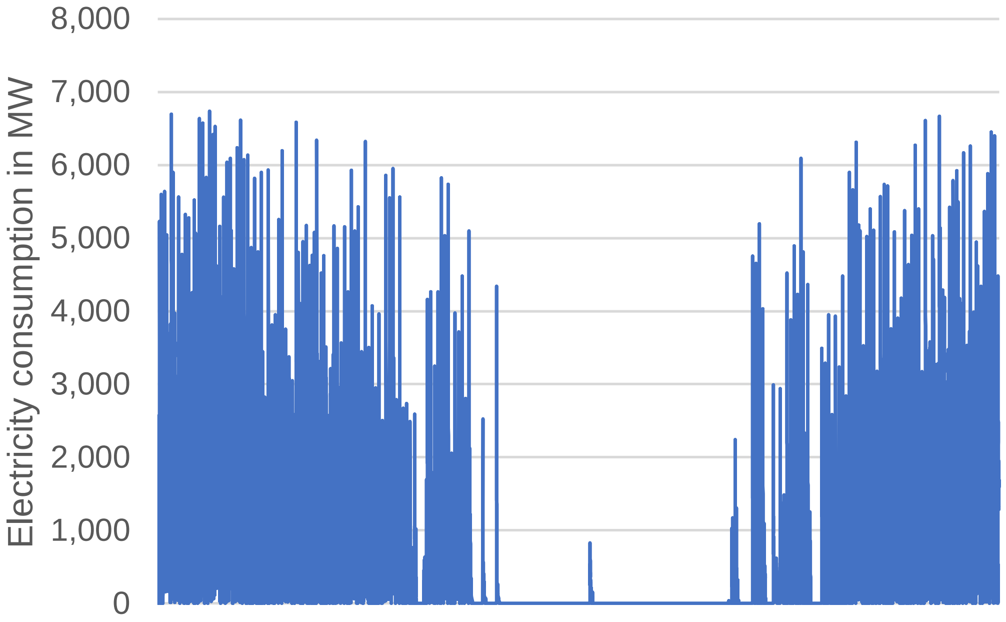


1) Sperber, Frey, Bertsch: Reduced-order models for assessing demand response with heat pumps – Insights from the German energy system, Energy & Buildings vol. 223, 2020

Heat pump model: Aggregation of individual household decisions



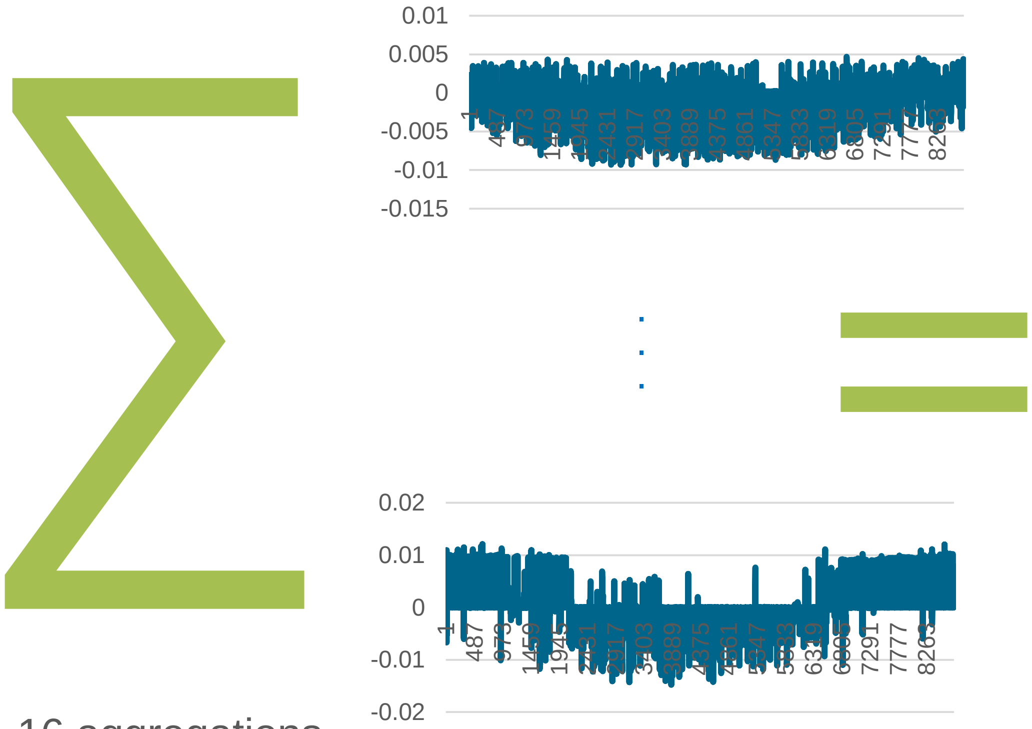
- Building types
- User comfort types
- Heat pump types



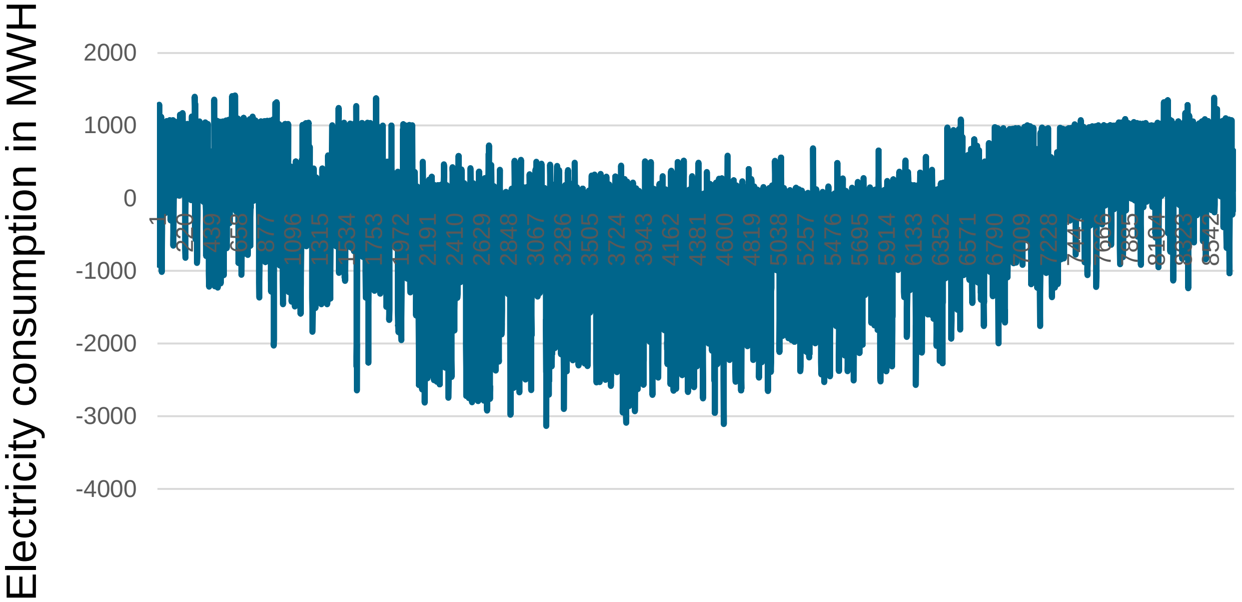
- **Best Model** = LSTM with 500 K params
- **Look-back-size**: 24 h
- **Train / Predict**: 5 locations / 1 other location
- **Data resolution**: 8760 h in ¼ h resolution

Aggregation of individual household decisions

PVS micro-model

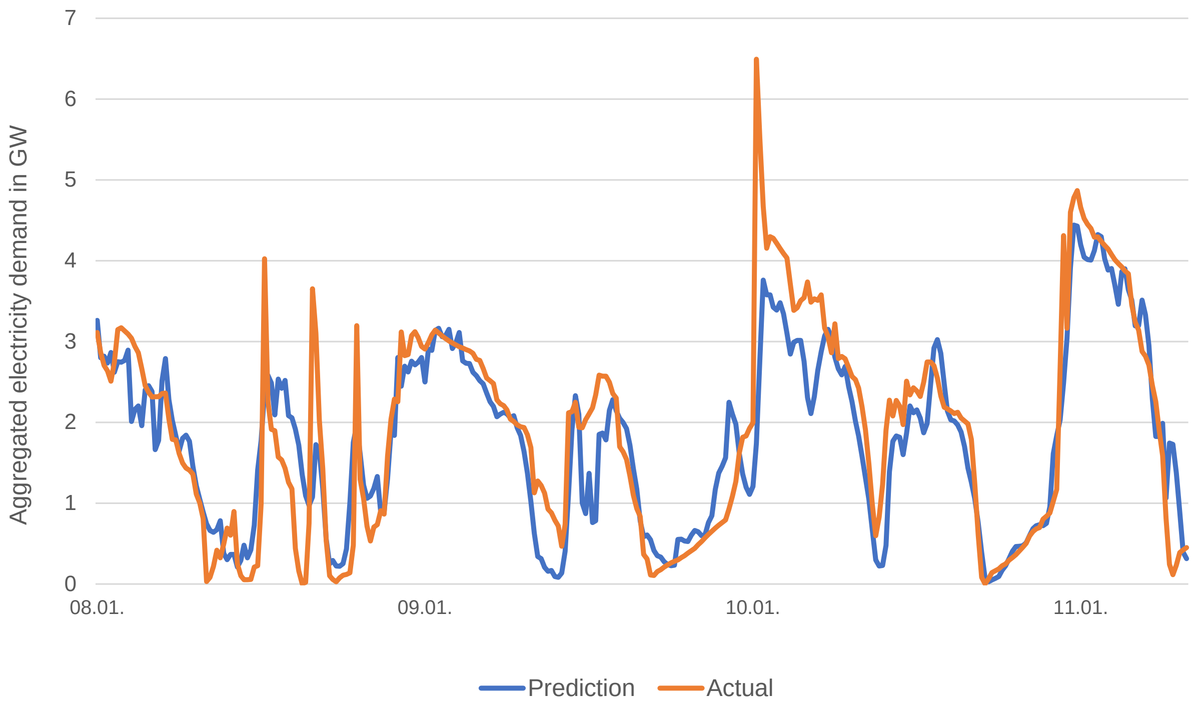


- 16 aggregations
- 40 Mio HH
- HH types
- PVS settings

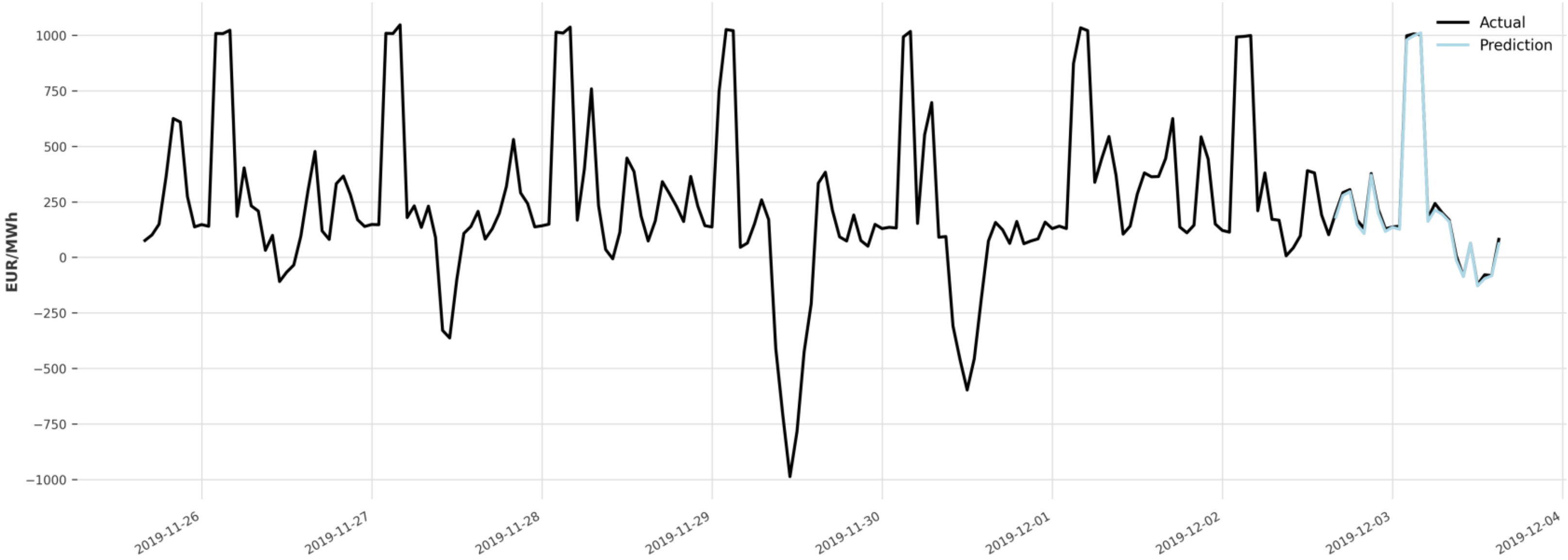


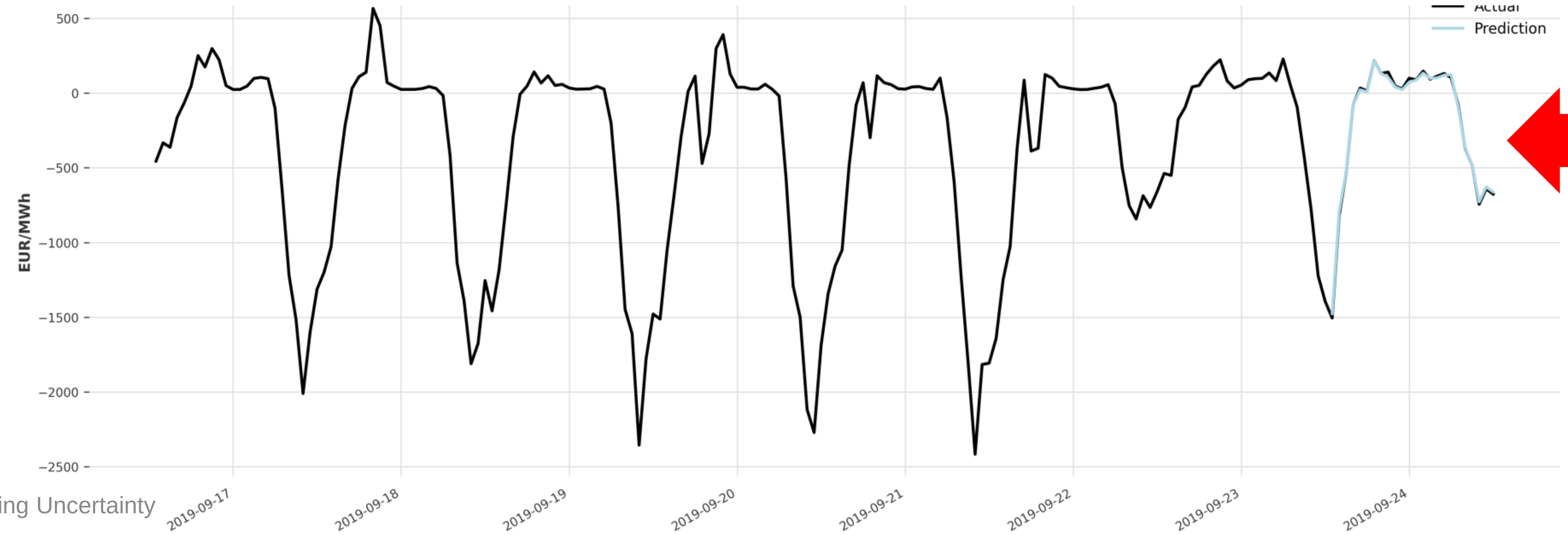
- **Best Model:** Temporal Fusion Transformer
- **Look-back-size**: 24 h
- **Train / Predict**: 5 locations / 1 other location
- **Data resolution**: 8760 h resolution
- **Error**: MAE: 296 MWH for range -3200 / +1414

Heat pump model: Encapsulating aggregated household decisions with ML



Results: PVS with ML, exemplary predictions





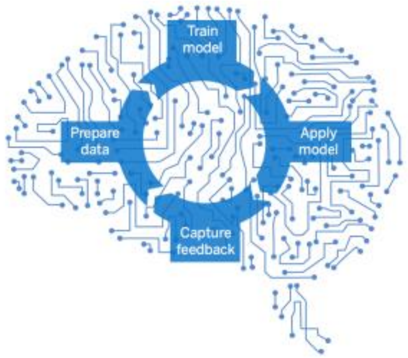
Nearly perfect predictions

CONCLUSION

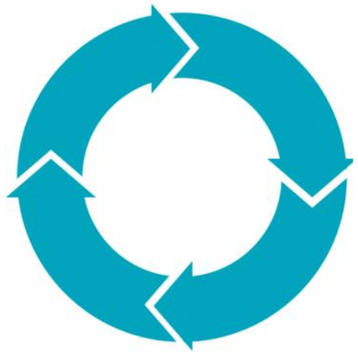
High-level Conclusion

- Model coupling helps to analyze multiple aspects of the energy system at the same time

- Abstracting individual decisions with ML is a general solution for integrating computationally intensive tasks into simulations that were previously impossible



- Combining an ABM in a feedback-loop with an optimization model produces robust scenario pathways that are in fact economically viable



Supported by:

Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag

THANK YOU!

Contact: ulrich.frey@dlr.de

Karlsruher Institut für Technologie

DLR

Supported by:

Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag

BACKUP

Contact: ulrich.frey@dlr.de

Karlsruher Institut für Technologie

DLR

Diffusion model: Survey + latent class analysis

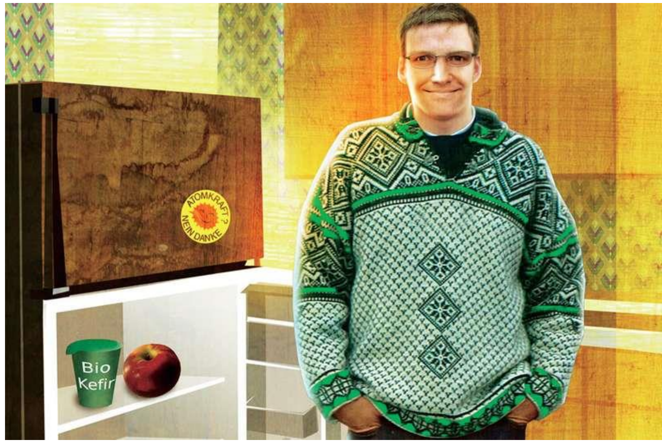
LCA resulted in a ***4-class model***

(1) Non-adopters of renewable energy technologies (84.5%)

(2) PV owners living in (semi-)detached houses (5.4%)

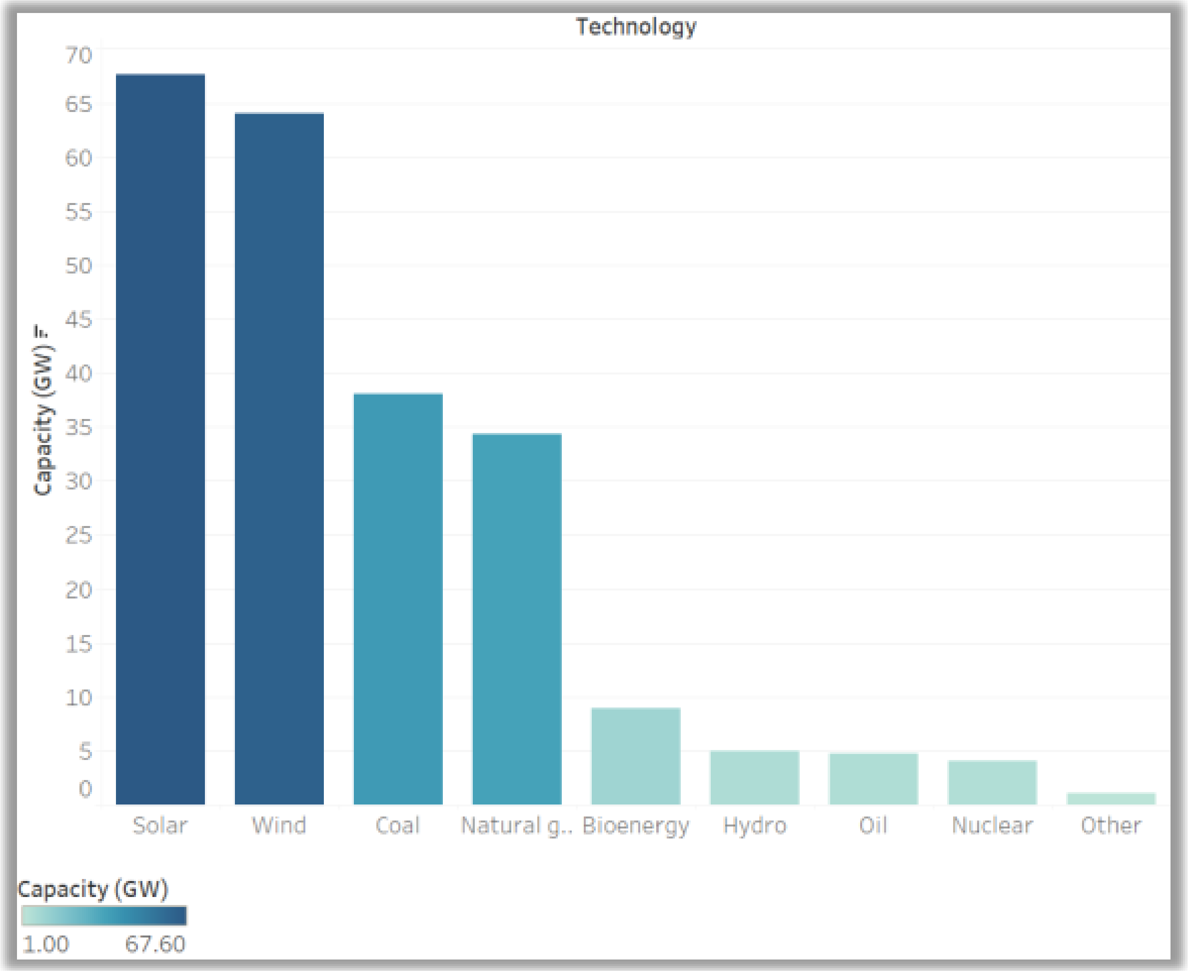
(3) Heat pump owners with comprehensive retrofit (7.05%)

(4) Multiple renewable energy technology adopters (3.0%)

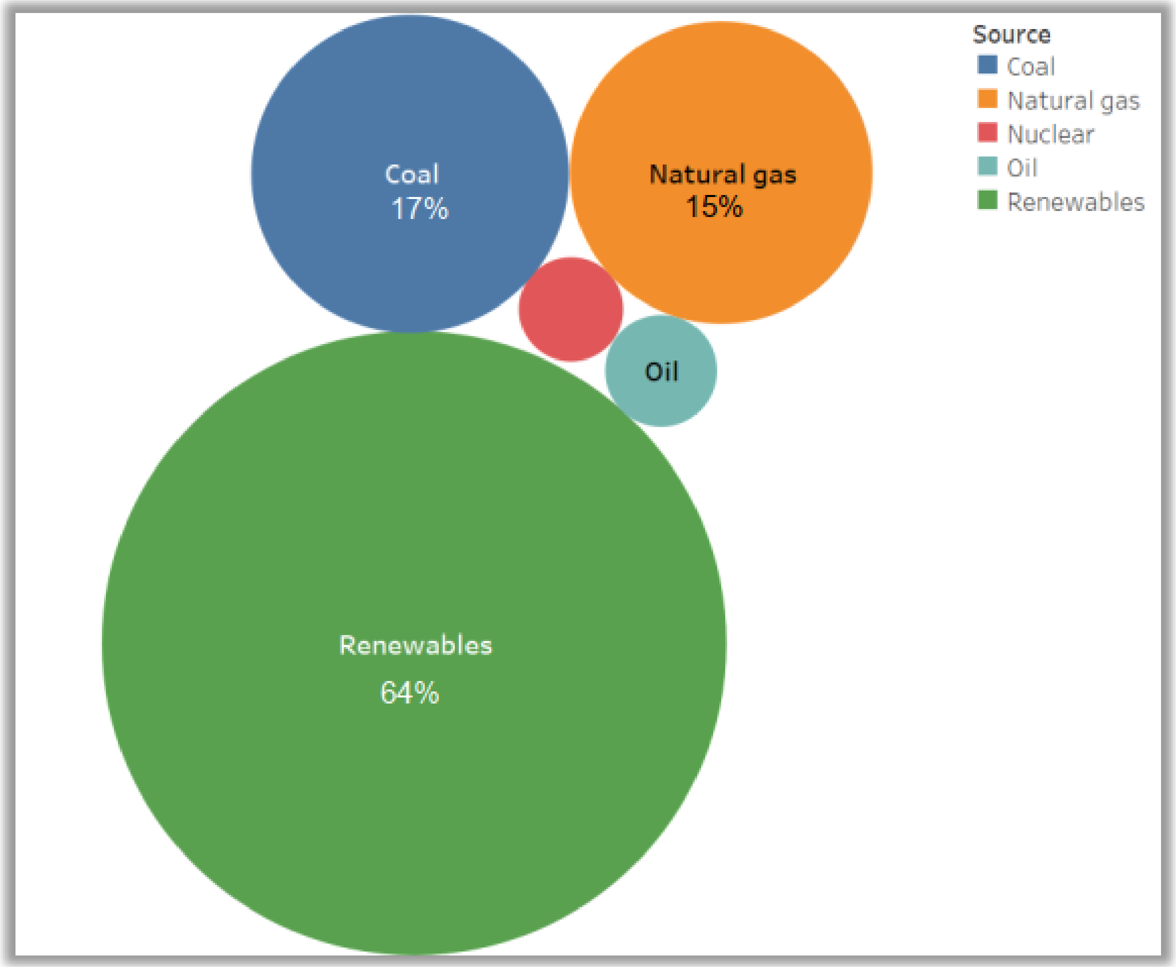


Stochastic optimization: Power production in TWh

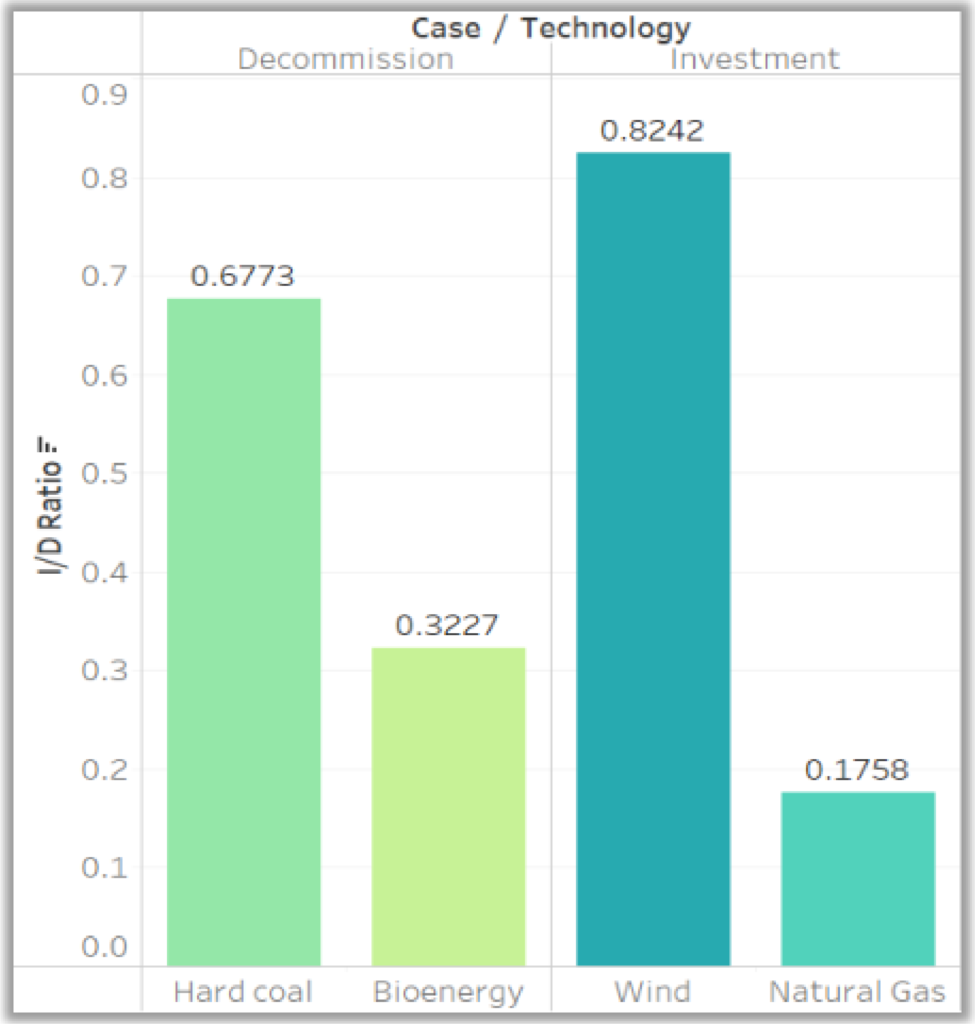
Capacity per technologies



Capacity per sources



Stochastic optimization: first results



Observations:

- **Planning horizon:** Direct impact on retirement decisions and investment on renewables
- **Wind yield profile per state:** Investment projects with higher yield profiles are prioritized..