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CAPTURING UNCERTAINTIES OF HOUSEHOLD DECISION MAKING WITH MACHINE LEARNING IN AN AGENT-BASED MODEL

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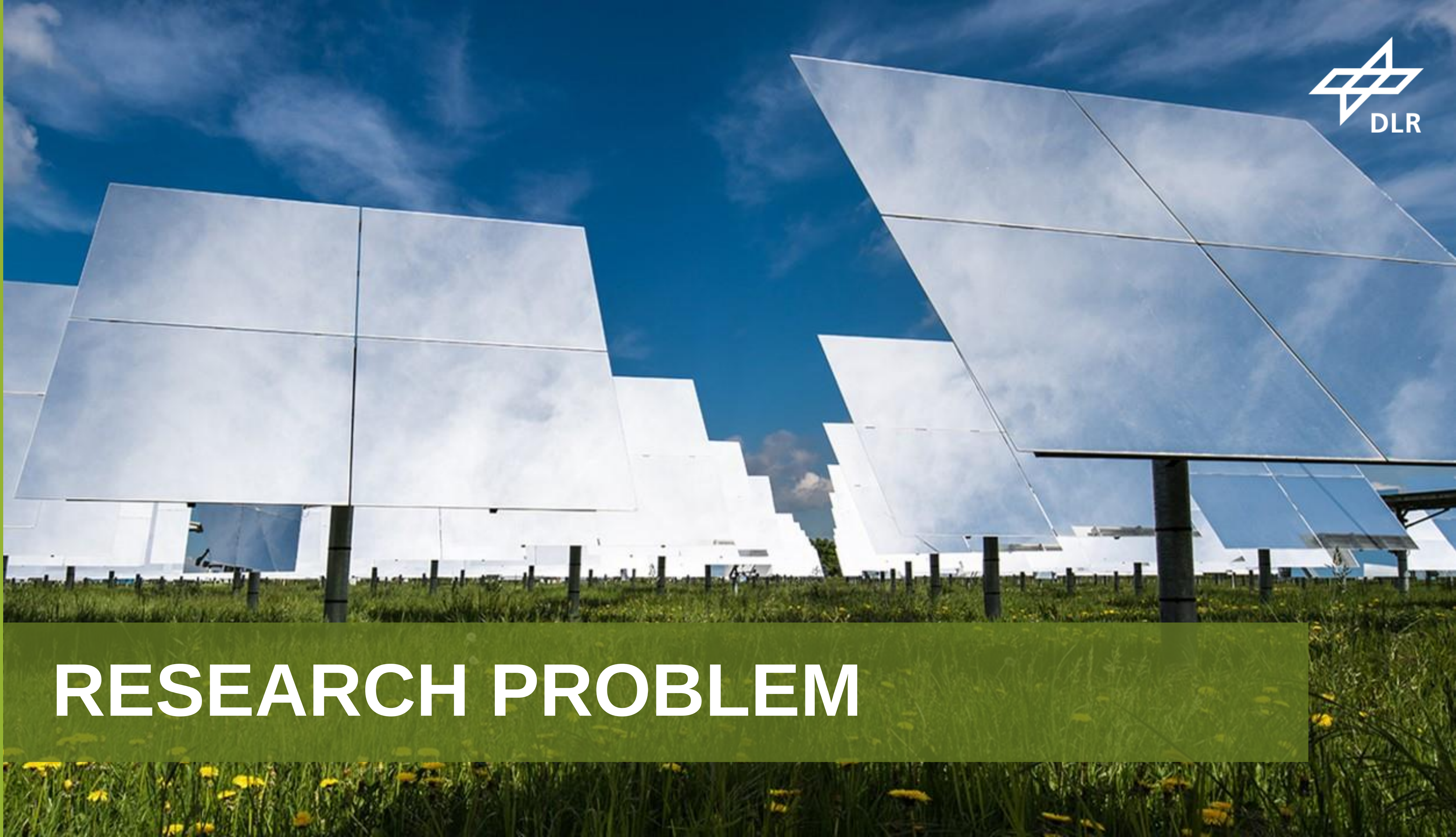
Project: EN4U, FKZ 03EI1029A



RESEARCH PROBLEM

Motivation: Massive uncertainties

- Recent geopolitical disruptions increase uncertainties & change prosumer reactions

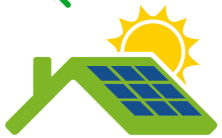
→ Energy systems pathways highly uncertain

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

→ Prosumer reactions largely unknown

  - Buy an electric vehicle (EV)?

  - Buy PV + storage (PVS)?



  - Buy a heat pump (HP)?

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?

How to model individual household decisions?

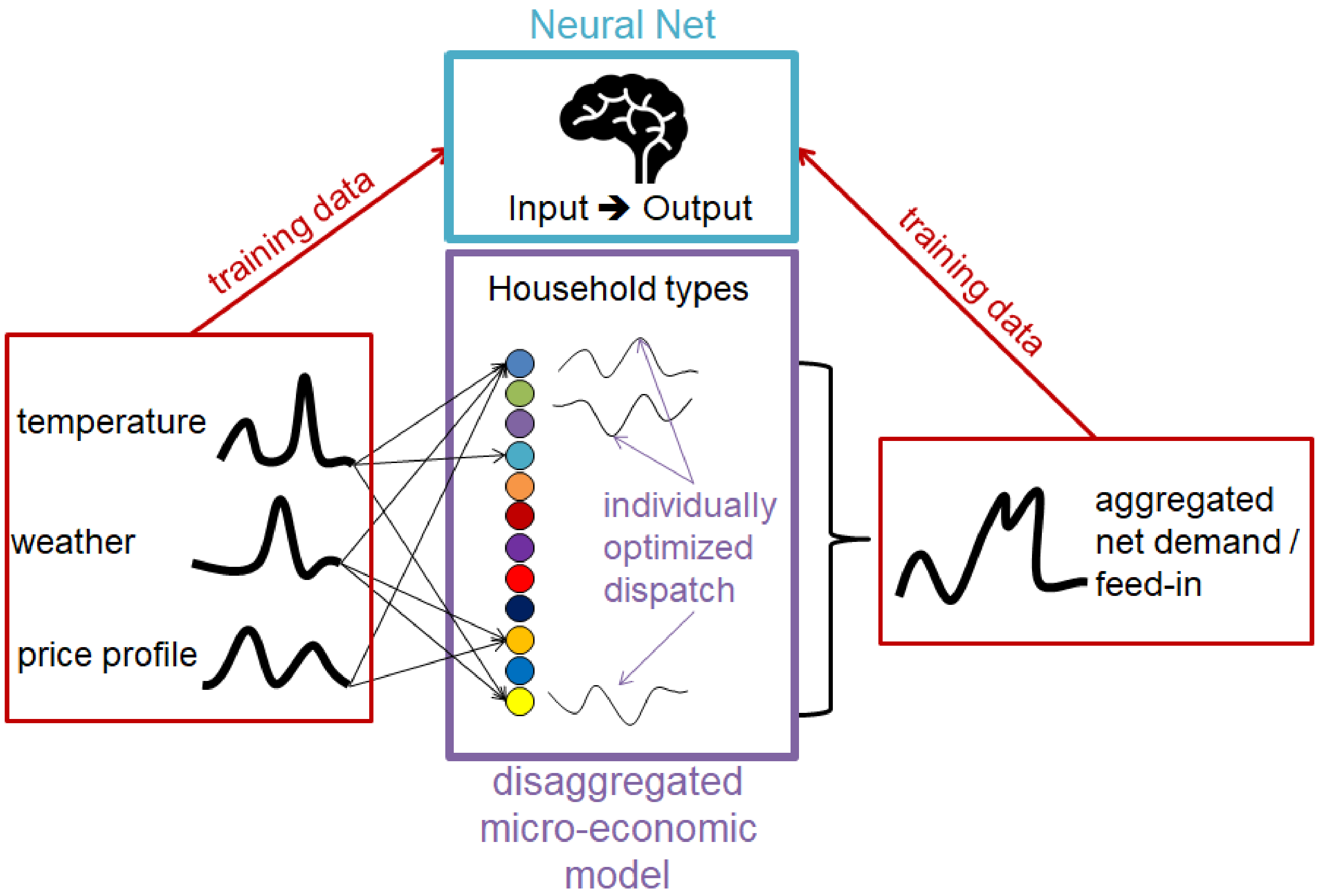
Problem

- 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



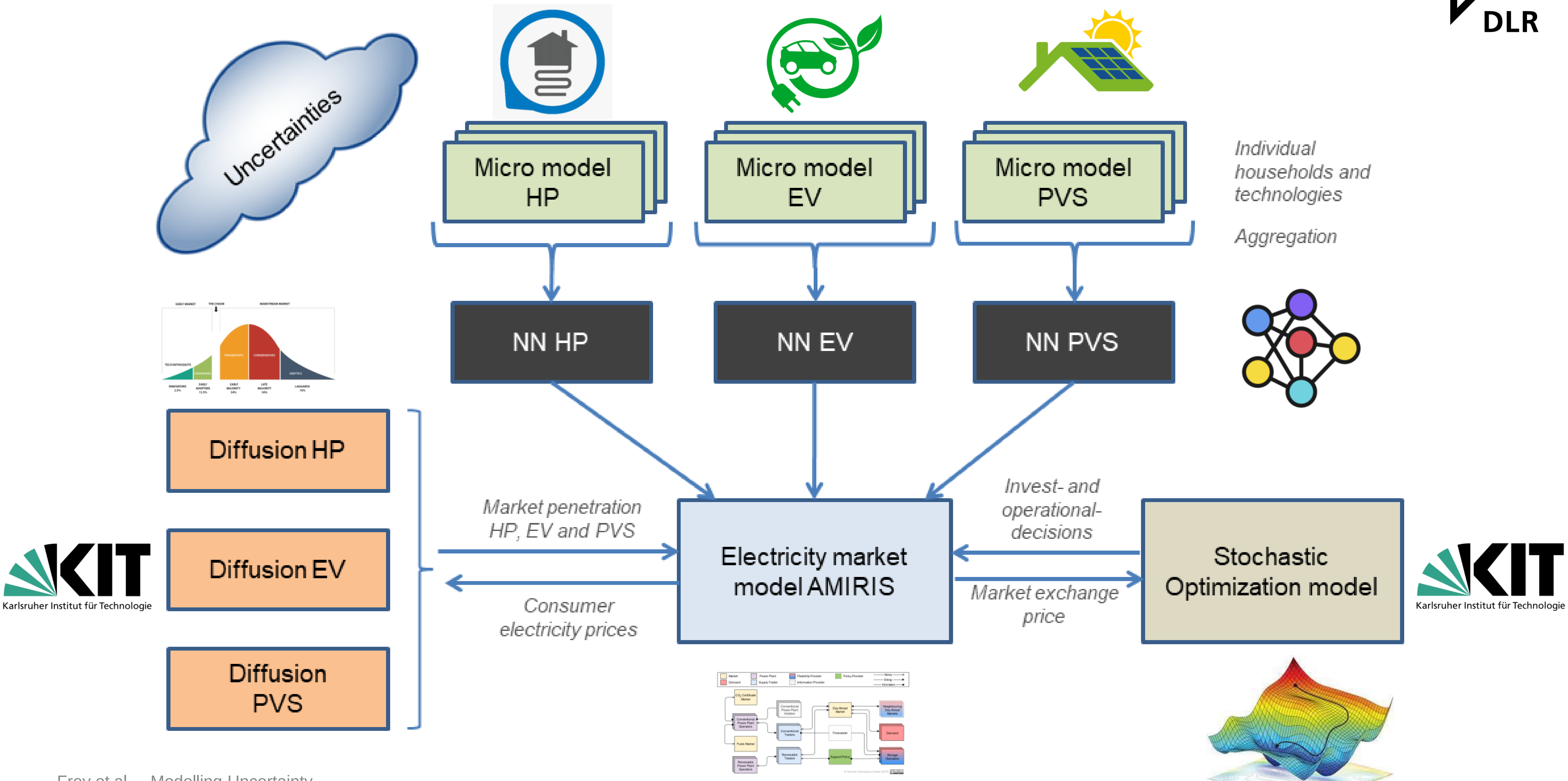
General idea to answer the research questions

- Model **individual** decisions:
  - Simulate **optimal** operation of PVS, HP, EV
  - **Diffusion model** of household investment decisions in PVS, HP, EV
  - **Learn** aggregated demand of individual households **via ML**

- Large energy system models:
  - Bring ML-agents into an **agent-based simulation** of electricity markets, AMIRIS
  - Couple AMIRIS with a **stochastic optimization model** for the supply side

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

Model Setup



Uncertainties
Micro model HP
Micro model EV
Micro model PVS
Individual households and technologies
Aggregation
NN HP
NN EV
NN PVS
Diffusion HP
Diffusion EV
Diffusion PVS
Karlsruher Institut für Technologie
Market penetration HP, EV and PVS
Consumer electricity prices
Electricity market model AMIRIS
Invest- and operational-decisions
Market exchange price
Stochastic Optimization model
Karlsruher Institut für Technologie

GETTING THE DATA

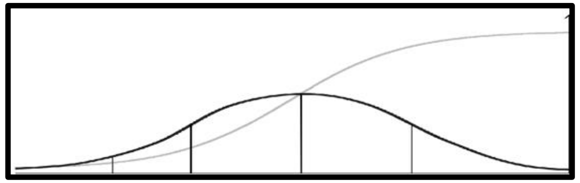
Survey for individual household characteristics

Representative survey (n=809)

	%
Building ownership	
Household property	45.5
Rented building	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 OF INDIVIDUAL DECISIONS

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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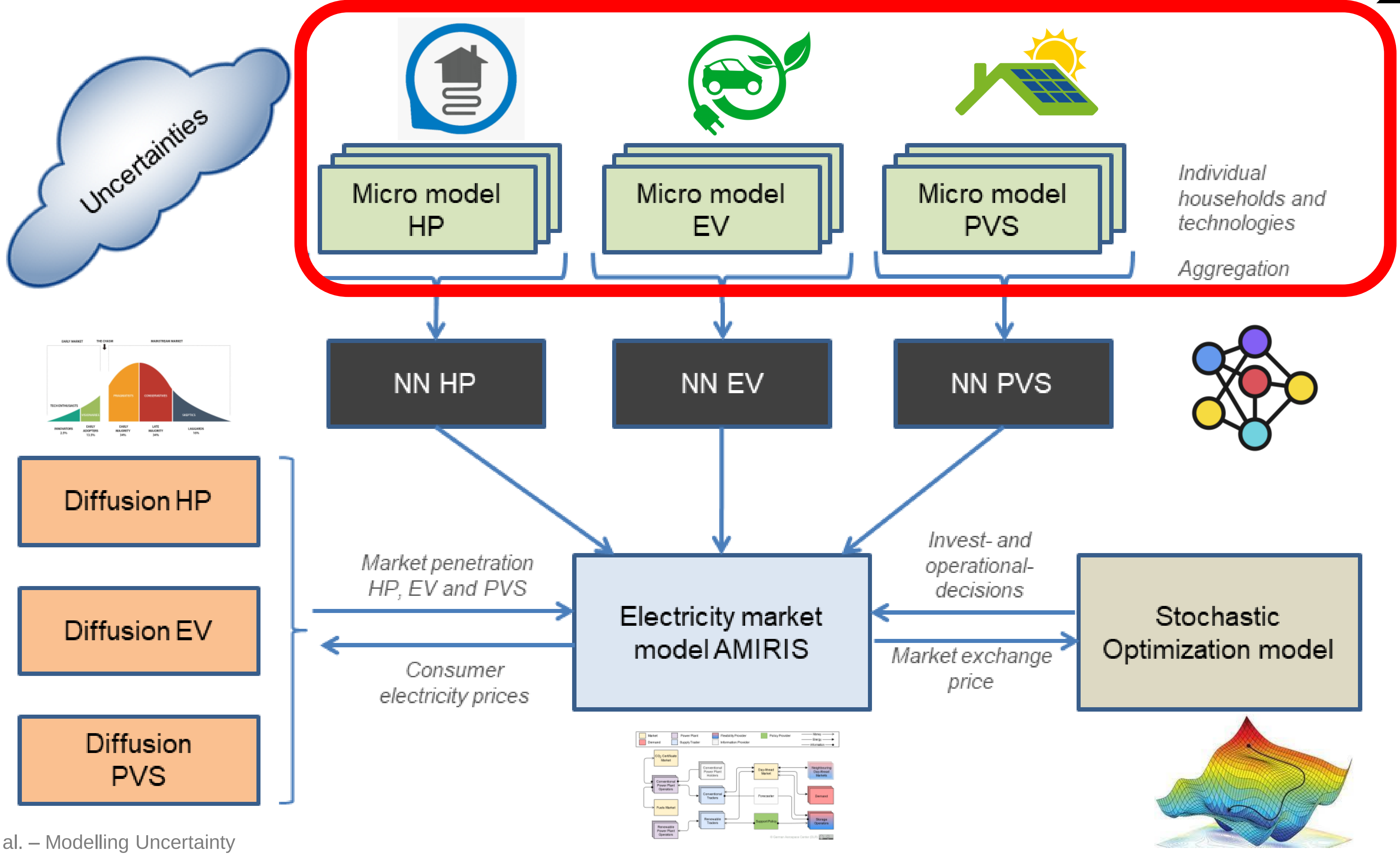
MODELING INDIVIDUAL DECISIONS

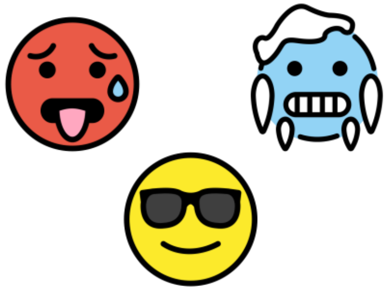
Optimization models

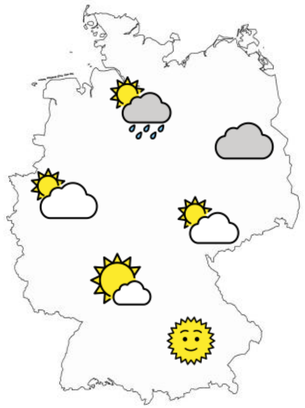


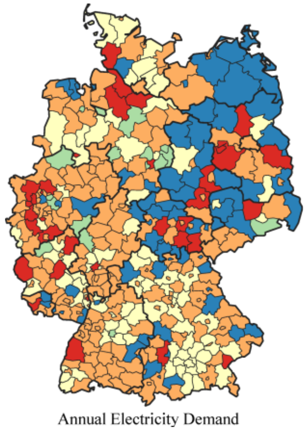
Heat pump model:
Input variations

Exploring various household's decisions

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

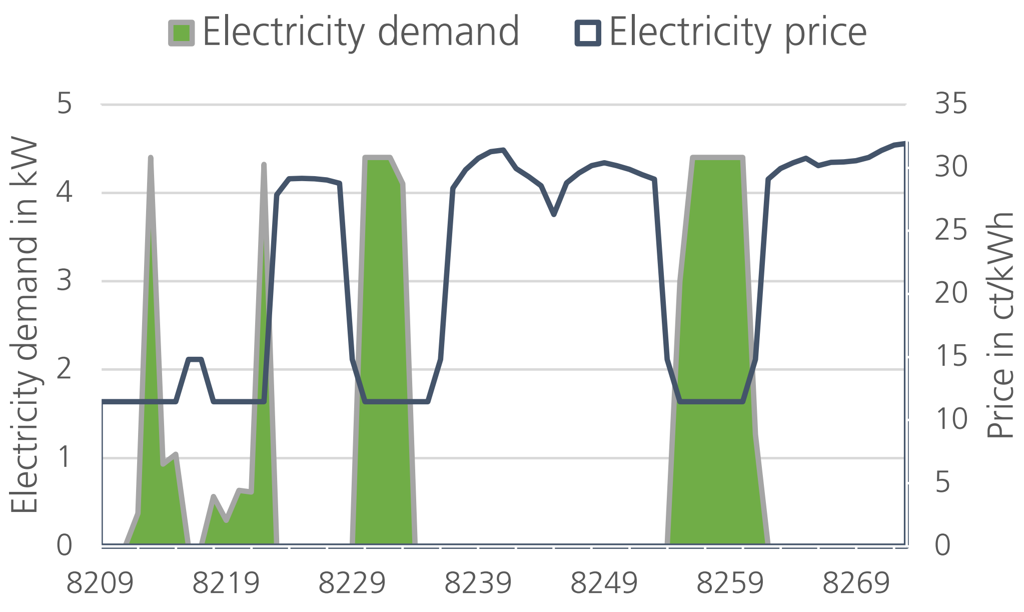


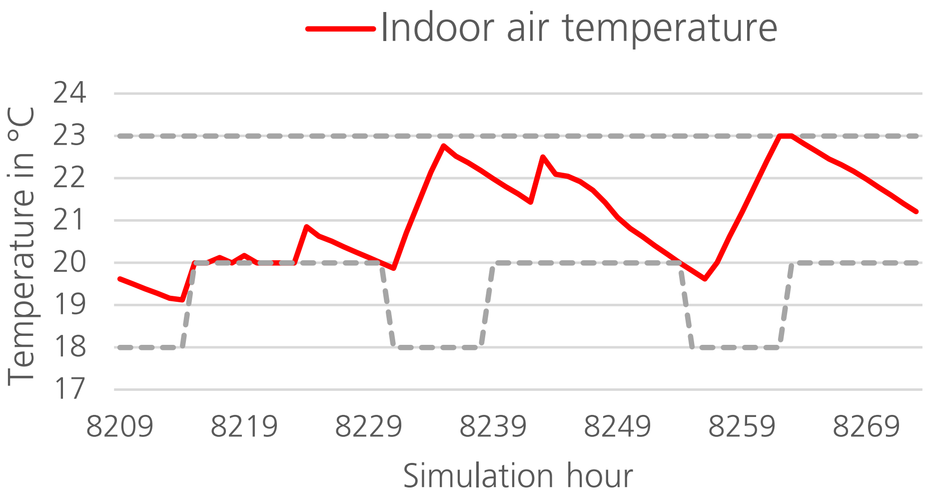




Heat pump model:
Optimizing operating costs

- **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)]



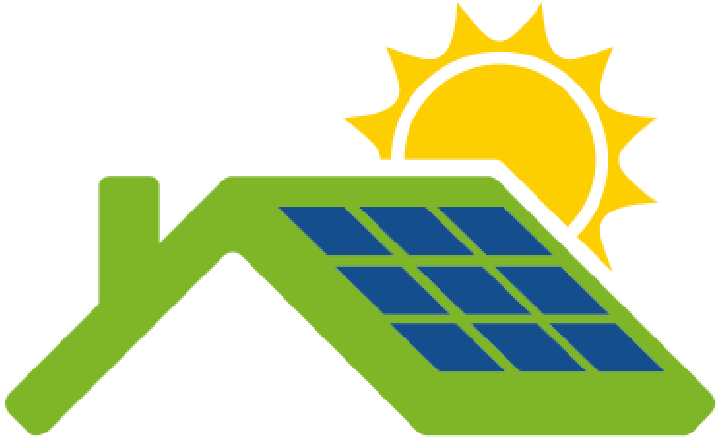


1) *Sperber, Frey, Bertsch: Reduced-order models for assessing demand response with heat pumps – Insights from the German energy system, Energy & Buildings vol. 223, 2020*

Electric vehicle model & Photovoltaic + storage model

- Same approach like heat pump model
- Optimization of demand given varying inputs like weather or electricity prices

Open Source Model: https://pypi.org/project/vencopy/

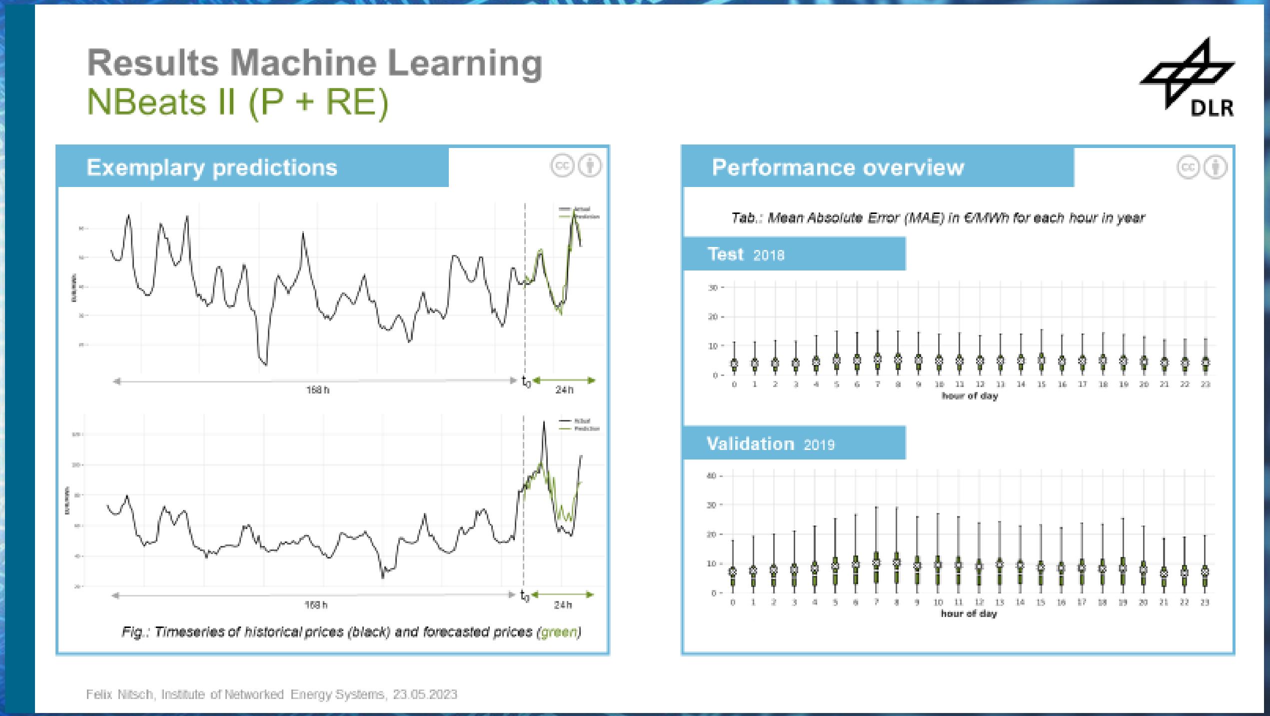


Modified version of AMIRIS

USING ML TO FORECAST DEMAND

Comparison of Machine Learning Architectures

The competitors:
- Naive Seasonal
- Exponential Smoothing
- ARIMA
- Linear Regression Model
- LightGBM Model
- LSTM
- Random Forest
- NBEATS
- TFT

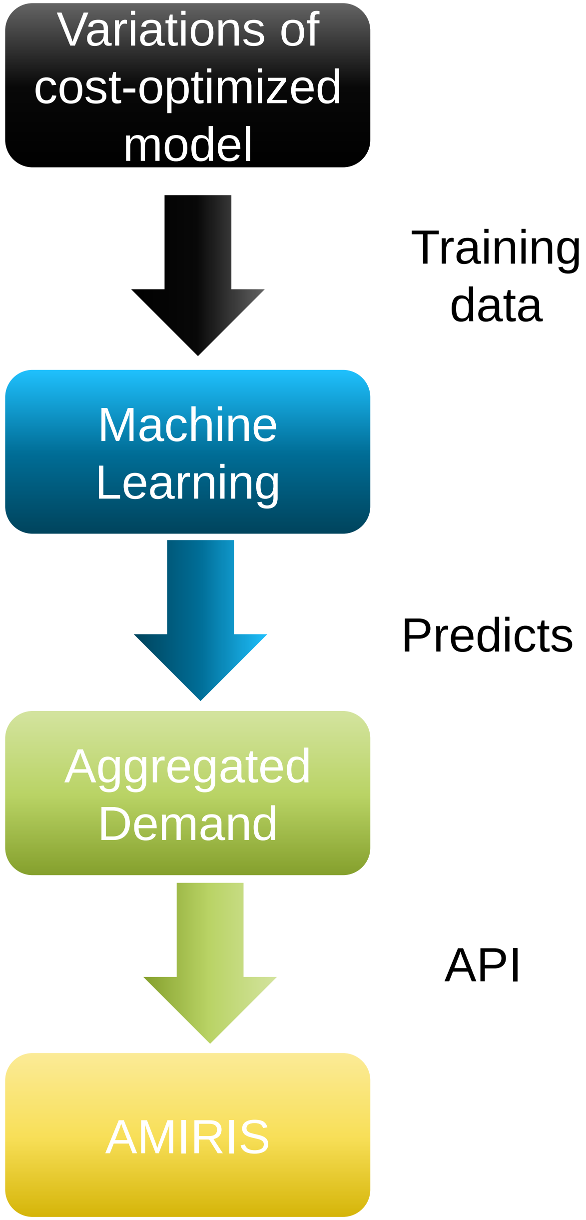


And the winner for the aggregated demand of typical households are…

Long Short-term Memory Models (LSTM)

Machine Learning Models:
Predicting demand for Germany for EV, PVS, HP

- Cost-optimized models provide training data
- Machine Learning models train from individual household data given different inputs
- ML models predict aggregated demand from individual households
- ML models connect to ABM AMIRIS via Fast-API



RESULTS

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%)

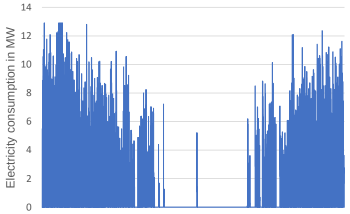
(4) Multiple renewable energy technology adopters
(3.0%)

Heat pump model:
Aggregating individual household decisions

∑

- Building types
- User comfort types
- Heat pump types
- Weather locations

1



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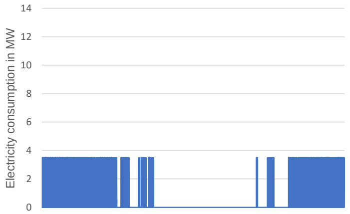

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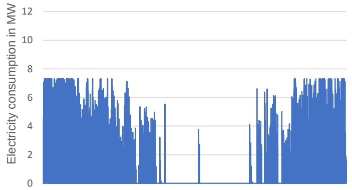

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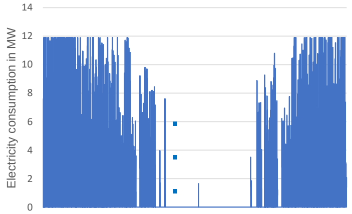

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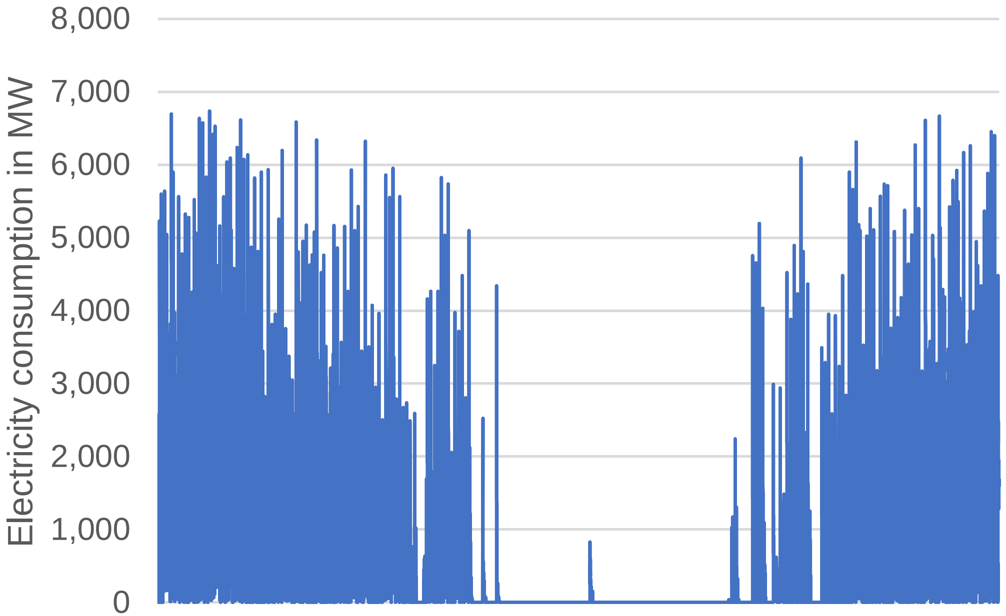
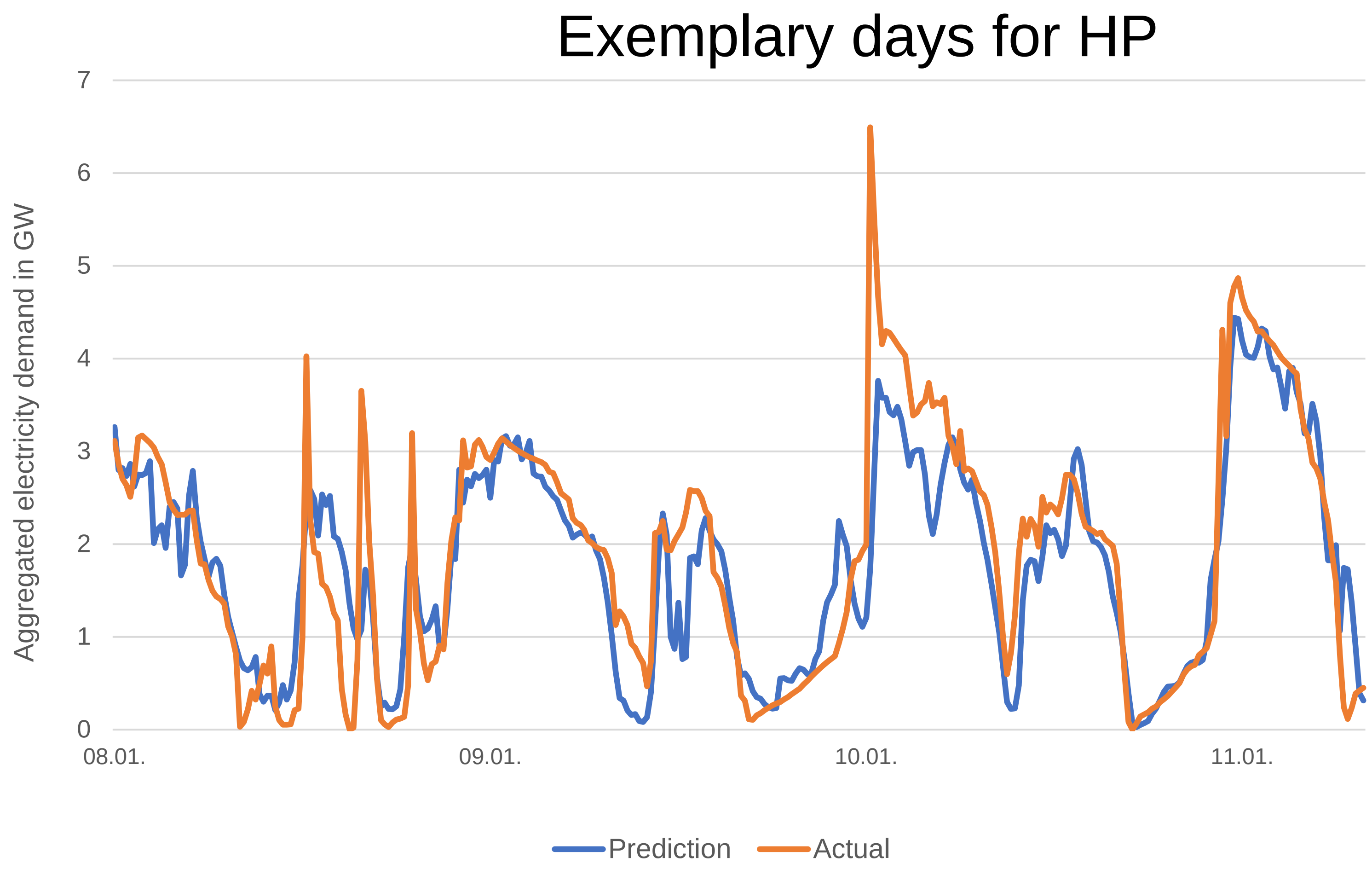


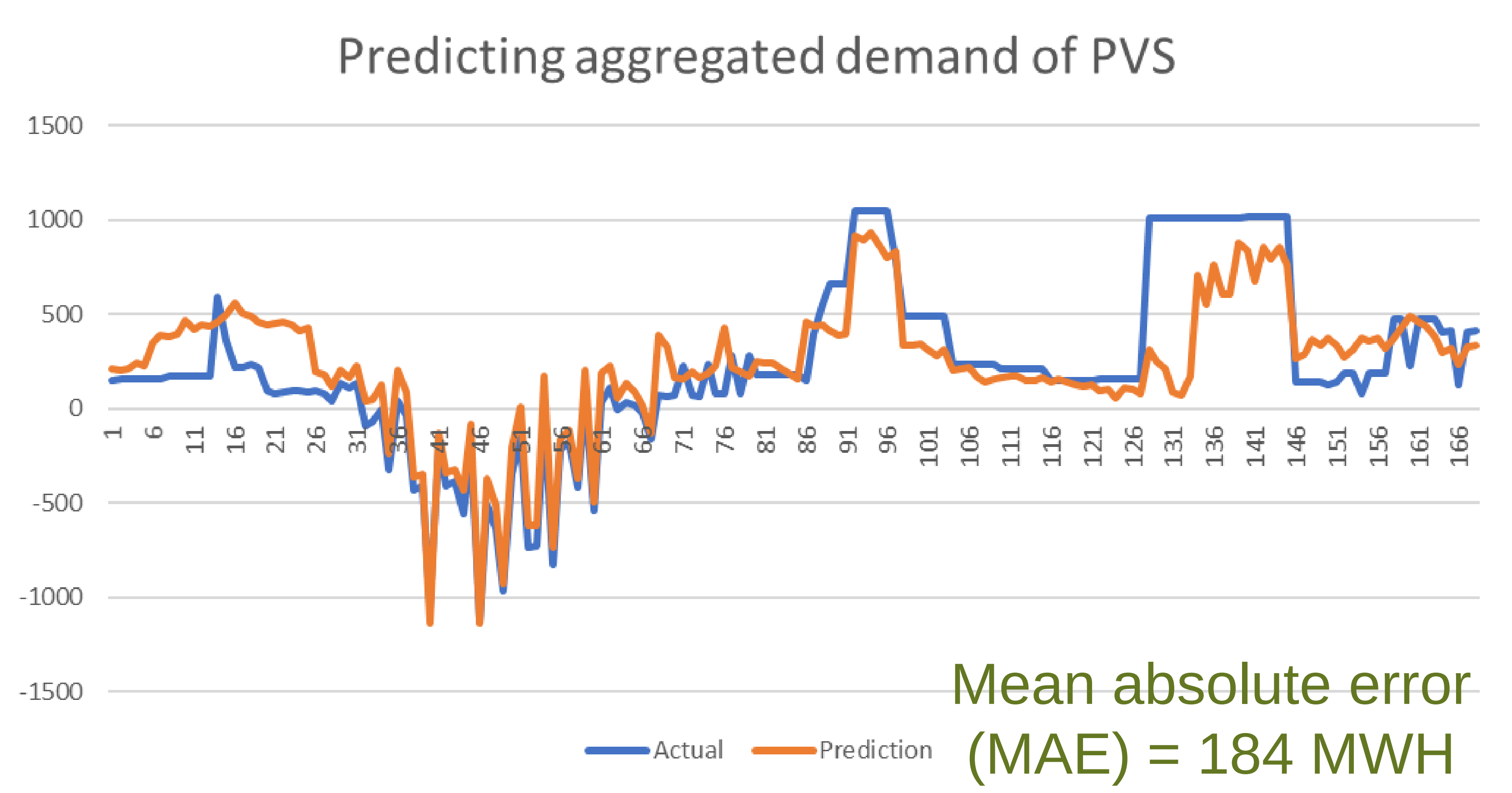
- **Best Model:** LSTM with 15 K params
- **Look-back-size**: 24 h
- **Train / Predict**: 5 locations / 1 other location
- **Data resolution**: 8760 h in ¼ h resolution

Heat pump model:
Predicting aggregated demand for Germany



- **Best Model:**
  LSTM, 16 K params
- **Look-back-size**:
  24 h
- **Train / Predict**:
  5 locations / 1 other location
- **Data resolution**:
  8760 ¼ h resolution
- **Error**:
  ~ 8 % error

Photovoltaic + Storage model:
Predicting aggregated demand for Germany



Mean absolute error (MAE) = 184 MWH

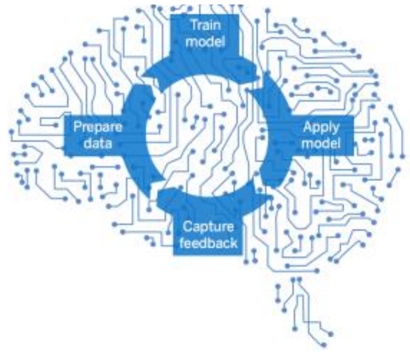
- **Best Model:**
  LSTM, 16 K params
- **Look-back-size**:
  24 h
- **Train / Predict**:
  5 locations / 1 other location
- **Data resolution**:
  8760 h resolution
- **Error**:
  ~ 6% error

CONCLUSION

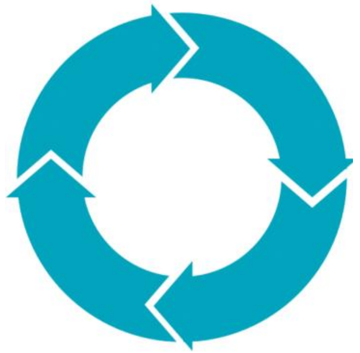
High-level Conclusion

- **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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THANK YOU!

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Image sources

- AI-Brain: https://www.linkedin.com/pulse/so-what-difference-between-ai-ml-deep-learning-kanishka-mohaia
- Uncertainty: https://uncertain2degrees.blogs.uni-hamburg.de/?p=2157
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