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MODELLING ACTORS’ BEHAVIOR IN A DECENTRALIZED ENERGY SYSTEM WITH MACHINE LEARNING

GOR, 25th of October 2023, Zürich

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Karlsruher Institut für Technologie

DLR

Project: EN4U, FKZ 03EI1029A

Motivation: Massive uncertainties

- Recent geopolitical disruptions increase uncertainties & change prosumer reactions
  - Buy an electric vehicle?
  - Buy PV + storage?
  - Buy a heat pump?

→ Prosumer reactions are largely unknown

→ Energy systems pathways highly uncertain

→ Fuel price and other assumptions of existing scenarios might be totally off

Research questions

- How to model prosumer investment decisions under uncertainty?
- How to abstract individual decisions of prosumers so they can be integrated in energy systems models?
- How to produce robust scenario pathways that are economically viable?

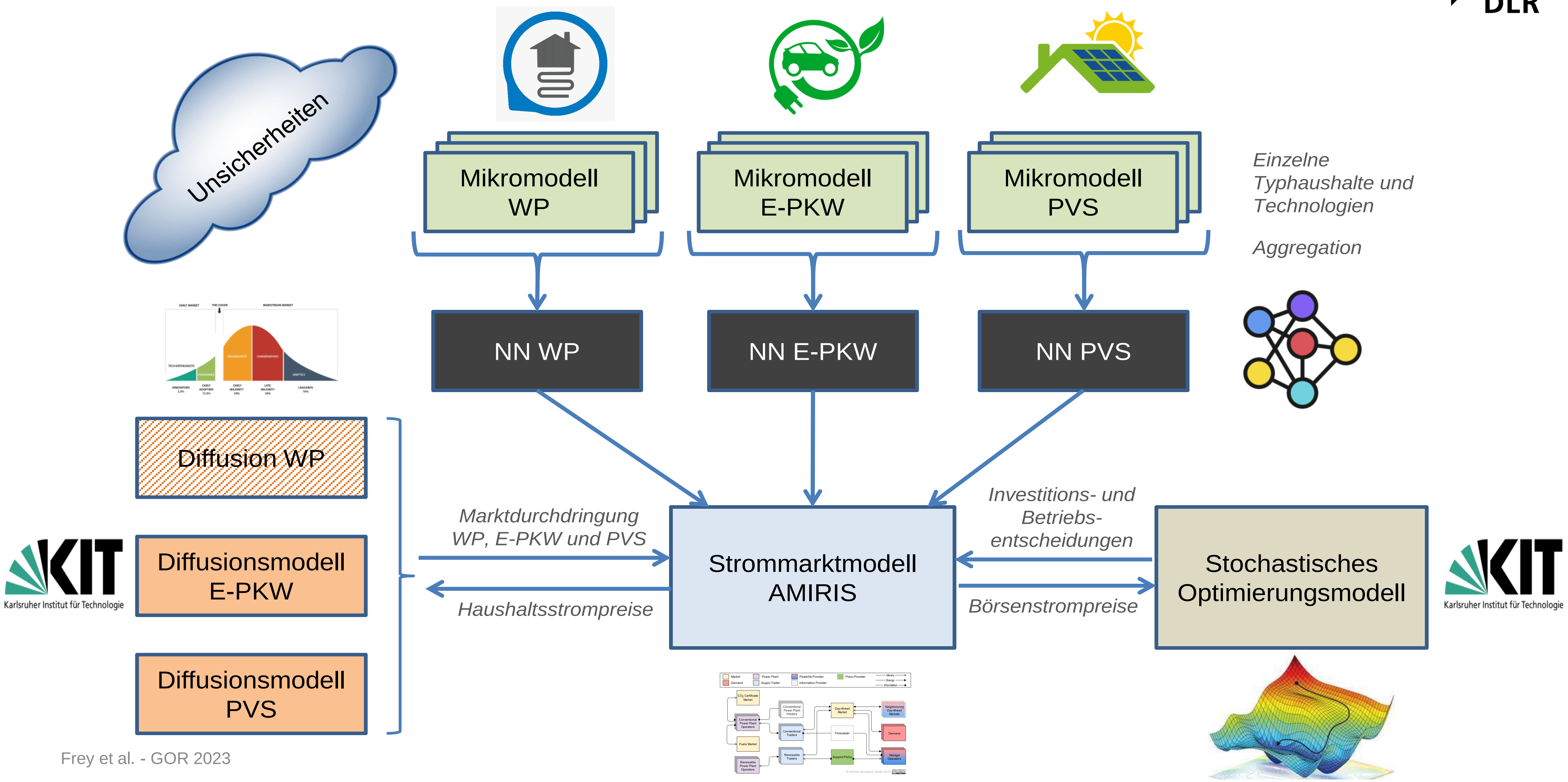
Idea

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

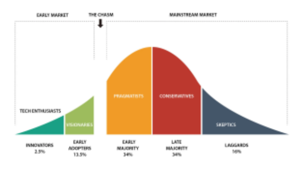
→ **Ability** to model uncertainties between all these components of the energy system comprehensively

METHODS

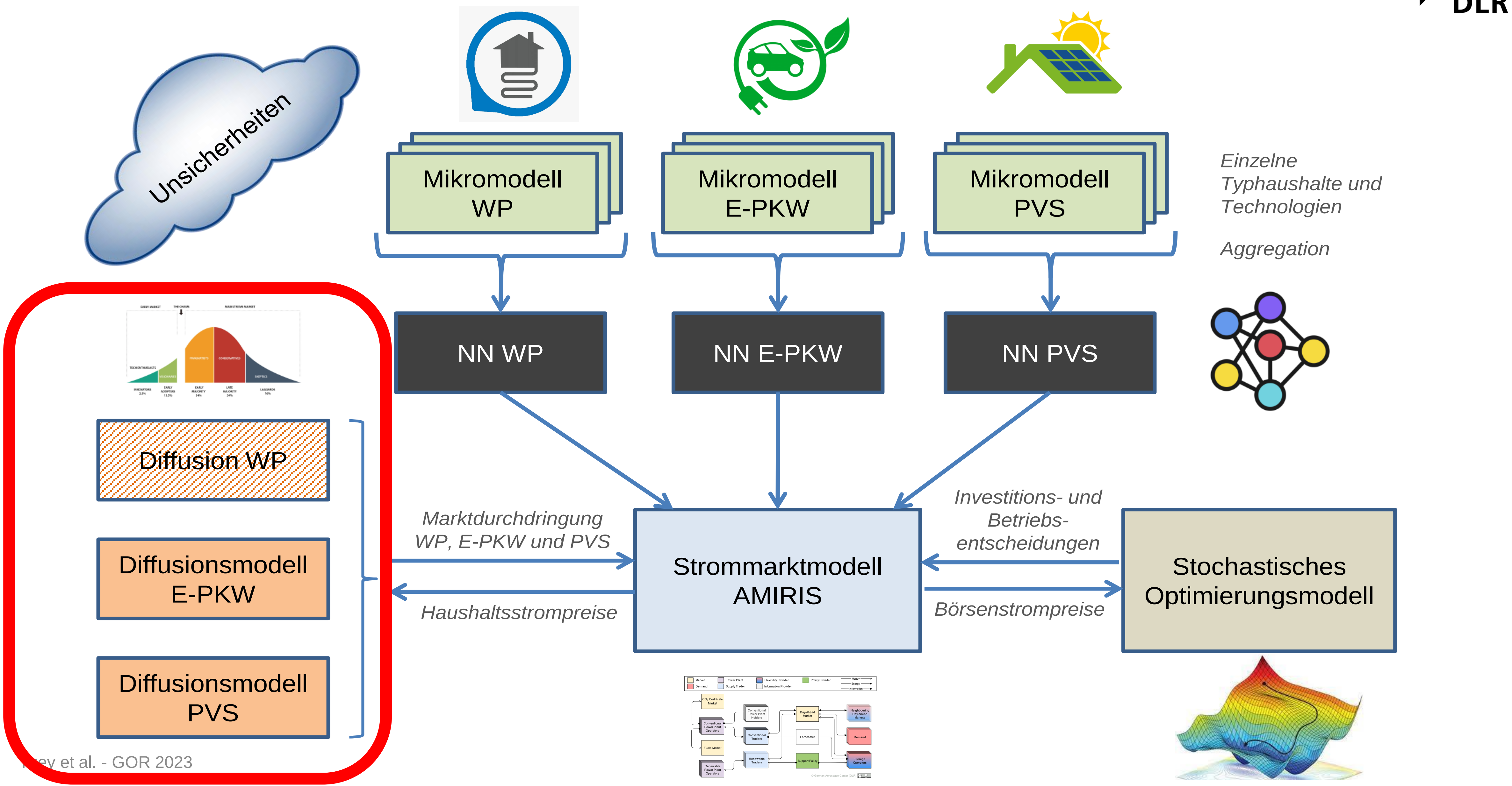
Coupling models with RCE



DIFFUSION MODEL



Coupling models with RCE

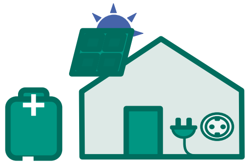
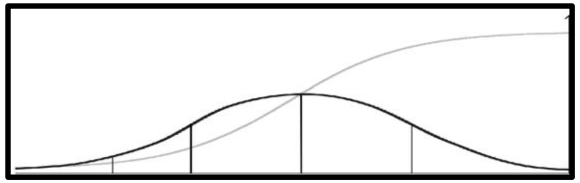
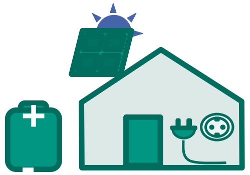


Survey for individual household characteristics

- Representative survey (n=809)

	%
Building ownership	
Household property	45.5
Rented builidng	54.5
State of renovation	
Extensive retrofit	30.7
Replacement of the windows	21.3
No retrofit	48.1
Installed technologies	
Photovoltaic	9.9
Battery storage system	4.6
Heat pump	13.3
Electric vehicle	10.4

Diffusion model

Identification of adopters among German households	Diffusion process	Investment decision
 Latent Class Analysis *(based on overall German population)*	 Bass diffusion modell	 Optimizing investment (*NPV*)
• Potential prosumer groups • Resulting load profiles	• Number of potential prosumers	• Optimal PV size • Optimal battery storage size

Cumulative capacities of PV and storage

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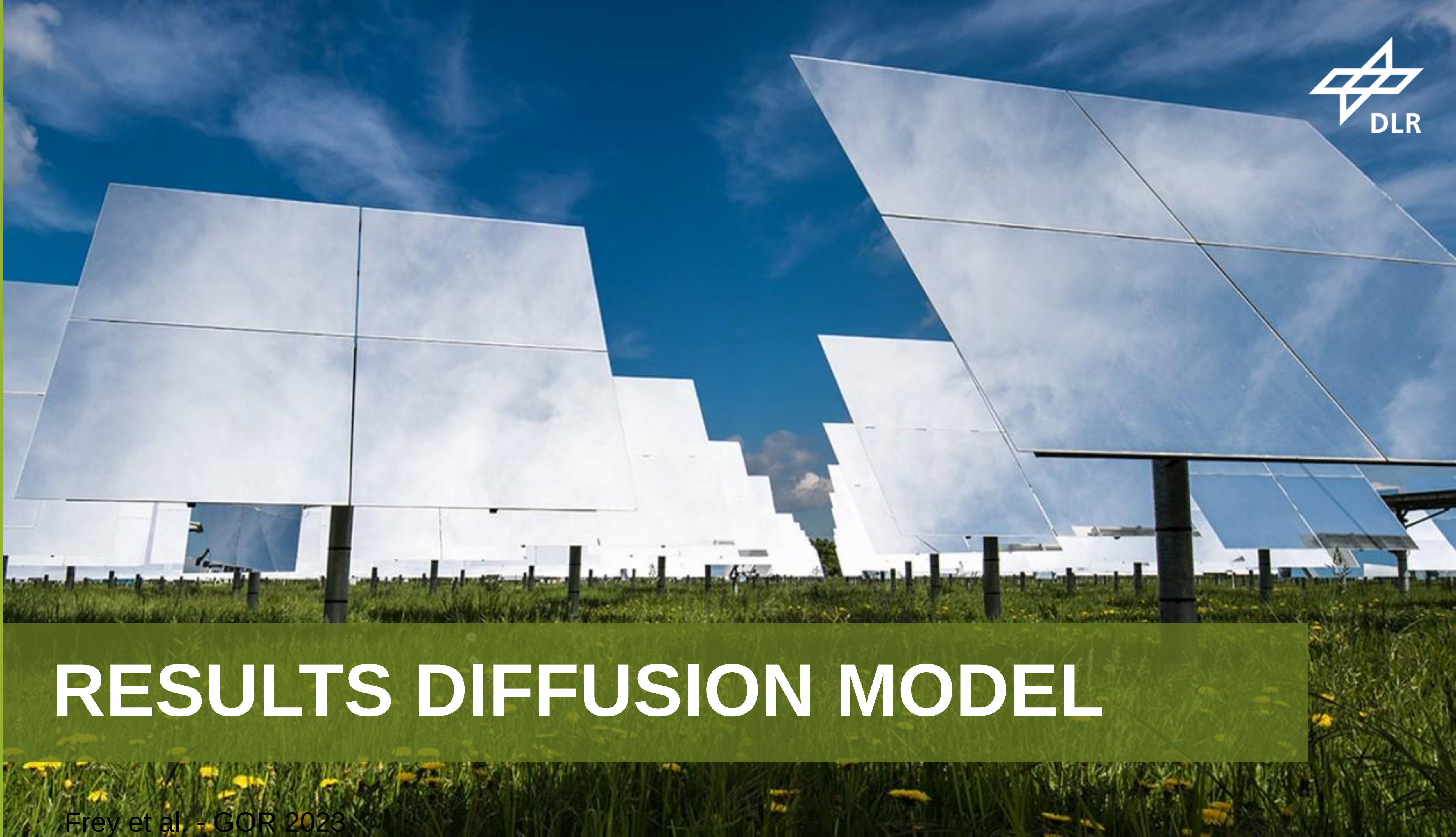


RESULTS DIFFUSION MODEL

Diffusion model: Survey + latent class analysis

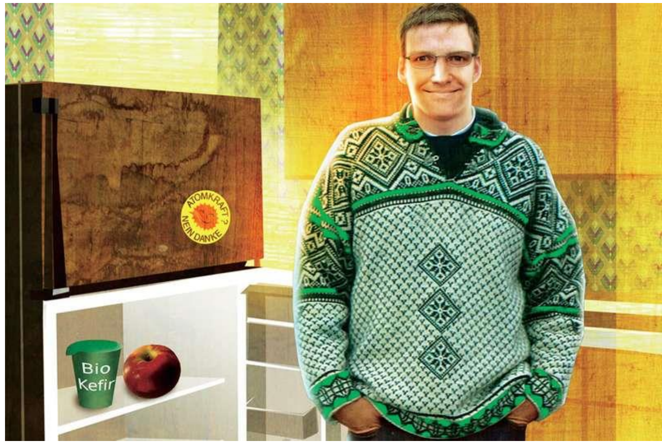
LCA resulted in a ***4-class model***

(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%)



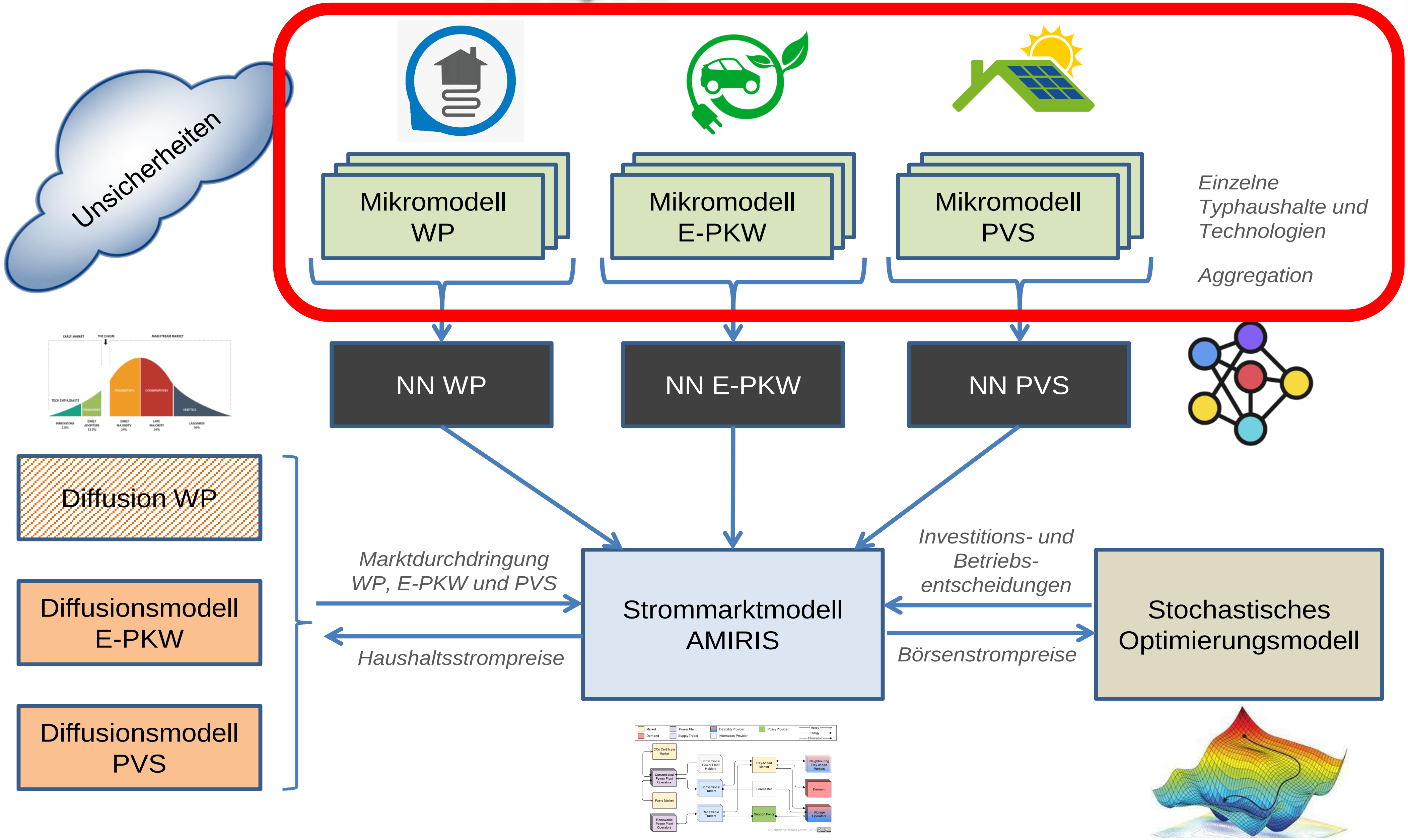
Further results of diffusion model

- **Interested households** tend to install multiple electric technologies together
- A household's technology profile is influenced by **age** and **education**, certain **housing characteristics**, and others
- Household income do not significantly predict class membership
- Classes of adopters are relatively small compared to the overall sample (for the final micro-models: 3 out of 20 types of households)

→ Output for other models: market penetration for PVS, HP, EV until 2050

3 MICRO-MODELS

Coupling models with RCE



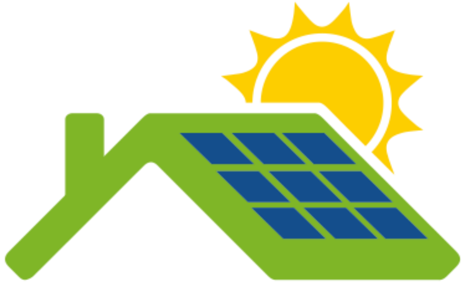
Development of 3 cost-optimising micromodels depending on electricity price

- E-Mobility: VencoPy
  (optimises charging)

- Heat pumps: GAMS optimization model

  (optimizes heating)

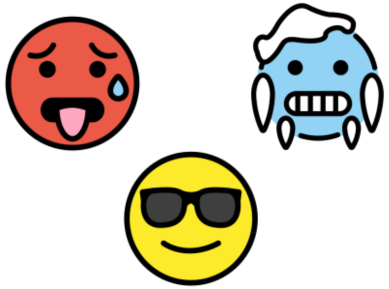
- PV-Storage: Decoupled ABM (AMIRIS) model
  (optimises feed-in)

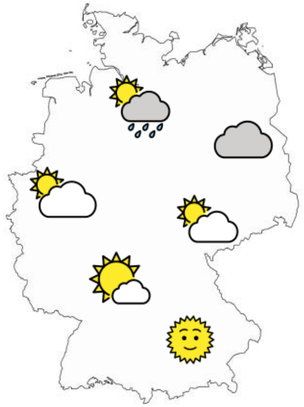


Example: Input variation for heat pump model

- Exploring various household's decisions

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

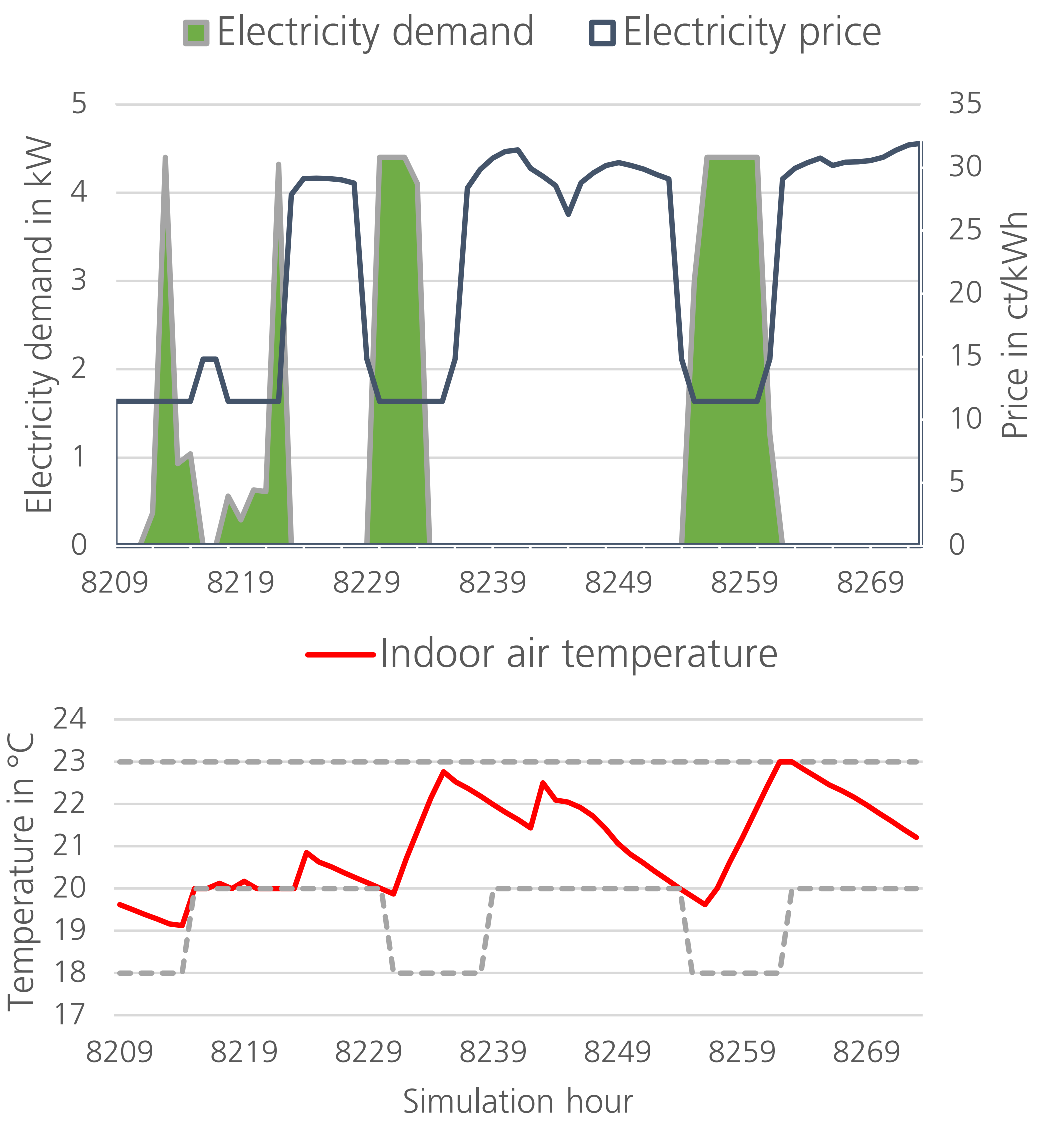




- *Problem*: High **computation effort** per optimization → Individual dispatch optimization of all household types not possible within AMIRIS
- *Solution*: Train **Neural Net** to predict household **aggregated** behavior and include feedback in AMIRIS

Heat pump model

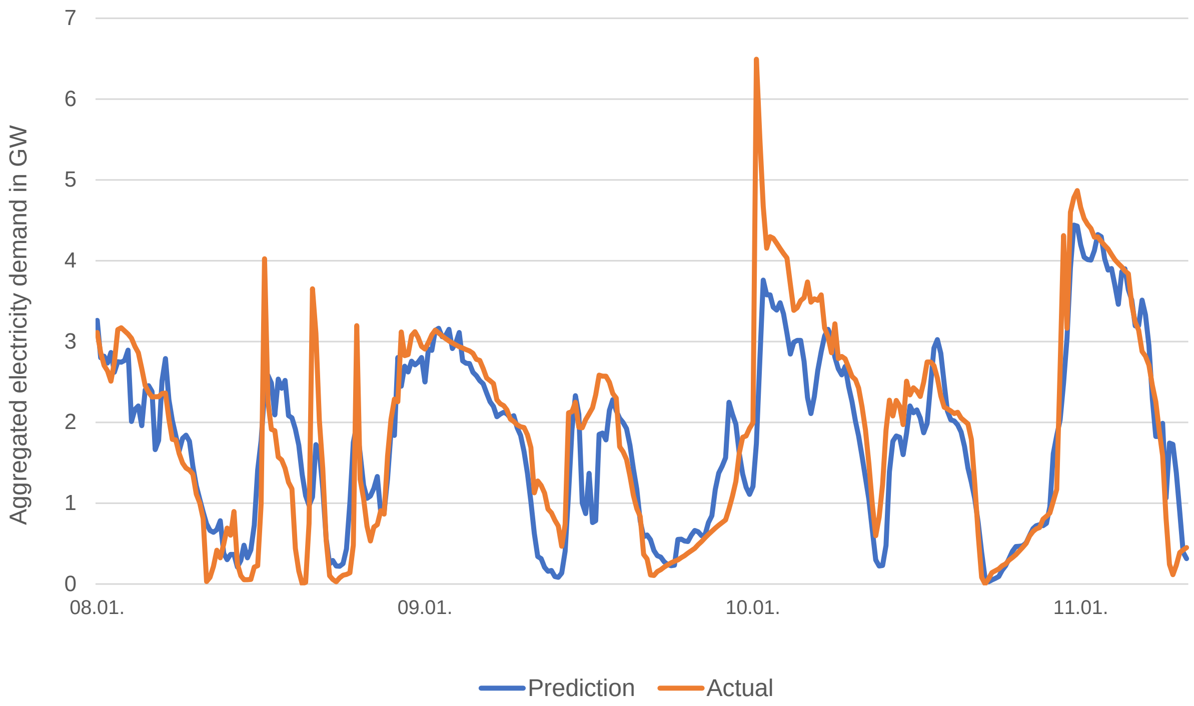
- **GAMS optimization model:**
  - Minimizes operating cost of residential heat pumps
  - Flexibility by varying temperature within boundaries
  - Electricity demand calculated bottom-up by reduced-order thermodynamic models of building archetypes[1)]

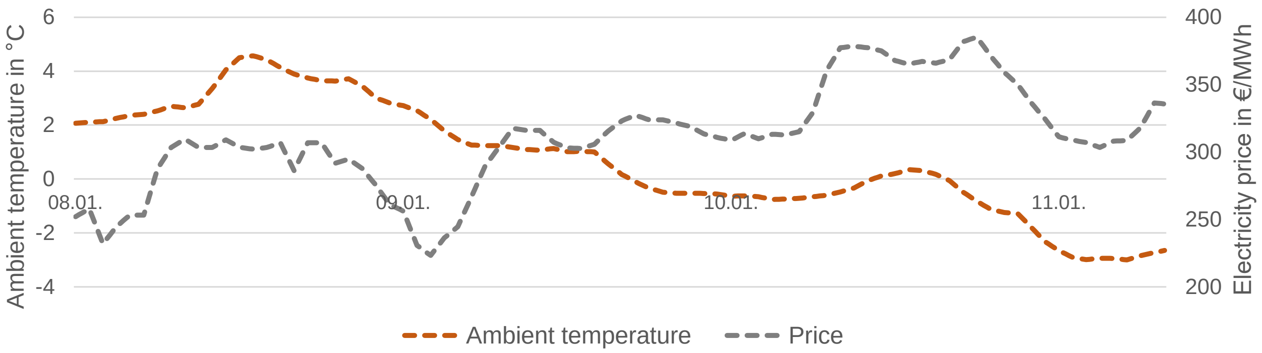


1) Sperber, Frey, Bertsch: Reduced-order models for assessing demand response with heat pumps – Insights from the German energy system, Energy & Buildings vol. 223, 2020

RESULTS MICRO-MODELS

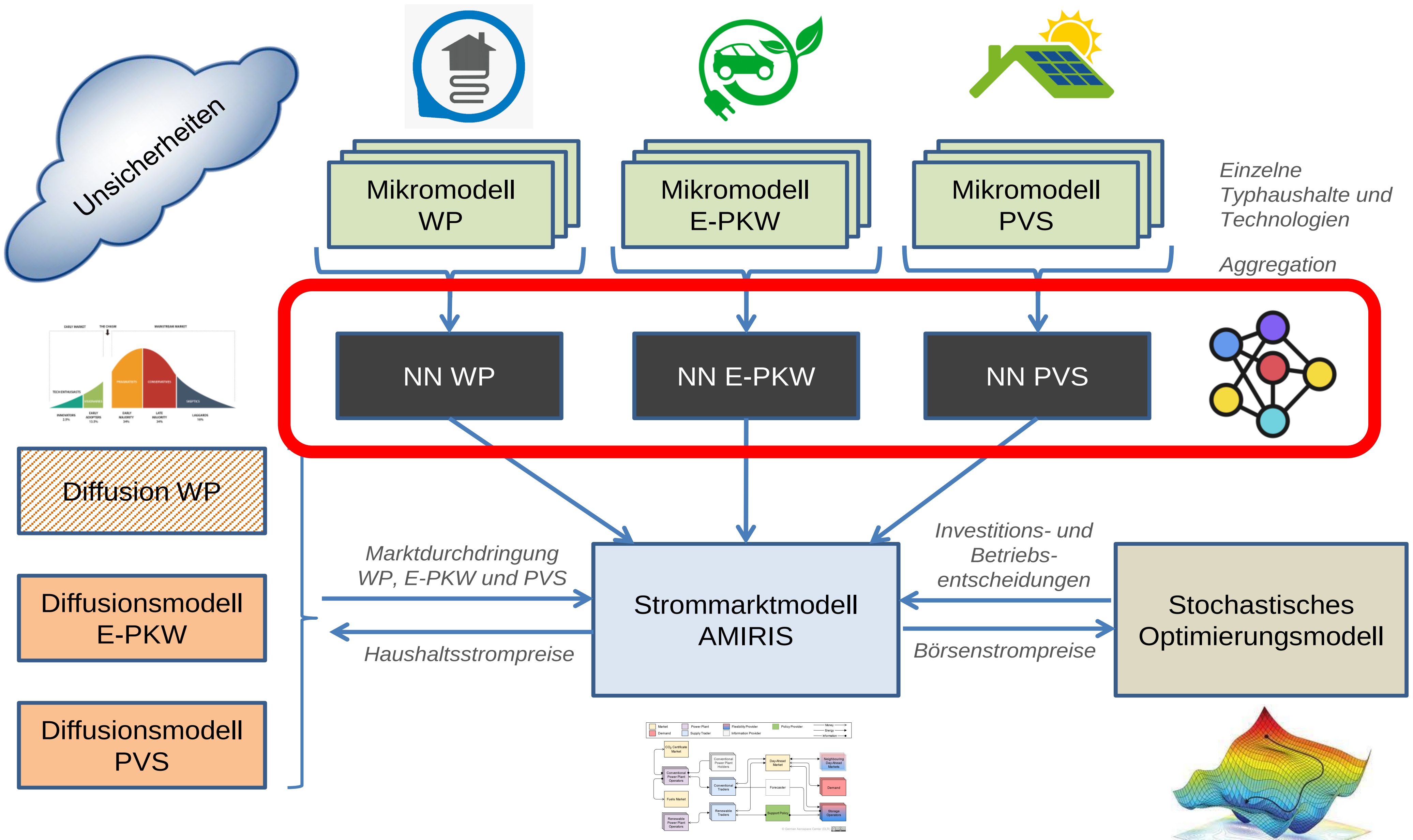
Heat pump model: Validating aggregated household decisions with ML (predicted demand vs. real demand)





FORECASTING WITH ML

Coupling models with RCE



Modeling individual household decisions

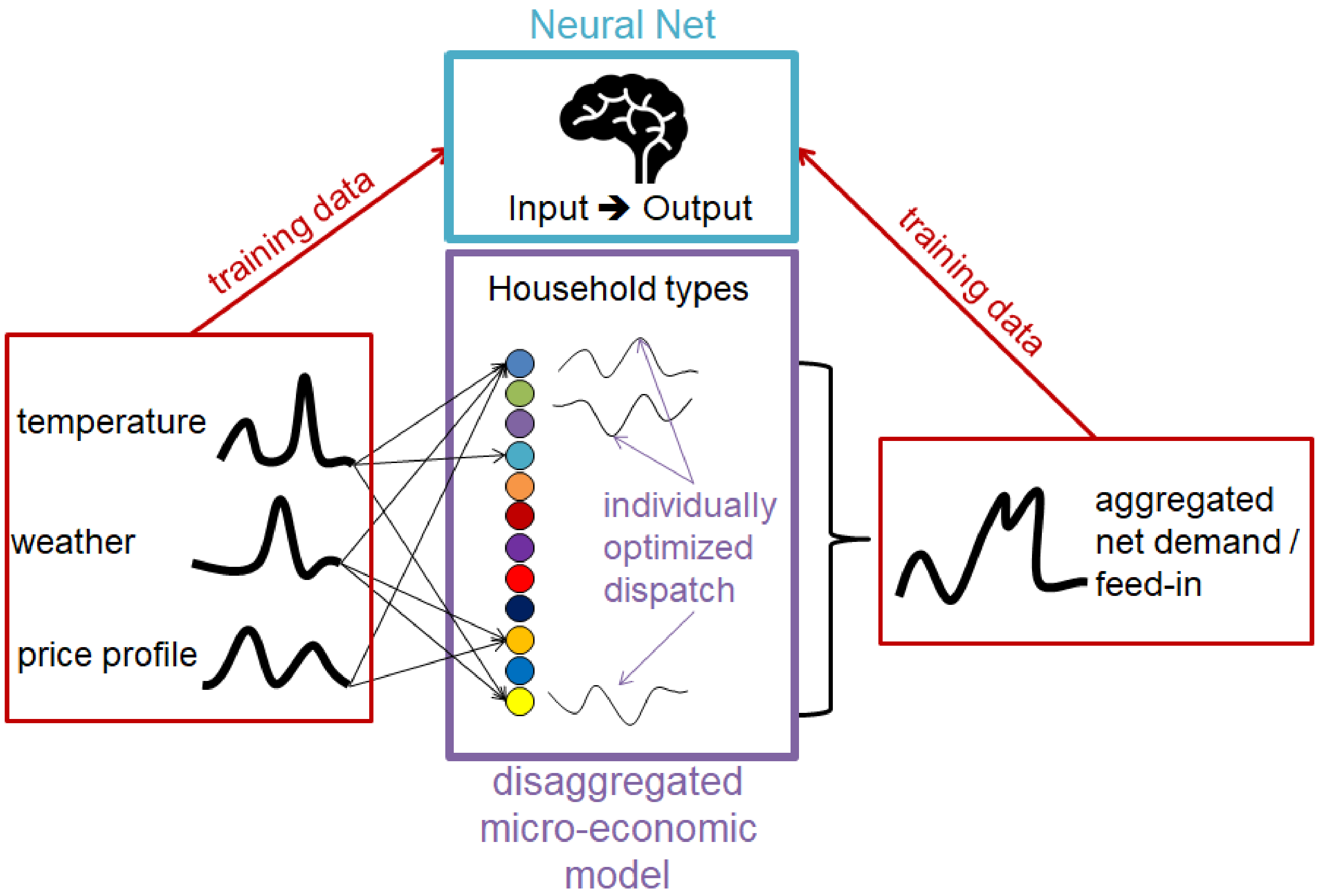
Problem

- Many different households
- High computational effort per optimization

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

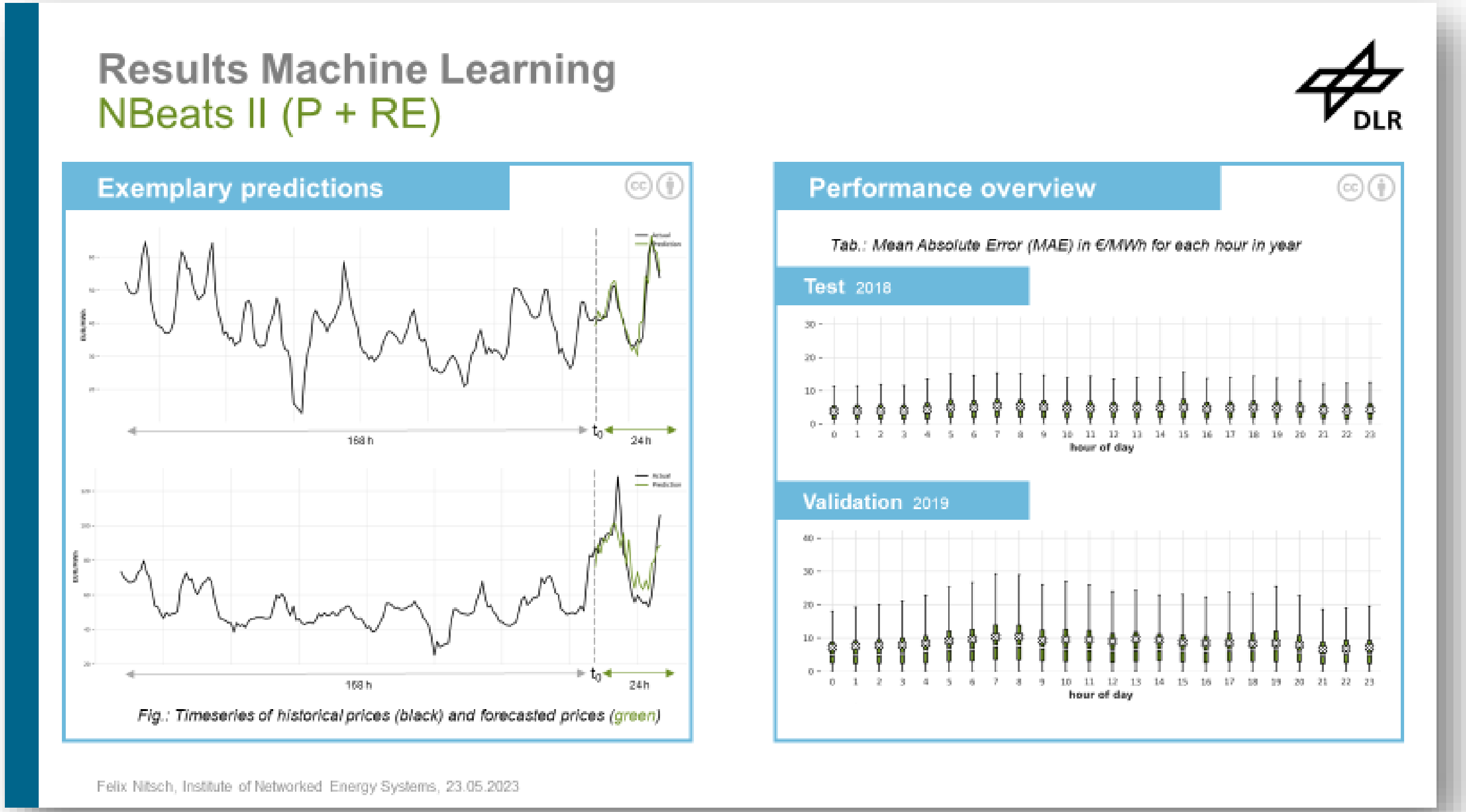
Idea

- 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



Comparison of Machine Learning Architectures

Using open FOCAPY https://gitlab.com/focapy



The competitors:

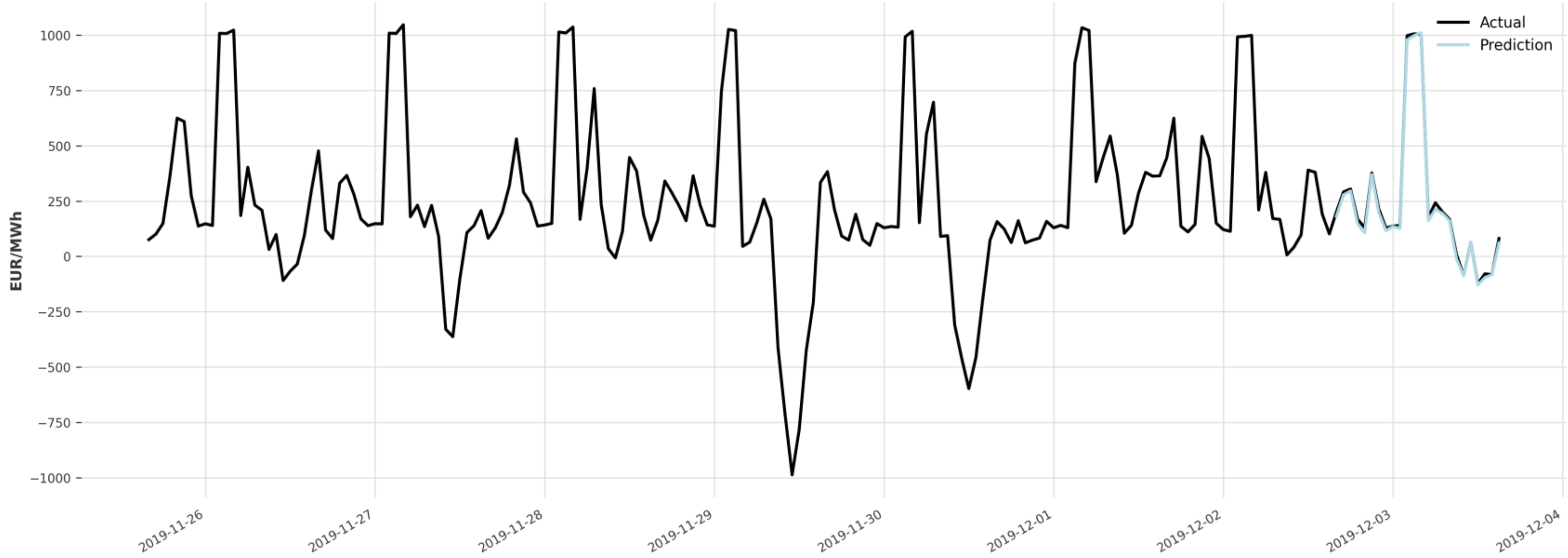
- NaiveSeasonal
- ExponentialSmoothing
- ARIMA
- LinearRegressionModel
- LightGBMModel
- RandomForest
- NBEATS
- RNN
- TFT

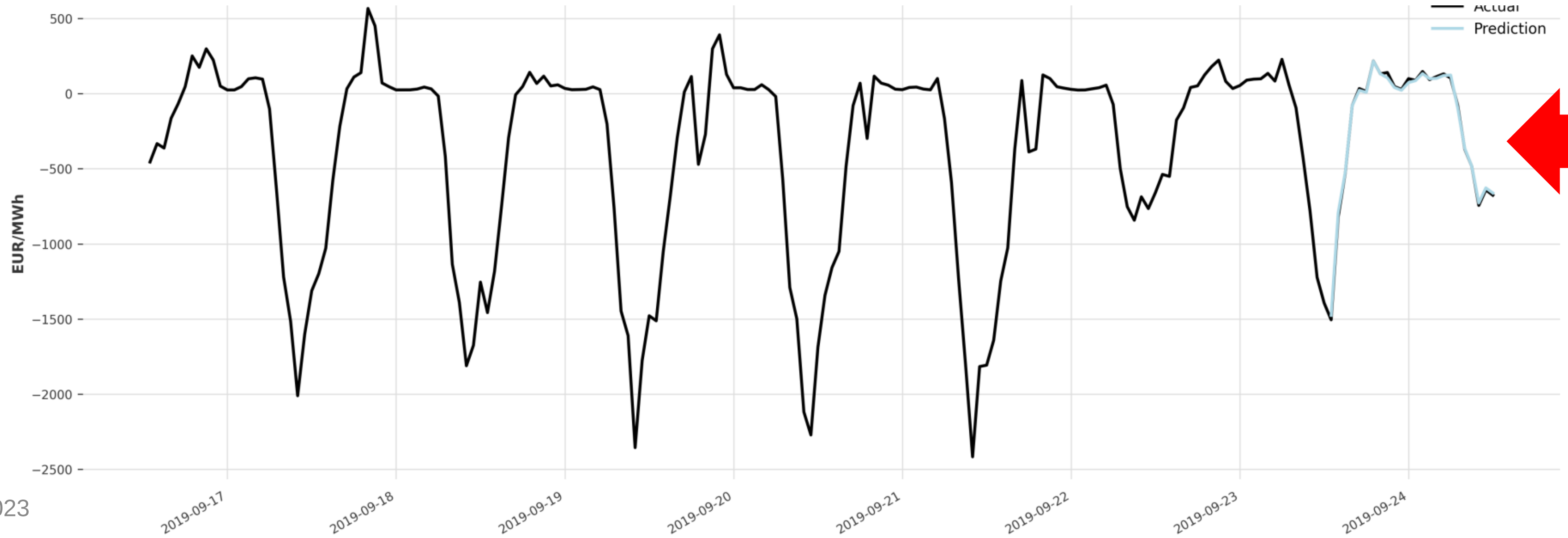
Schimeczek, C und Nitsch, F (2019) Modelling forecast errors for day-ahead electricity market prices. 8th INREC 2019 - Uncertainties in Energy Markets, 25.-26. Sept. 2019, Essen. https://elib.dlr.de/129448/

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

TFT = Temporal Fusion Transformers

Results: PVS with ML, exemplary predictions

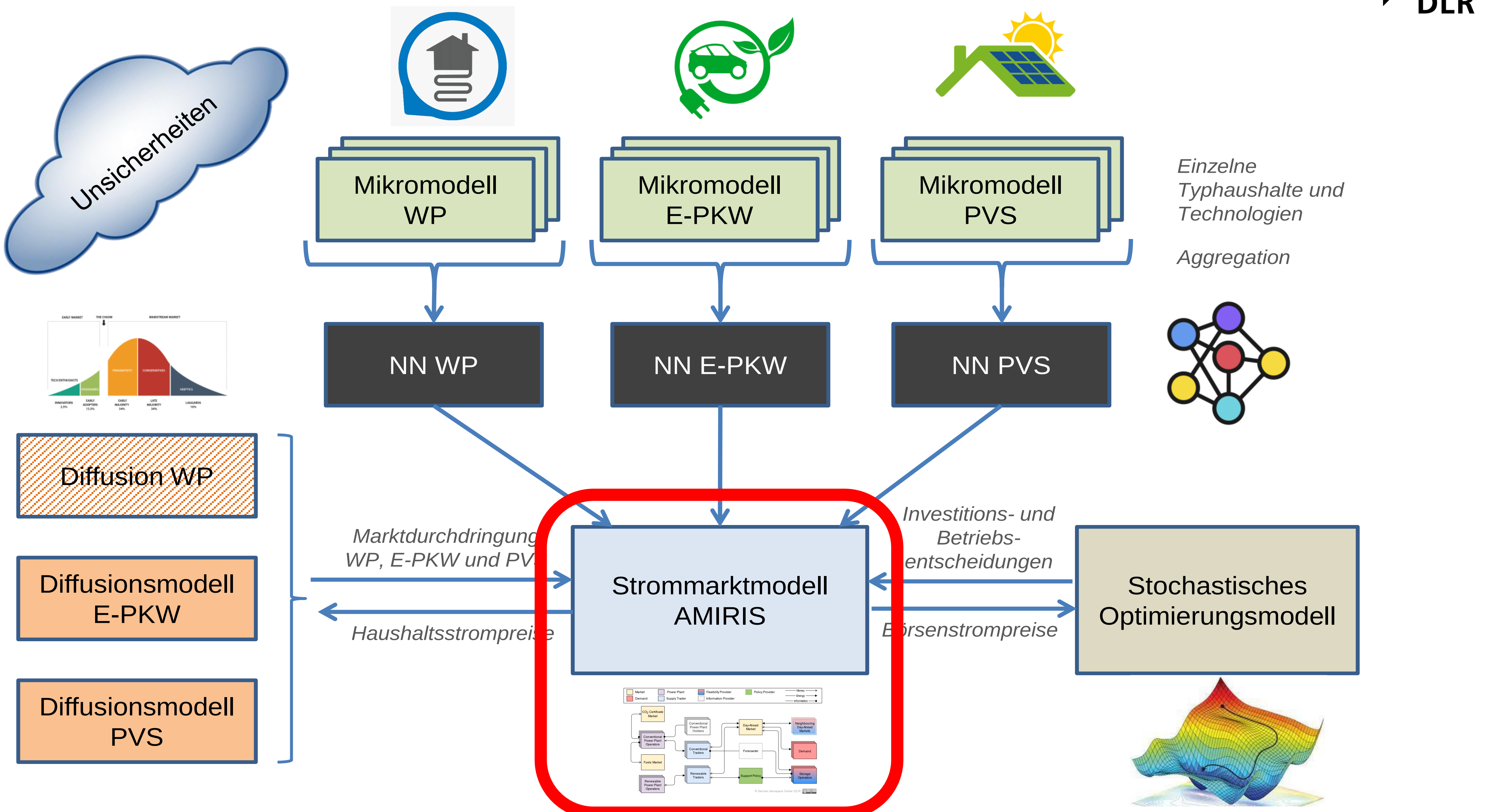




Nearly perfect predictions!

AGENT-BASED MODEL (AMIRIS)

Coupling models with RCE



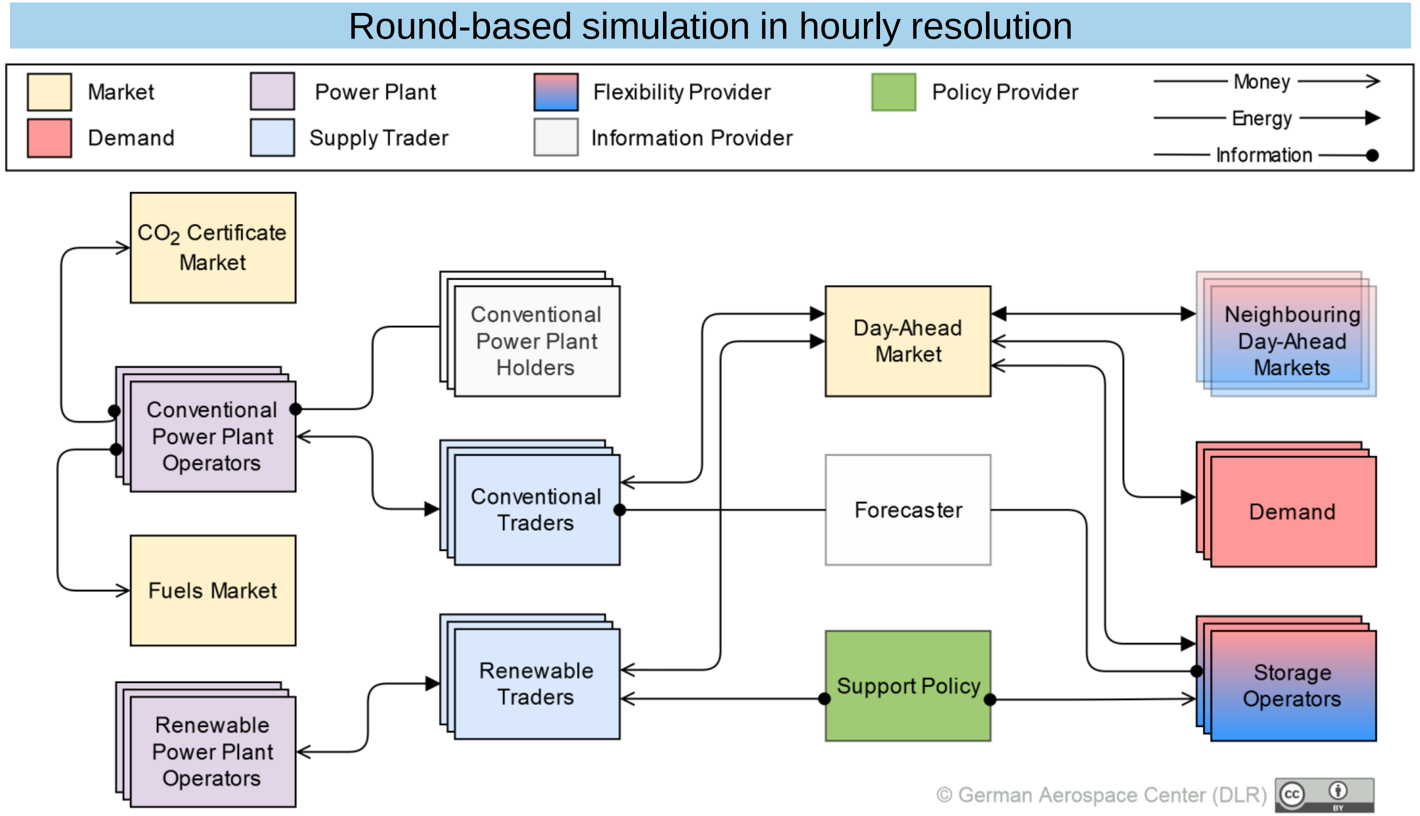
Simulating Electricity Markets with AMIRIS

Input

- RE feed-in
- Load
- Power plant park
- Efficiencies
- Fuel & CO_2 costs

Output

- Electricity prices
- Power plant dispatch
- Market values
- Emissions
- System costs



Schimeczek et al., (2023). AMIRIS: Agent-based Market model for the Investigation of Renewable and Integrated energy Systems. Journal of Open Source Software, 8(84), 5041, https://doi.org/10.21105/joss.05041

Published **open source** under Apache 2 license
See also https://dlr-ve.gitlab.io/esy/amiris/home/

Which study to use for background data for stochastic optimization and AMIRIS?

- BMWK Langfristszenarien 3, ongoing
  - no report available yet

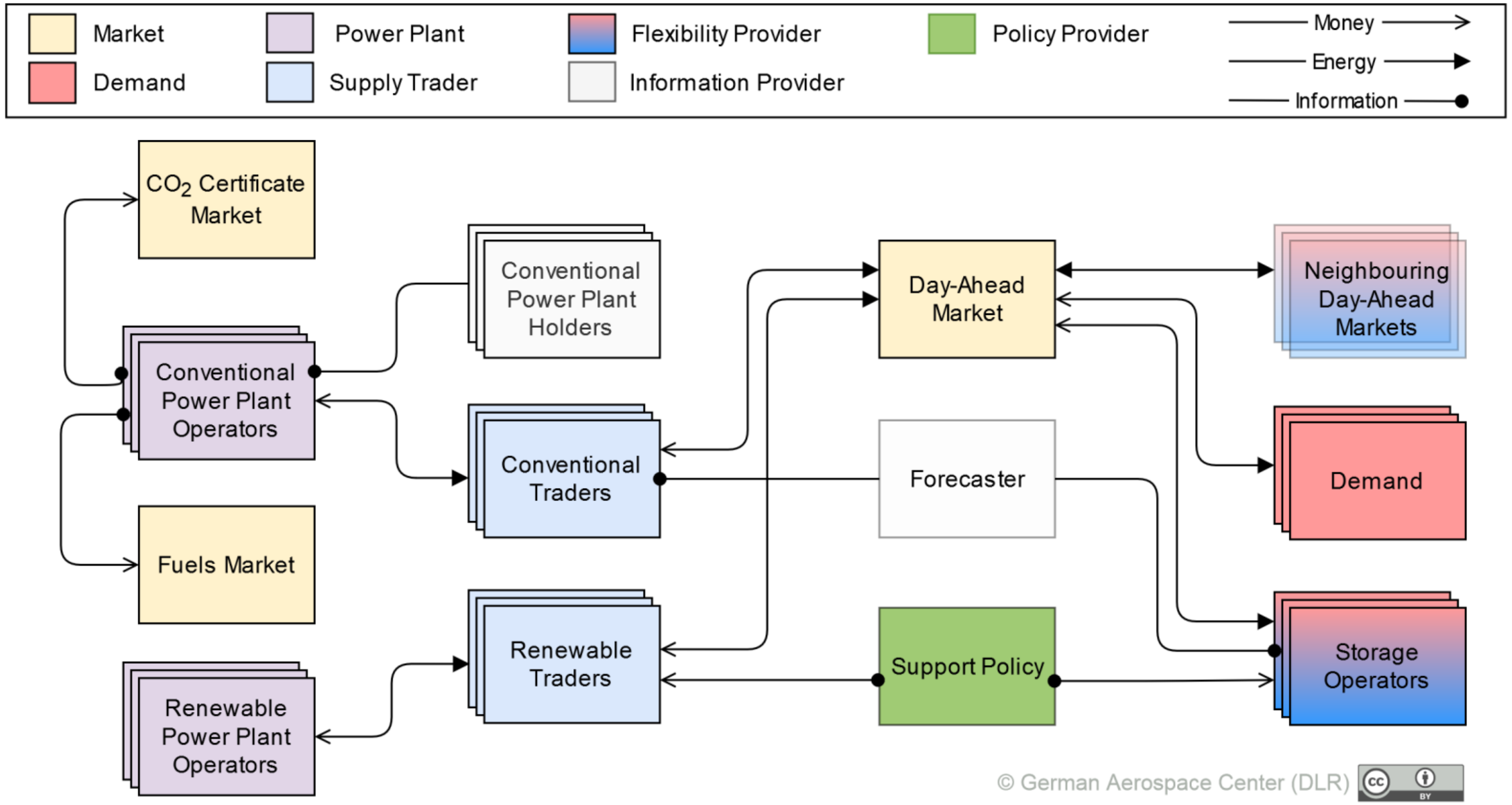
- Agora „Klimaneutrales Stromsystem 2035“, 2022
  - no cost data available
  - data available only until 2035

- ARIADNE Report, 2022
  - ✓ extensive data base available that contains most of required input data, e.g. fuel prices, OPEX, efficiencies, demand, capacities

RESULTS AMIRIS

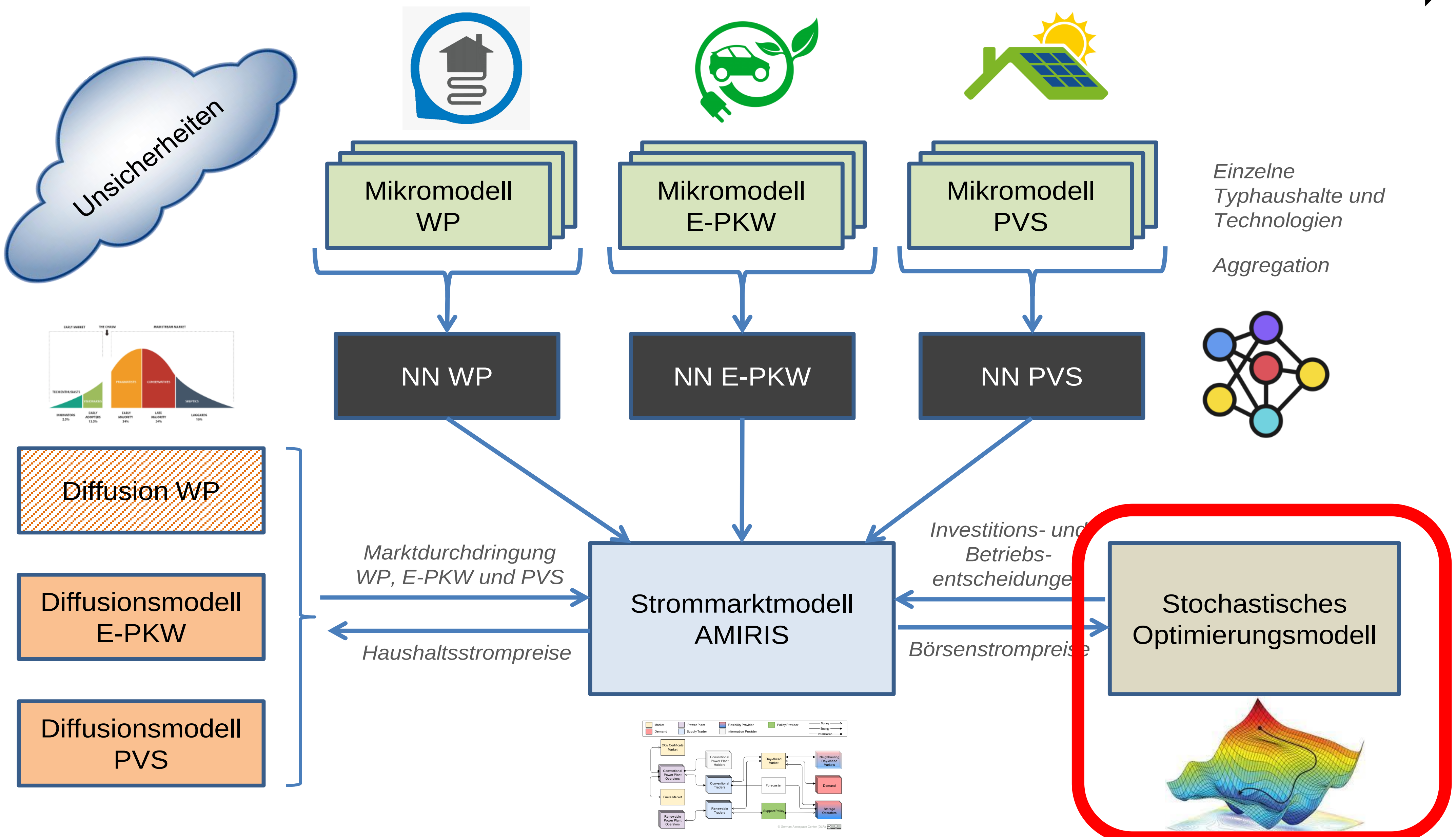
AMIRIS run coupled with stochastic optimization based on ARIADNE background data

- **Mean electricity price:** 31.2 Euro / MWH
- **Planned**: influence of feed-in tariffs, variable market premia, etc. on results
- Ongoing coupling results to be expected



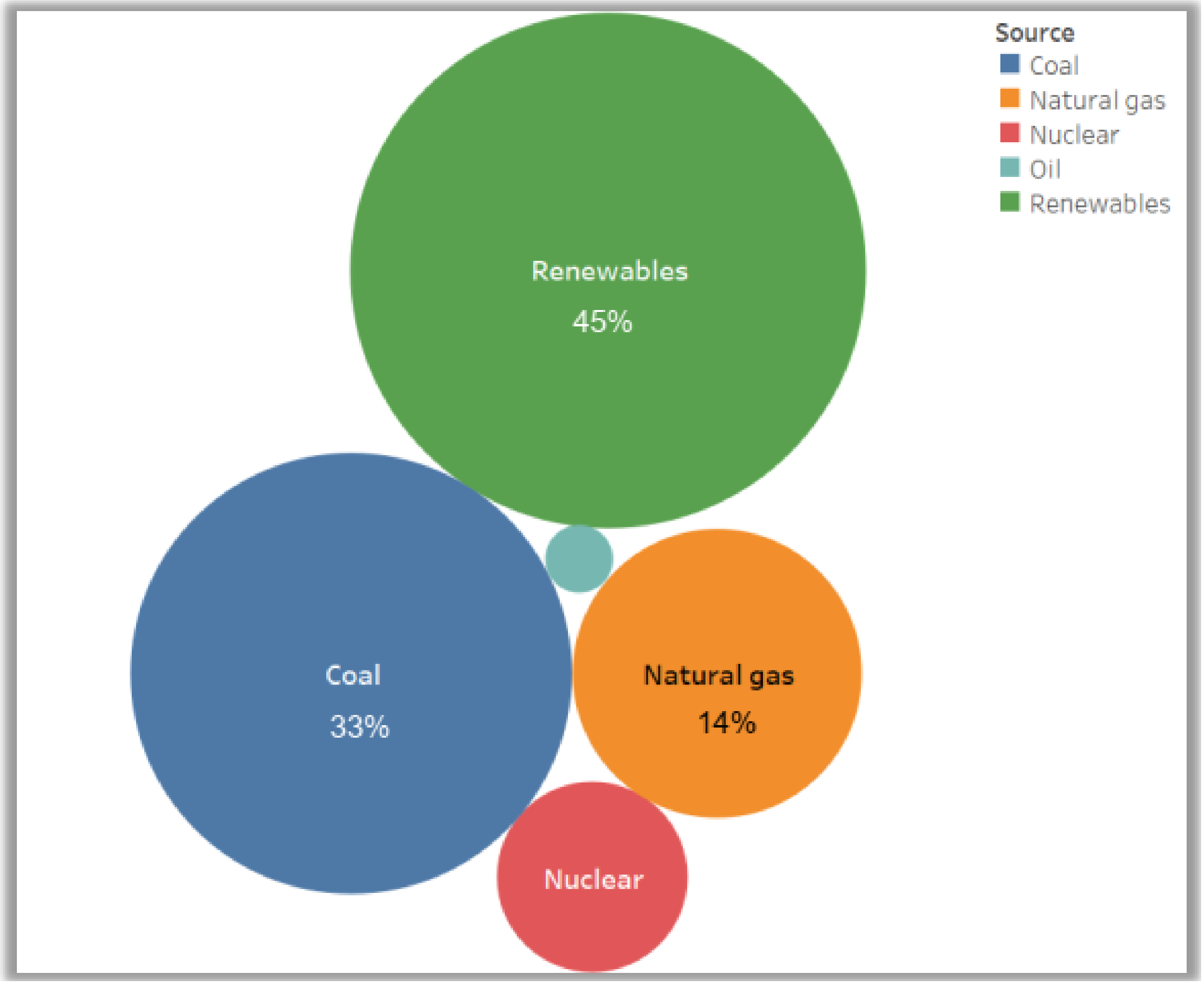
STOCHASTIC OPTIMIZATION MODEL

Coupling models with RCE

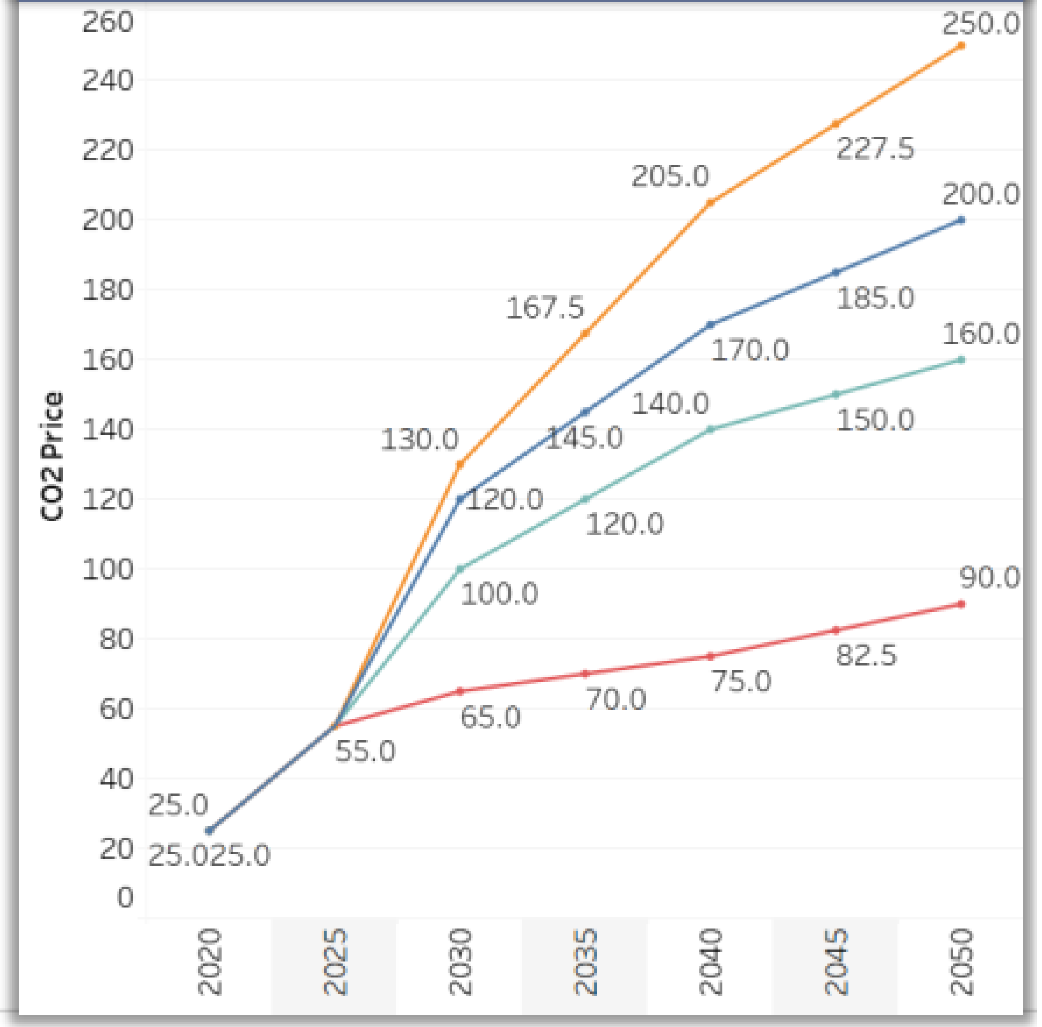


Stochastic optimization: Power production (TWh) & CO2

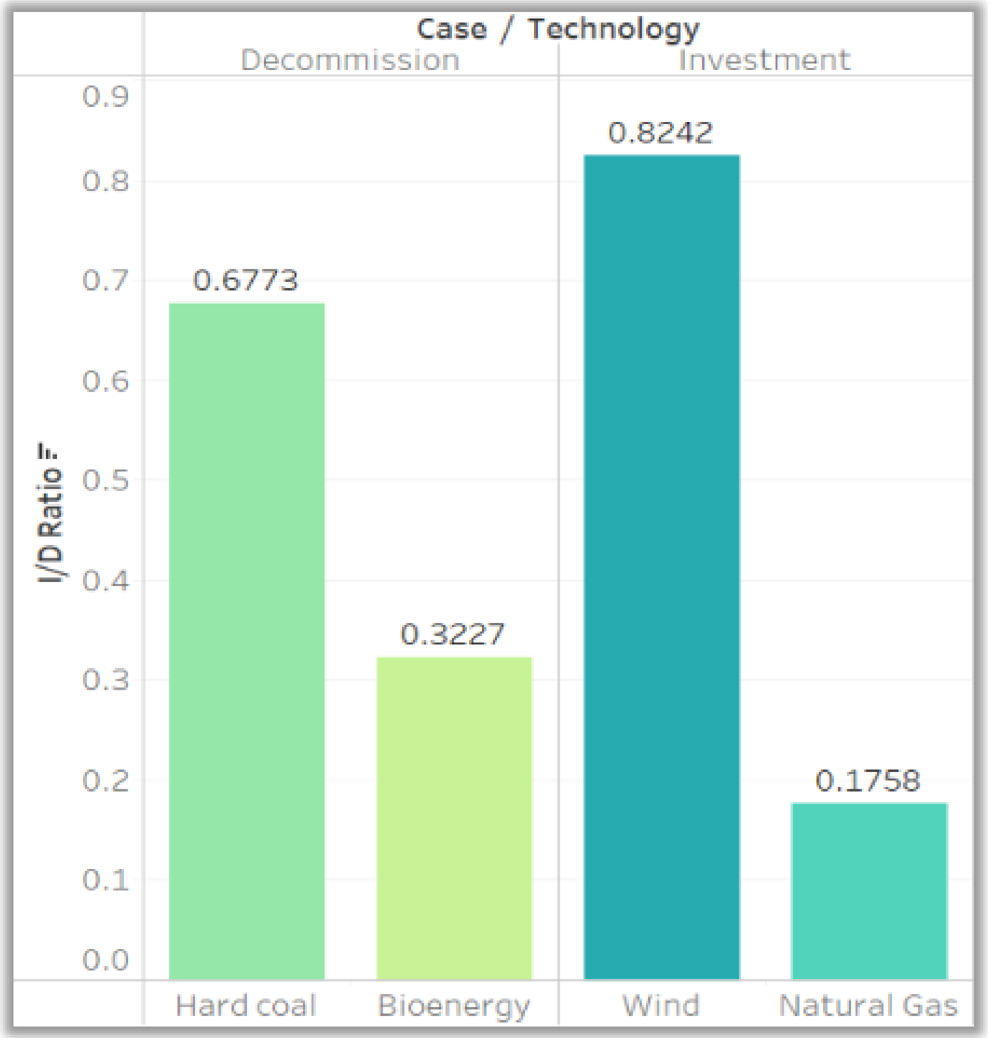
Production per sources



CO2 Price (WEO)

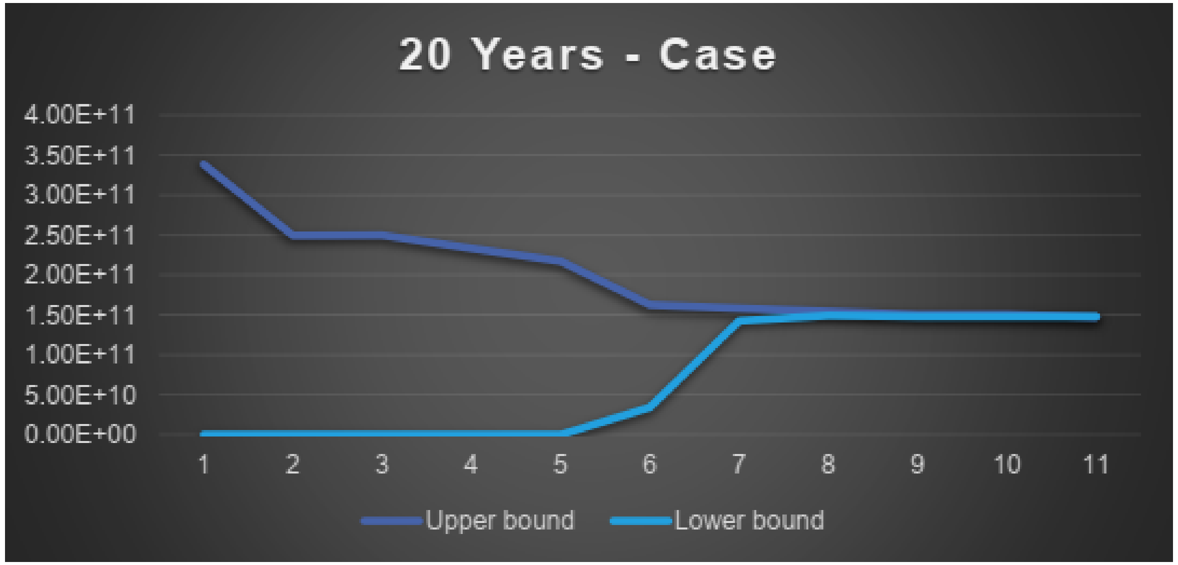


Stochastic optimization: first results



Observations:

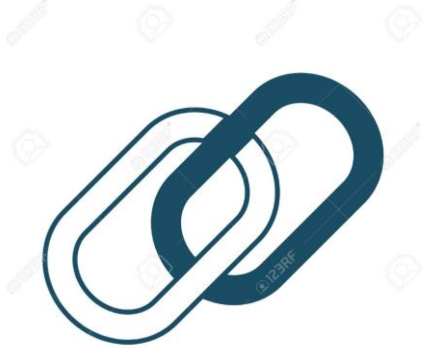
- **Planning horizon:** Direct impact on retirement decisions and investment on renewables
- **Wind yield profile per state:** Investment projects with higher yield profiles are prioritized..



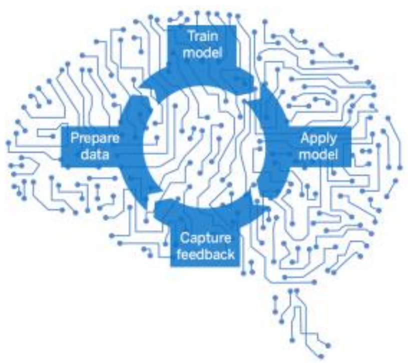
CONCLUSION

High-level Conclusion

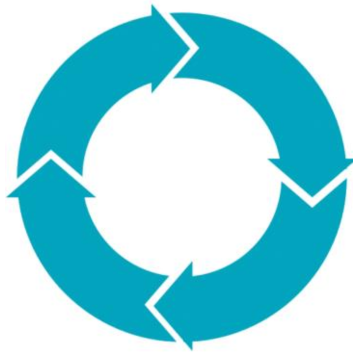
- Model coupling helps to analyze multiple aspects of the energy system at the same time



- 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



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Contact: ulrich.frey@dlr.de

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