TIME SERIES FORECASTING USING MACHINE LEARNING IN COMPLEX SYSTEMS UNDER UNCERTAINTY

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Motivation
What Will Electricity Markets Look Like in The Future?

- Well established field of energy systems modelling (ESM) Gilliland, 1975
- Modelling challenges due to growing complexity Pfenninger et al., 2014, Pye et al., 2021

- Agent-based modelling (ABM) – a promising approach
  - incorporating the actors‘ perspective Nitsch et al., 2021
  - representation of heterogenous actors Kraan et al., 2018
  - execution of real-world examples computationally cheap Hansen et al., 2019

- Applying the ABM AMIRIS[1] to simulate electricity markets
  - integration of renewable energies & flexibility options in electricity systems
  - analysis of market effects caused by policy and remuneration schemes

[1] https://dlr-ve.gitlab.io/esy/amiris/home/

AMIRIS

Agent-based **M**arket model for the **I**nvestigation of **R**enewable and **I**ntegrated energy **S**ystems

Model

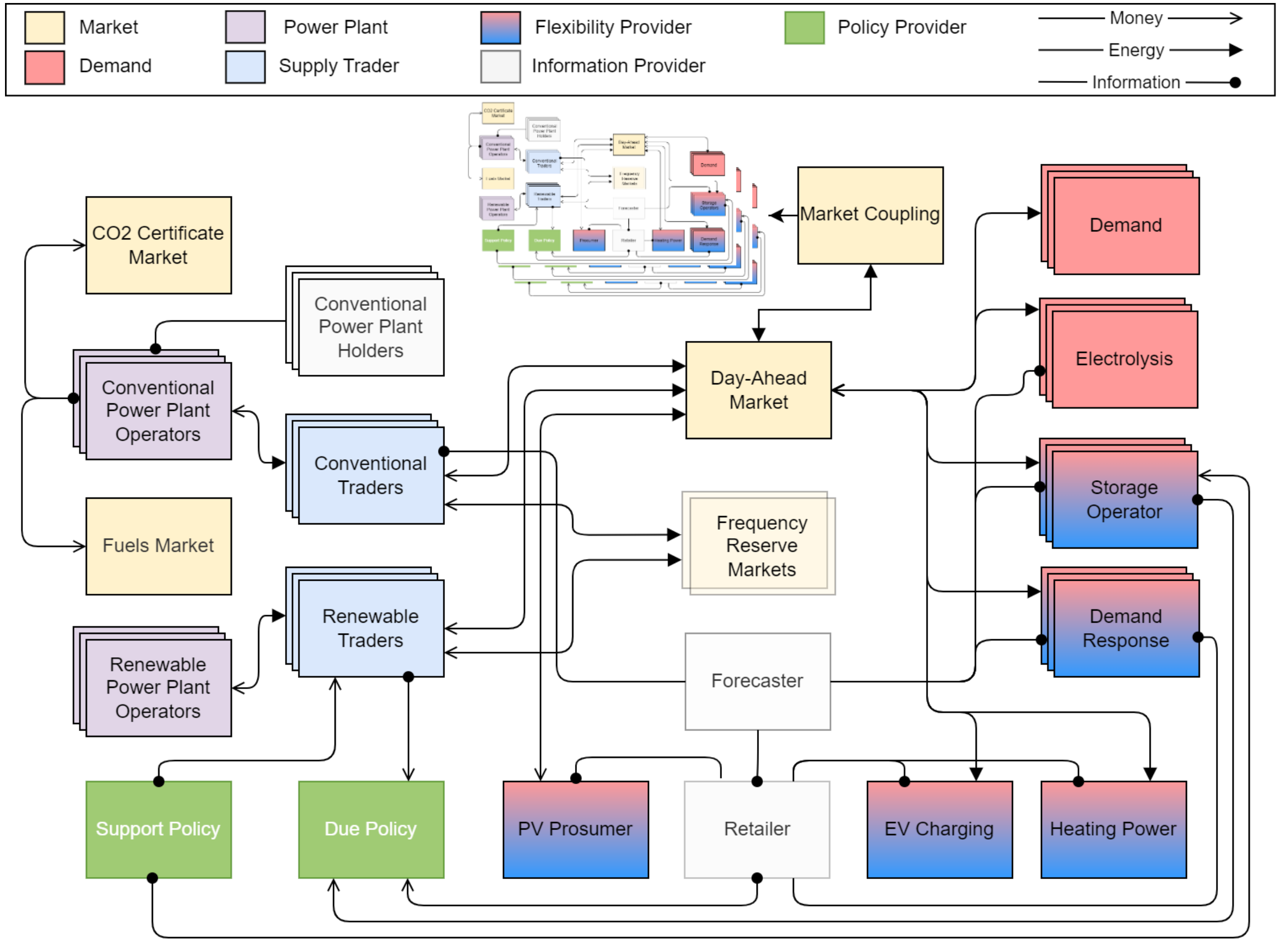
- Electricity market simulation
- Open source (Apache 2)

Agents

- Conventional Plants
- Renewable Plants
- Traders
- Flexibilities
- Markets
- Policy
- Forecasting

Calculates

- Electricity prices
- Plant dispatch
- Market values
- Emissions
- System costs

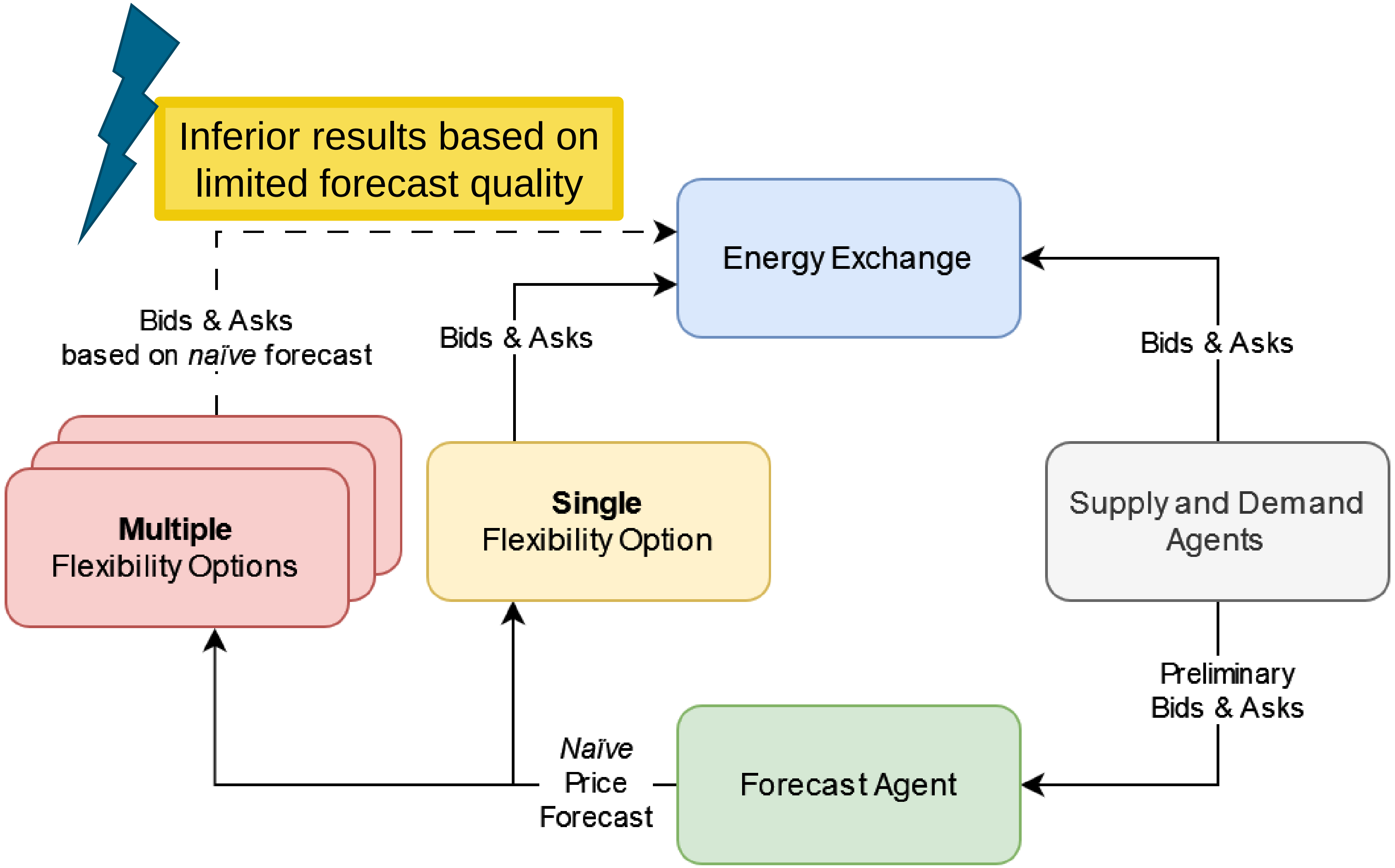


Input Data: Feed-in of renewables, temperature, balance energy price, marginal cost, load, ...

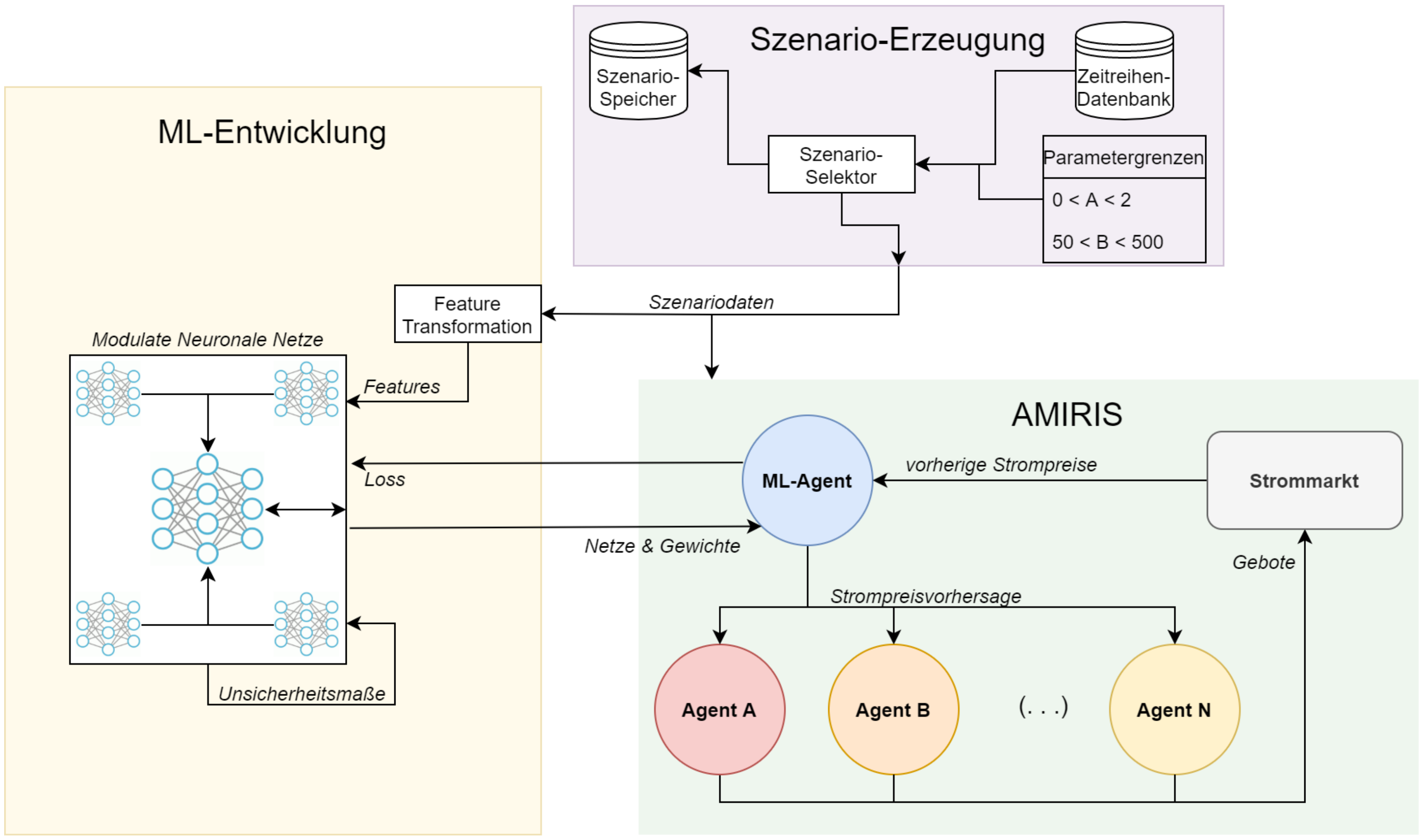
Schimeczek et al. (2023a). 10.21105/joss.05041
Schimeczek et al. (2023b). 10.21105/joss.05087
Nitsch et al. (2023a). 10.21105/joss.04958

Price Forecasting in AMIRIS

Limitations of Current Approach



FEAT Project
Flexible, Explainable, and Accurate Price Forecasts



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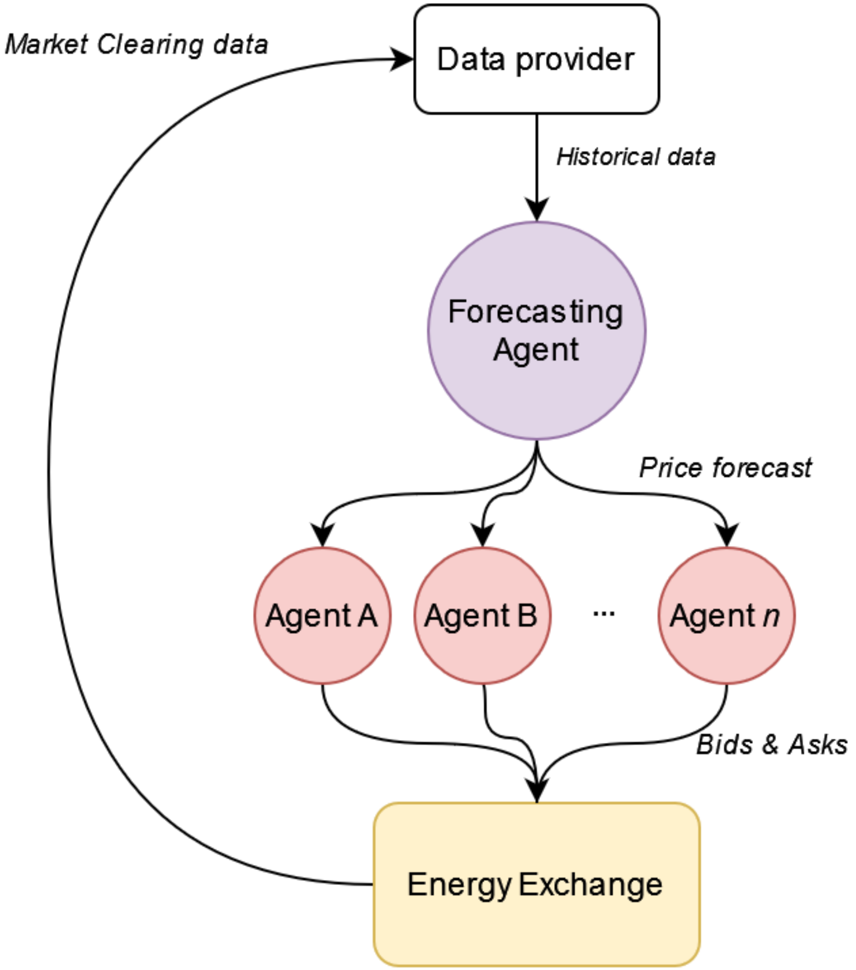
Concept of Improved Forecasting Agent
Providing Enhanced Price Forecasts

Aim
- Central forecast agent
- Price time series forecast of >=24h
- Input for schedule optimization of agents

Available Data
- Previous prices
- Previous residual load
- Future forecasted (residual) load
- Future forecasted RE generation



Concept of new Forecasting Agent in AMIRIS

Nitsch et al.(2023d). Time Series Forecasting in Energy System Models. To be published soon.

Methodology

Testing Multiple Methods in Two Main Scenario Sets

Naïve Methods

- t+1, t+24, naïve drifts

Serving as benchmarks

Regression Methods

- Linear Reg., LightGBM[1], Exp. Smoothing

Common statistical approaches

Machine Learning Methods

- NBeats[2], TemporalFusionTransformer[3], DeepAR[4]

State-of-the art machine learning methods

Data

- Timespan 2003 – 2019
- EEX:
  - Day-ahead auction prices
- Simulated market results by AMIRIS

Scenarios

I. Different shares of flexibility options

II. Varying renewable energy expansion

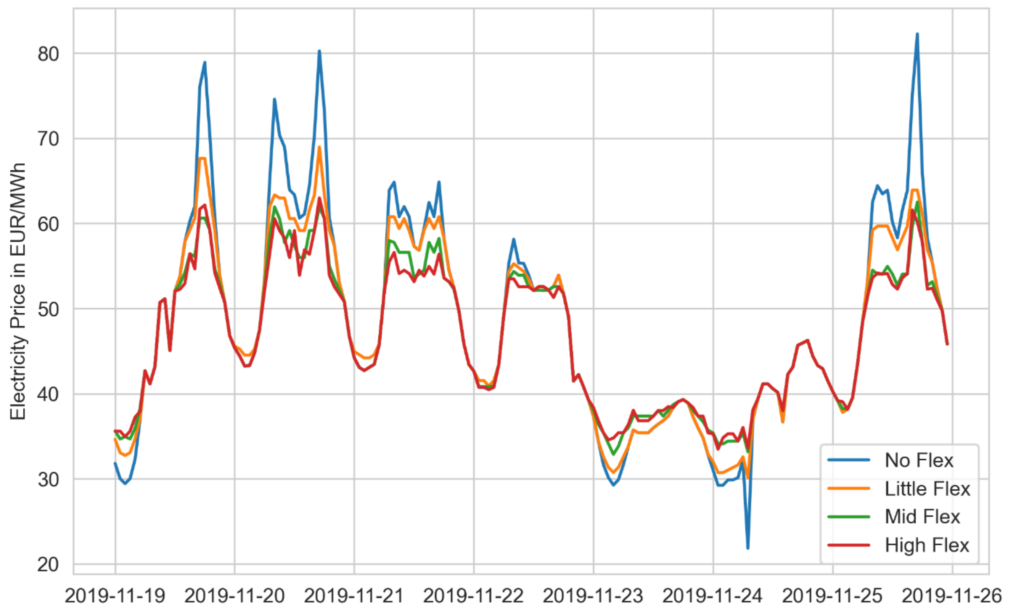
[1] Ke G. et al. (2017): https://papers.nips.cc/paper/6907-lightgbm-a-highly-efficient-gradient-boosting-decision-tree
[2] Oreshkin B. et al. (2019): https://doi.org/10.48550/arXiv.1905.10437
[3] Lim B. et al. (2021): https://doi.org/10.1016/j.ijforecast.2021.03.012
[4] Salinas D. et al. (2020): https://doi.org/10.1016/j.ijforecast.2019.07.001

Forecasting Performance – Flexibility Variation

Overview and Price Impacts

Mean Absolute Error (MAPE) for four test scenarios with rising flexibility capacities

Metric \ Scenario	I *No Flex*	II *Little Flex*	III *Mid Flex*	IV *High Flex*
Naïve t_1	9.29	7.78	6.76	6.45
Naïve t_{24}	8.57	7.54	6.27	5.91
Exponential Smoothing	8.06	6.70	5.73	5.46
N-BEATS	7.15	6.24	5.38	5.12
TFT	4.11	3.90	3.20	3.26
TFT w/ future covariates	3.12	3.45	3.26	2.86

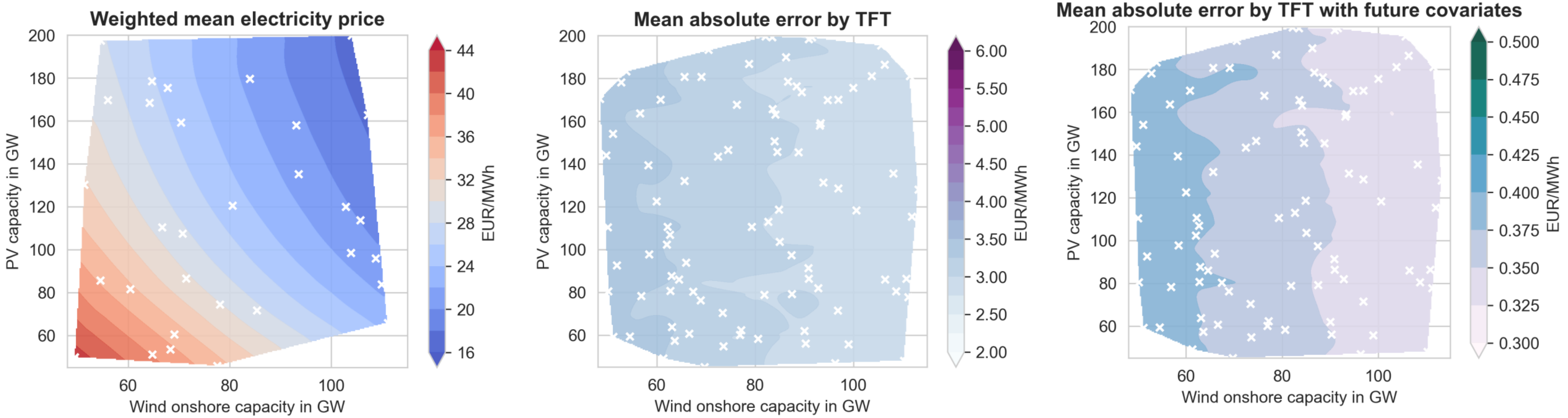


Price dampening impact of different flexibility capacities in the four scenarios on electricity prices over a one-week period in November 2019.

Forecasting Performance – Renewable Expansion

Day-ahead forecast applying TFT

Train | **Test I** | **Test II**



Forecasting performance in scenarios of varying renewable energy expansion

Note: Scenarios are considered as parameter variations and shall not be interpreted as definitive, and complete future electricity systems

Conclusion

- Motivation: Precise time series forecasts in energy system models
- Method: Comparison of methods (naïve, regression, machine learning)
- Results: ML outperforms other methods depending on input data
- Discussion:
  - Challenging integration in existing models
  - Training for future scenarios

Outlook

- Fine-tune and further test models
- Integrate architectures in AMIRIS enabling endogenous & comprehensive forecasts
- Further analysis in FEAT project, see https://www.mlsustainableenergy.com/

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Imprint

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