Supported by:

Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag

UNCERTAINTIES AND INTERACTIONS IN VARIOUS TRANSITION PATHWAYS OF A DECENTRALIZED ENERGY SYSTEM

INREC, 6th of September 2023, Essen

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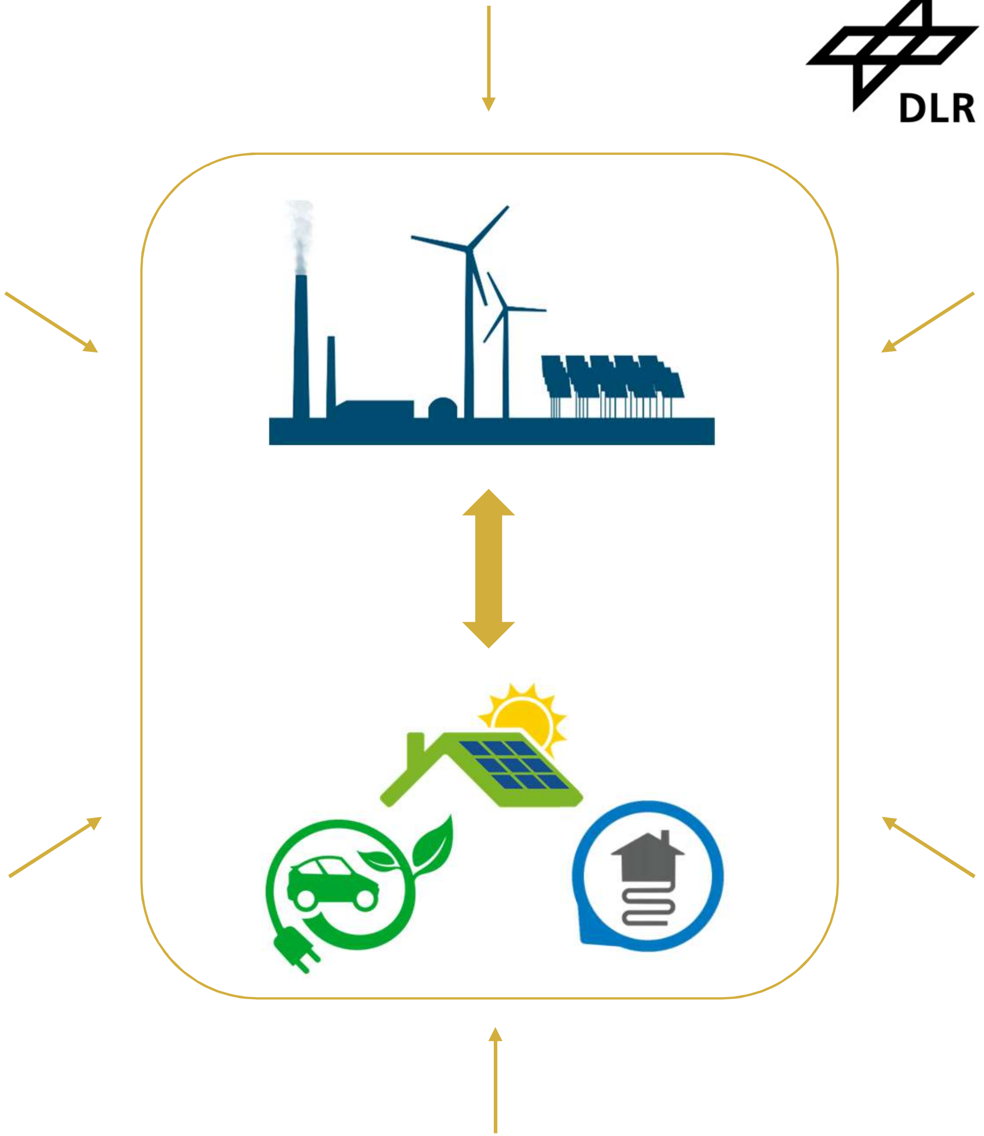
Motivation

Large flexibility potentials in the residential sector, especially by **electric vehicles, heat pumps and PV storage systems**

- ➢ Technology diffusion?
- ➢ Actors' dispatch decisions?
- ➢ Impact on tomorrow's energy system?

Idea of the En4U[1)] project (2021 - 2024):

➔ Analyze household's **operating** and **investment** decisions regarding these technologies while considering **uncertainties** and their **interaction** with the overall energy system

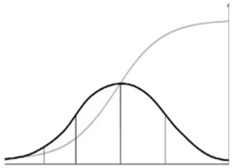


1) „Entwicklungspfade eines dezentralen Energiesystems im Zusammenspiel der Entscheidungen privater und kommerzieller Energieakteure unter Unsicherheit"

PROJECT OVERVIEW

The En4U project

Approach



- Model technology **diffusion** under **uncertainty**.

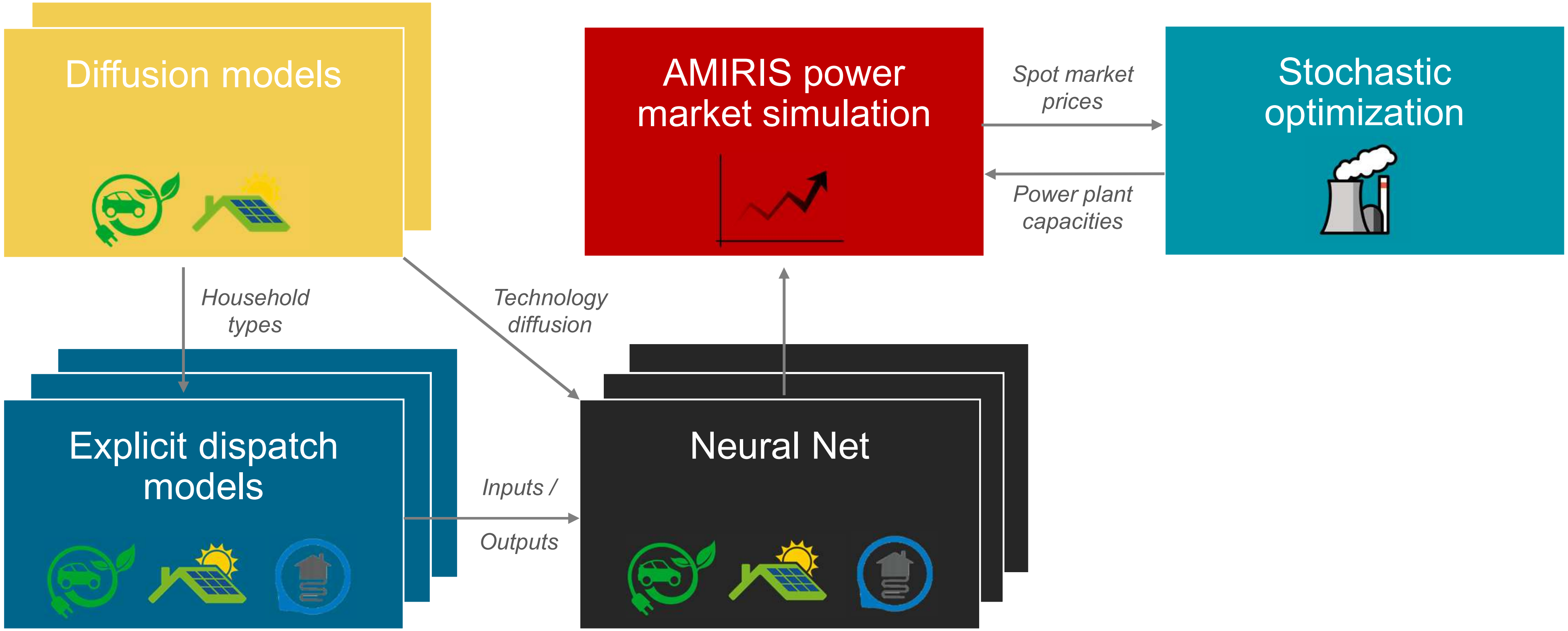
- Integrate **household's decisions** regarding the operation of residential flexibility options into electricity market models using Machine Learning.

- **Couple** diffusion model, stochastic optimization and agent-based simulation to capture complex **interactions**.

- Explore **pathways** to enable **policy** advice.

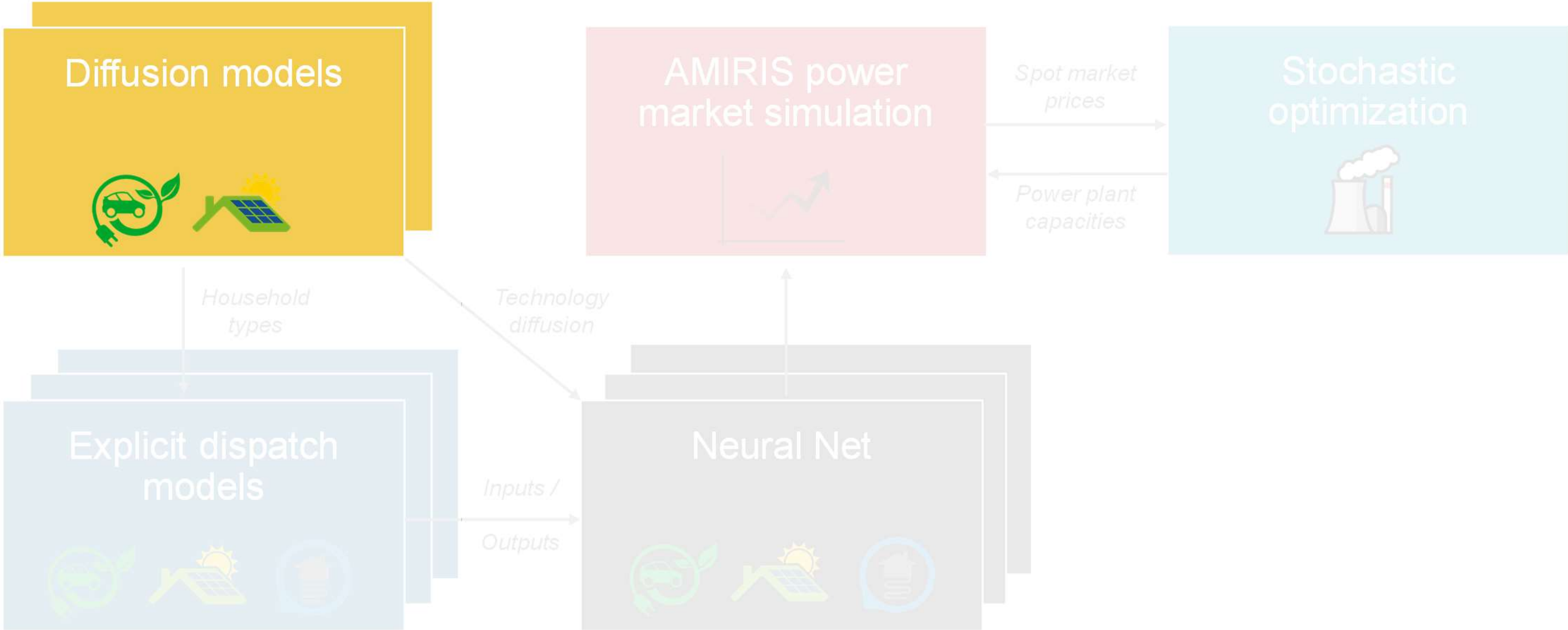
Methodology

Model coupling workflow



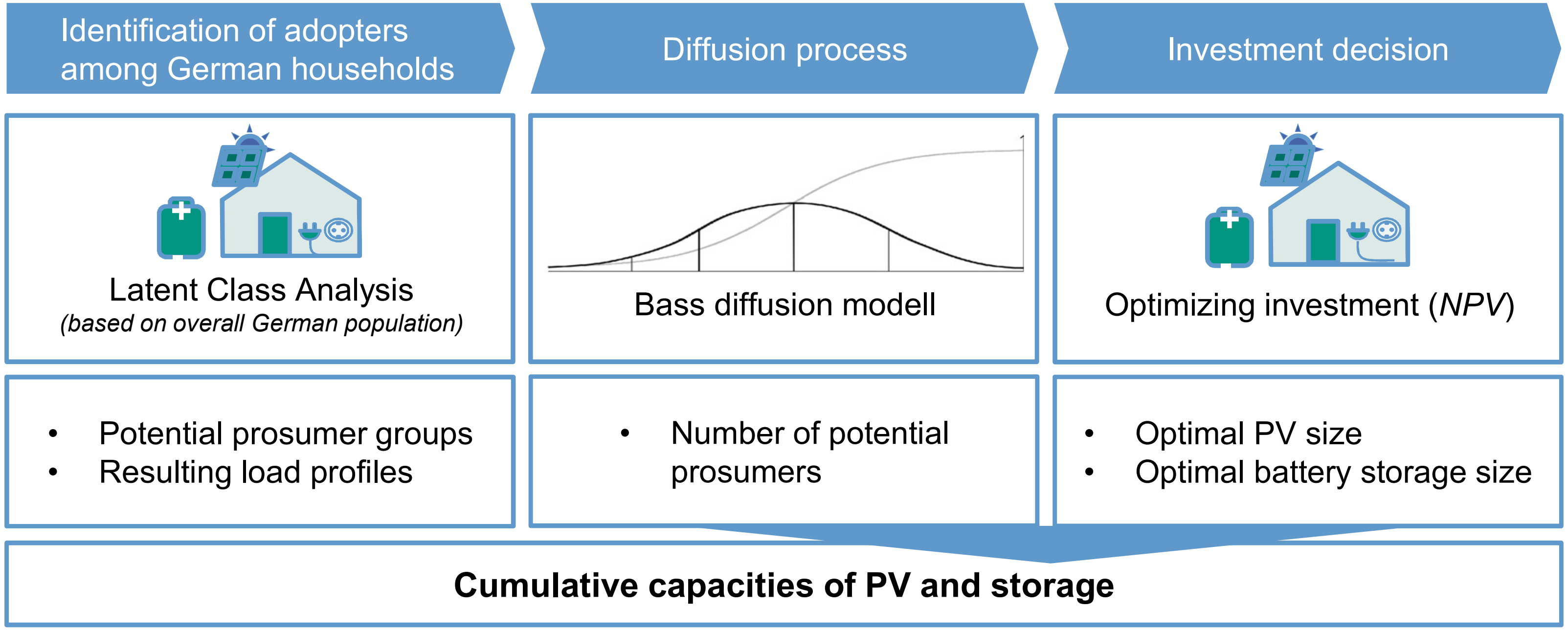
Methodology

Model coupling workflow



Diffusion model

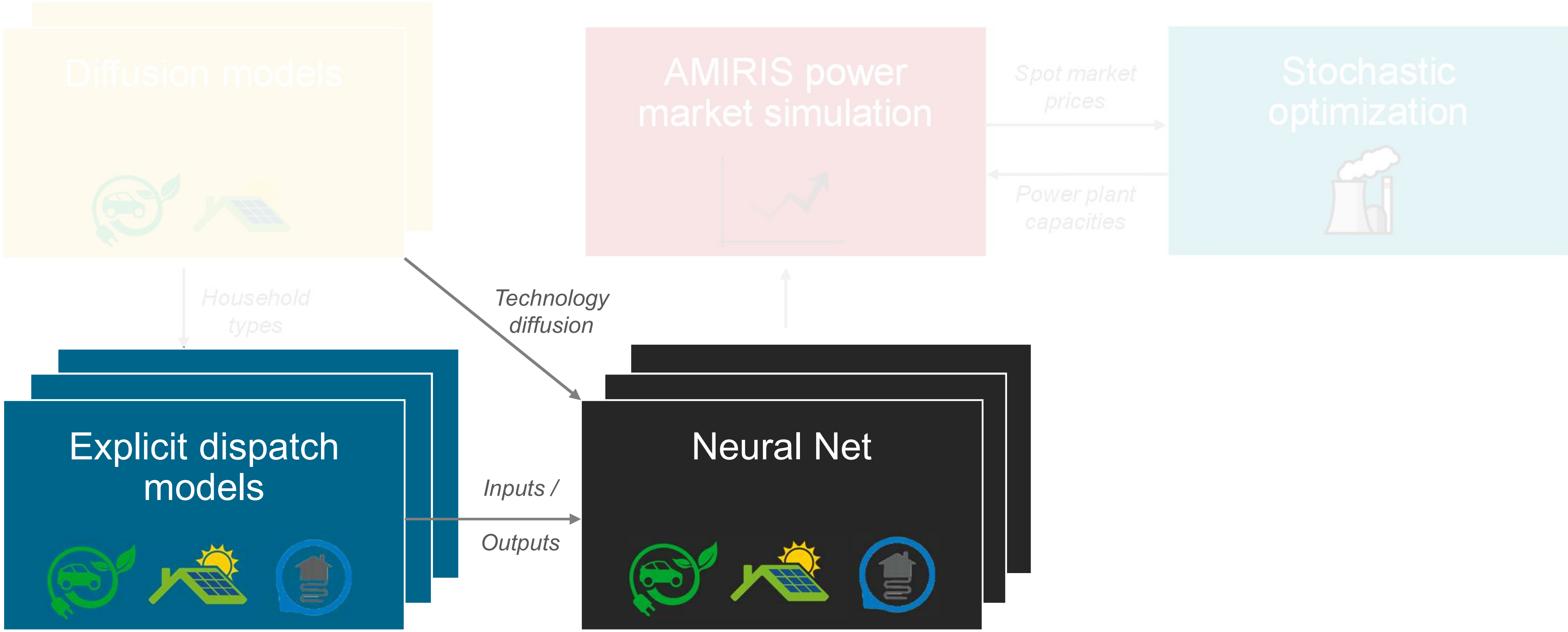
Modelling diffusion of PV storage systems



- Representative survey of around 800 participants
- Calculates diffusion of household technologies for typical households

Methodology

Model coupling workflow

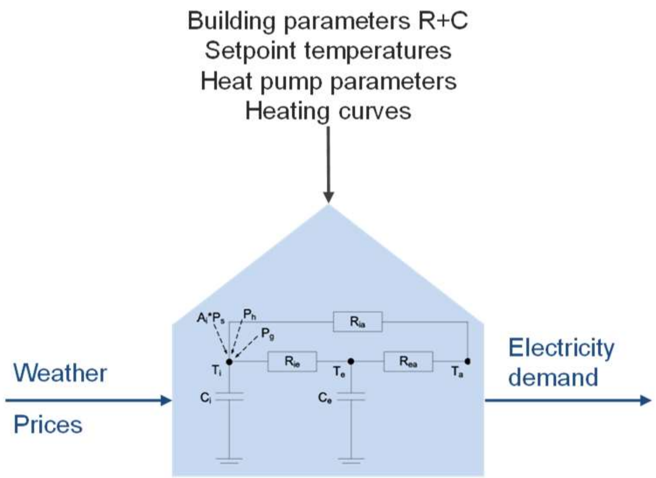


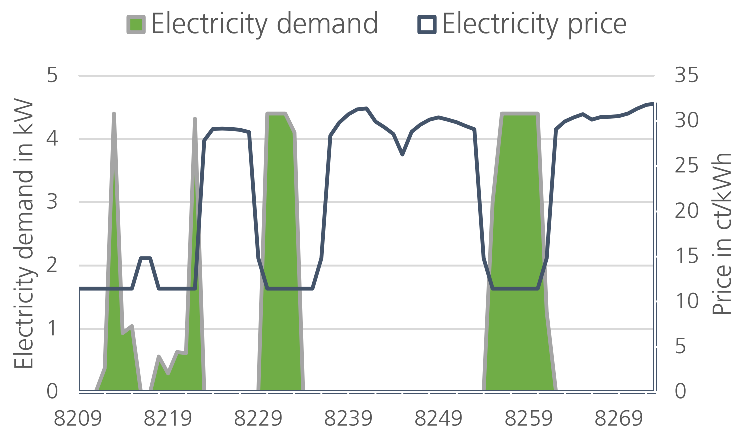
Explicit dispatch models

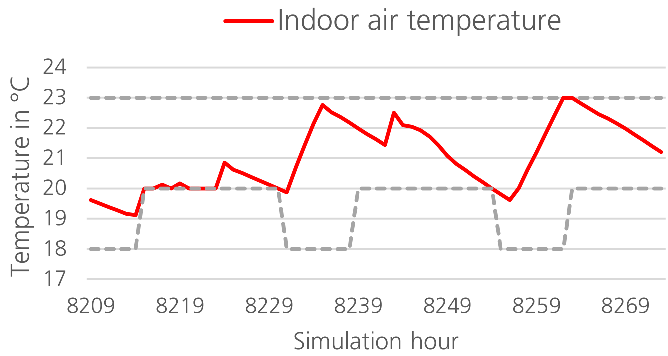
Heat pump micro-model

GAMS optimization model

- Minimizes operating cost of residential heat pumps
- Flexibility by varying indoor temperature within given 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

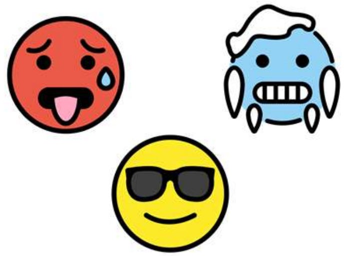
Explicit dispatch models

Heat pump micro-model

Exploring various household's decisions

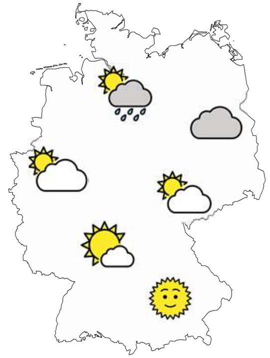
18 building types

3 user comfort types



2 heat pump types

6 weather locations



= 18 x 3 x 2 x 6 = 648 individual optimization problems!

Abstraction of individual household decisions

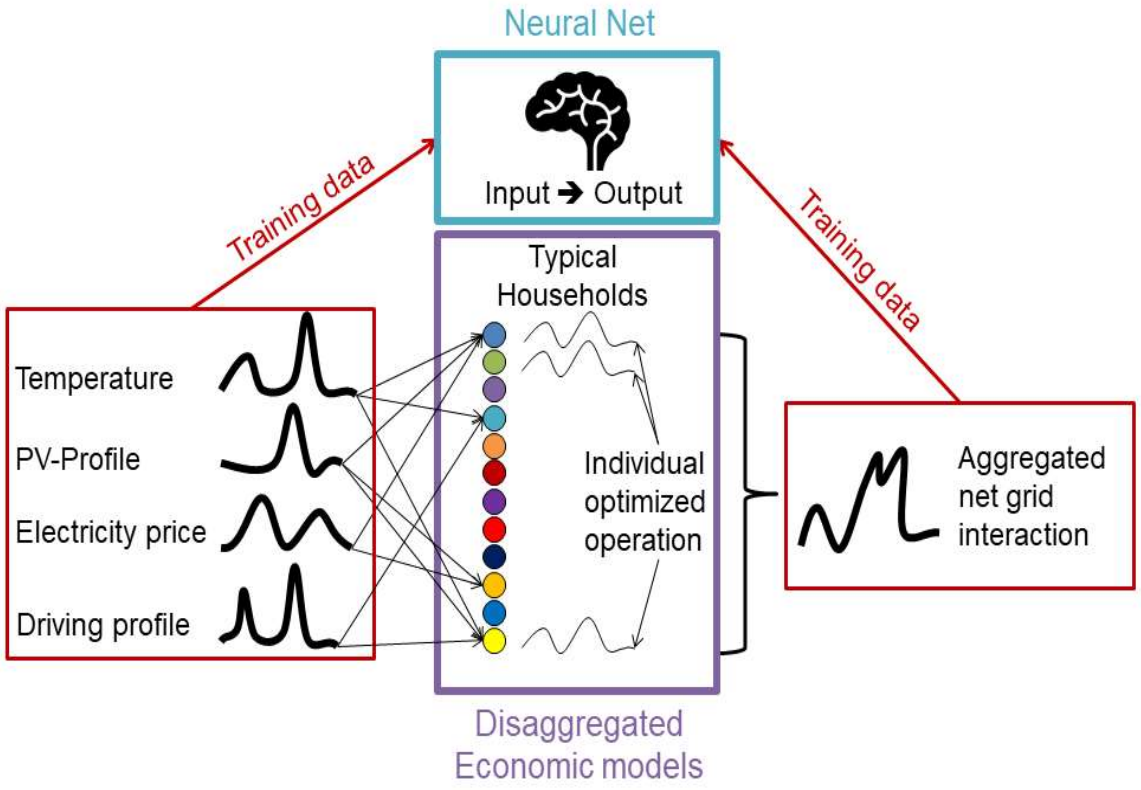
Problem

- Many different households
- High computation effort per optimization

➔ Individual dispatch optimization of all household types not possible within energy system model

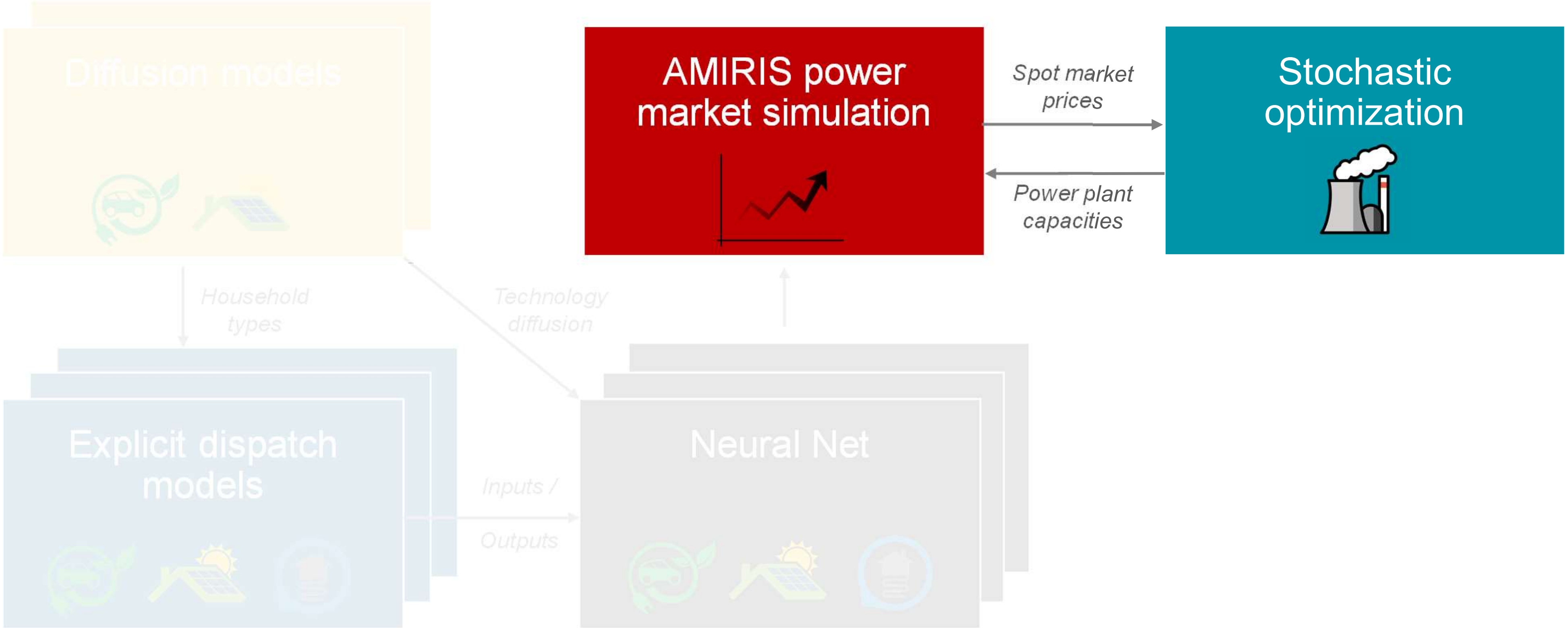
Idea

- Individual household dispatch optimization done for multiple input variations
- Aggregate household results
- Train Neural Net to predict household aggregated behavior based on given input variations
- Include Neural Net feedback in energy system model



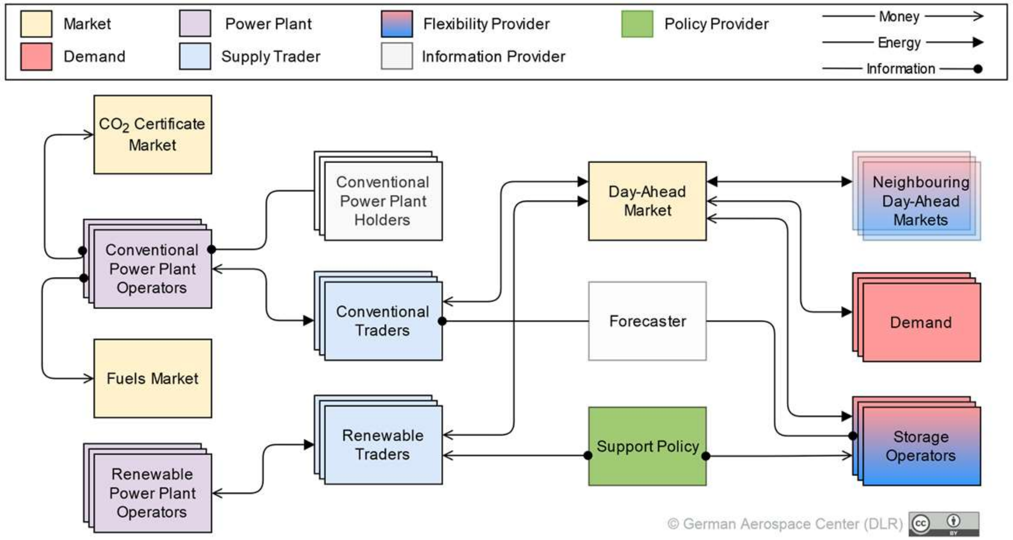
Methodology

Model coupling workflow



Coupling two energy market models

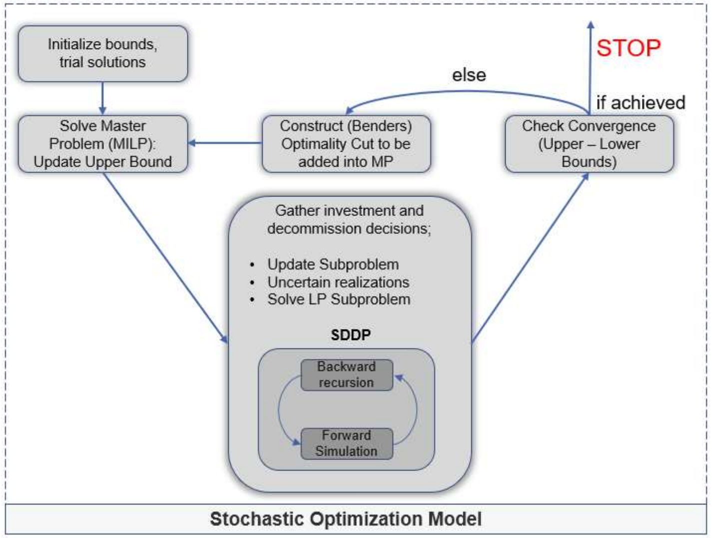
AMIRIS



Spot market prices

Power plant capacities

Stochastic optimization



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

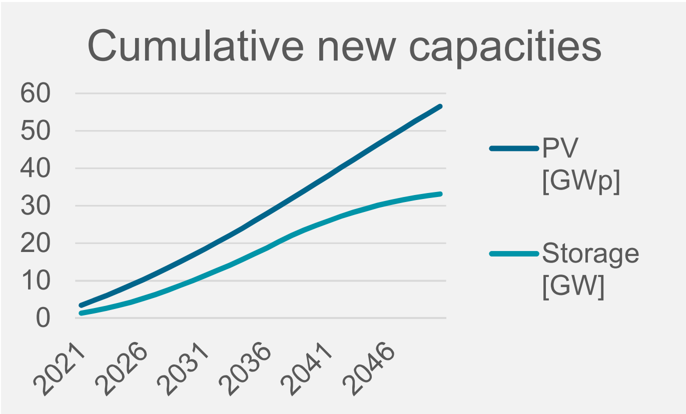
Rebennack, Steffen (2014): Generation expansion planning under uncertainty with emissions quotas. In: Electric Power Systems Research 114, S. 78–85. https://doi.org/10.1016/j.epsr.2014.04.010

FIRST RESULTS

Diffusion model

Results for PV storage systems

- LCA resulted in 19 subgroups of households with 4 different adopter profiles
  (based on sociodemographics, building characteristics, and technology adoption)
  - Two classes of PV only (3.6 %)
  - EV as well as heat pump adopters (1.7%)
  - Multiple electric technologies adopters (1.6 %)



Investment decisions

Median sizes:

PV system: 10 kWp

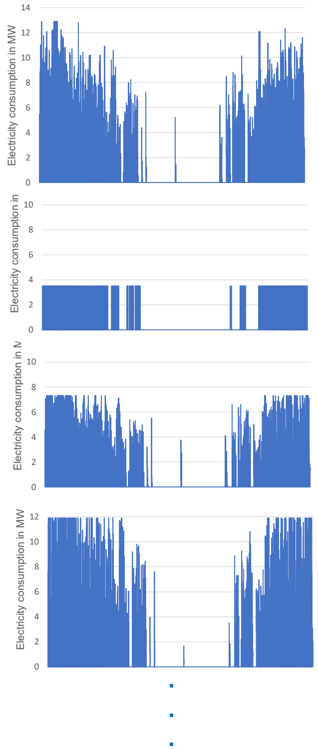
Storage system: 7.5 kWh

Aggregation of individual household decisions

Heat pumps

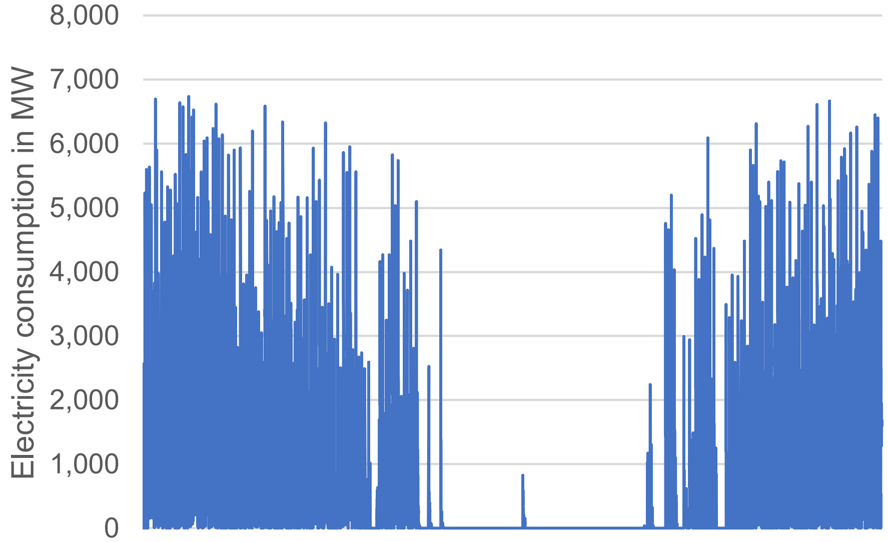
∑

- Building types
- User comfort types
- Heat pump types



108 individual consumption patterns per location

=



1 aggregated consumption pattern per location

Encapsulating aggregated household decisions with Neural Net

Heat pumps

Neural Net structure

- Explicit Long Short-Term Memory neuronal network (LSTM)
- Standalone TensorFlow-based tool

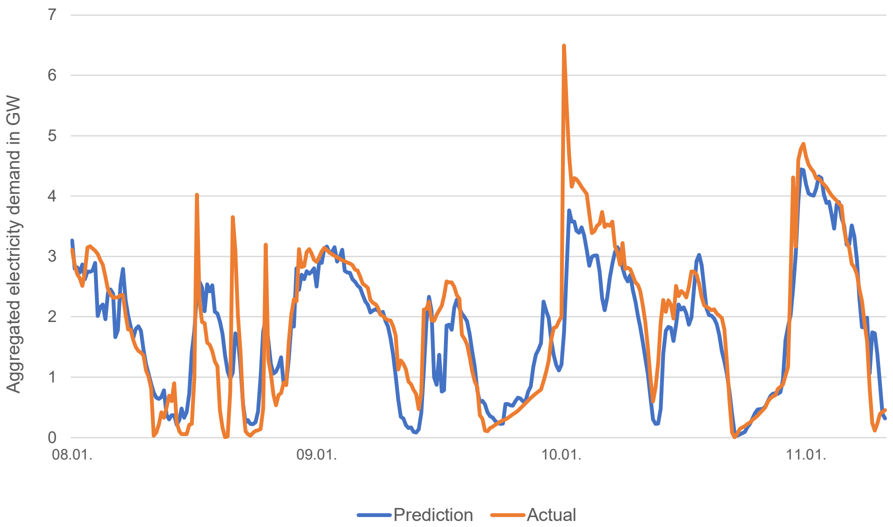
- Look-back-size: 24 h
- Training data: 85% of dataset for 5 locations
- Validation data: 15% of dataset for (the same) 5 locations
- Prediction: entire dataset of 1 (other) location
- Size of one data set: 8760 h in ¼ h resolution
- Epochs: 100

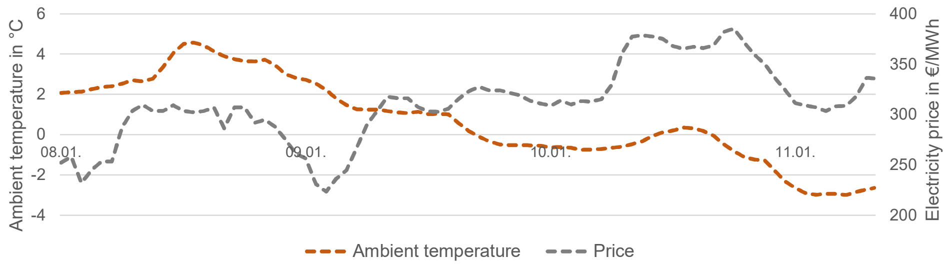
Layer (type)	Output shape	Param #
lstm (LSTM)	(None, 24, 64)	17,408
lstm_1 (LSTM)	(None, 24, 128)	98,816
lstm_2 (LSTM)	(None, 256)	394,240
dense (Dense)	(None, 64)	16,448
dense_1 (Dense)	(None, 1)	65

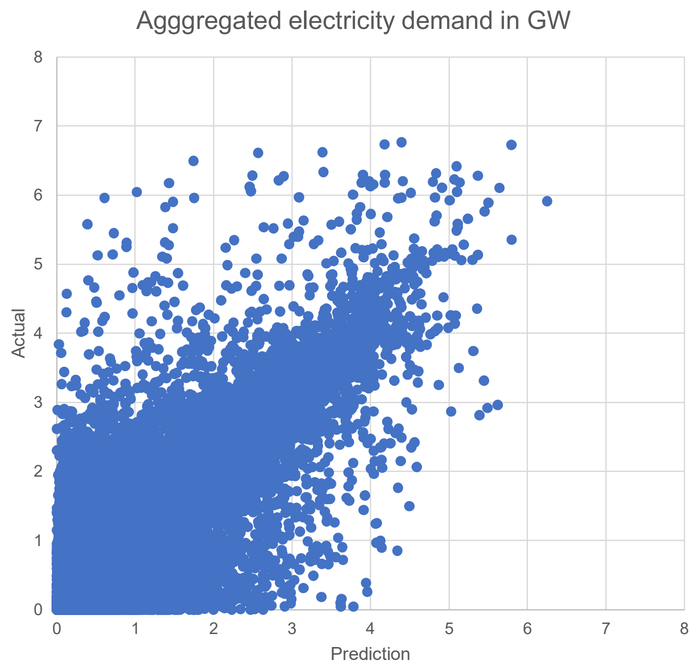
Task:
Predict aggregated heat pump electricity consumption for given
- Ambient temperature
- Solar radiation
- Real-time electricity price

Encapsulating aggregated household decisions with Neural Net
Heat pumps

Exemplary predictions







RMSE = 0.87 GW

Frey et al. - INREC 2023

Encapsulating aggregated household decisions with Neural Net

PV storage systems

Neural Net structure

- Using Focapy[1)], a Darts-based time series forecasting tool
- Best model: Temporal Fusion Transformer network (TFT)

- Look-back-size: 168 h
- Forecast period: 24 h
- Training data: entire data set for 1^{st} location
- Validation data: entire data set for 2^{nd} location
- Prediction: entire data set for 3^{rd} location
- Size of one data set: 8760 h in 1 h resolution
- Epochs:100

Task:

Predict aggregated PV grid interaction for given

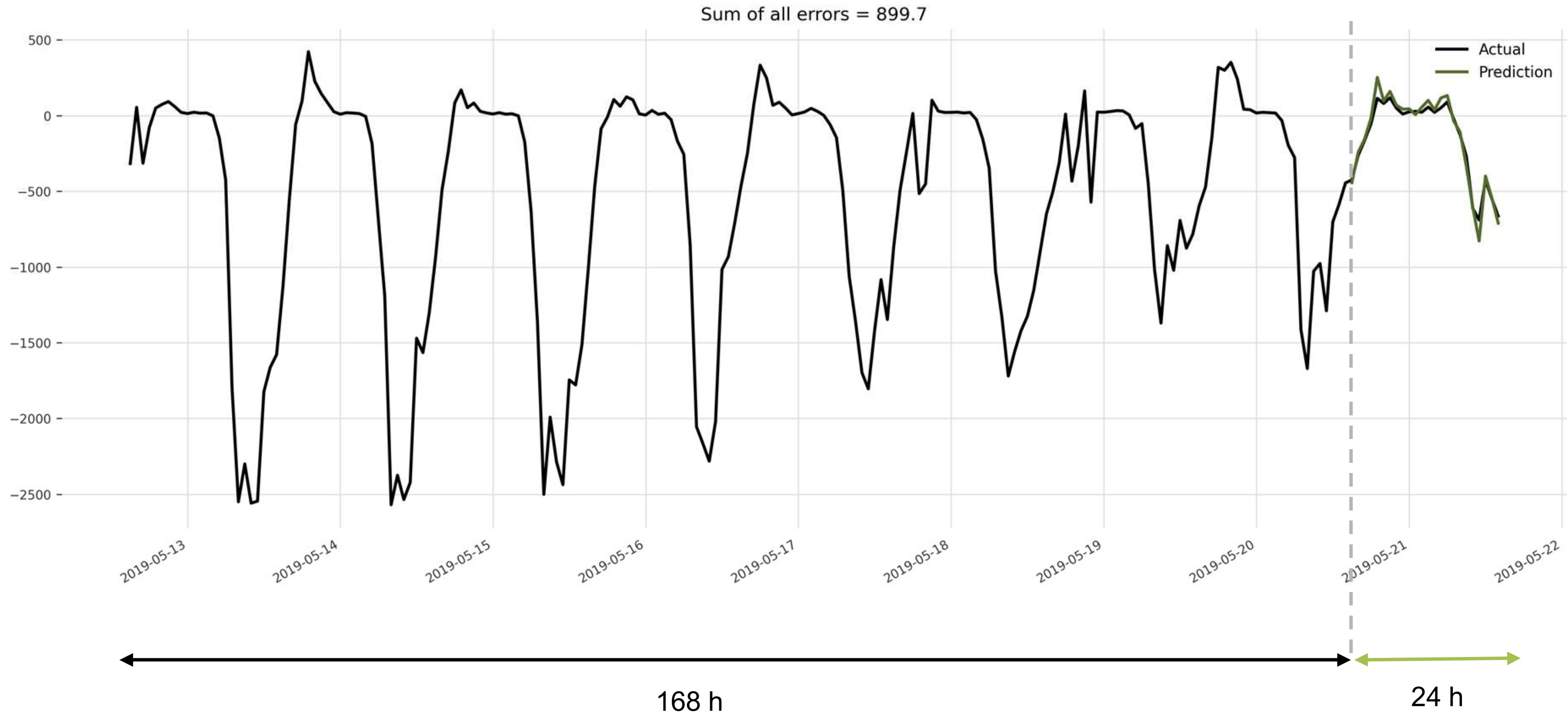
- Aggregated PV yield profile
- Aggregated household load profile
- Real-time electricity price

[1)] *Nitsch, F. (2023). focapy: Time Series Forecasting in Python. DOI: 10.5281/zenodo.7792751 (to be published in autumn 2023)*

Encapsulating aggregated household decisions with Neural Net

PV storage systems

Exemplary prediction



CONCLUSION

Conclusion and outlook

Conclusion

- **Model coupling** is necessary to represent individual decisions and their uncertainties in national energy system analysis simulations
- **Abstracting individual decisions** with Machine Learning
  - Is important for simulation speed
  - Could be a general solution for integrating computationally intensive tasks into simulations that were previously impossible

Outlook

- Investigating **market effects** through coupled model runs
- Analyzing impact of **regulatory framework conditions** on investments and system-friendly operation of household flexibility options

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THANK YOU!

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