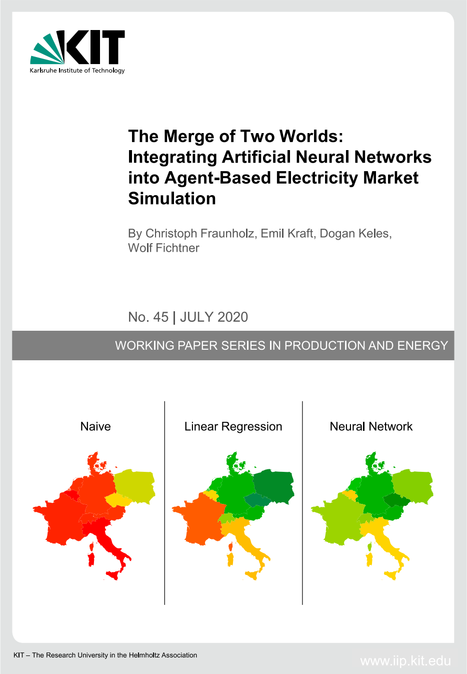
The Merge of Two Worlds: Integrating Artificial Neural Networks into Agent-Based Electricity Market Simulation

Christoph Fraunholz, Emil Kraft, Dogan Keles, Wolf Fichtner / GOR-Workshop, October 2020

Agenda

- Introduction to PowerACE
- Methodology
- Definition of the Case Study
- Results of the Case Study
- Conclusion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Naive | Linear Regression | Neural Network

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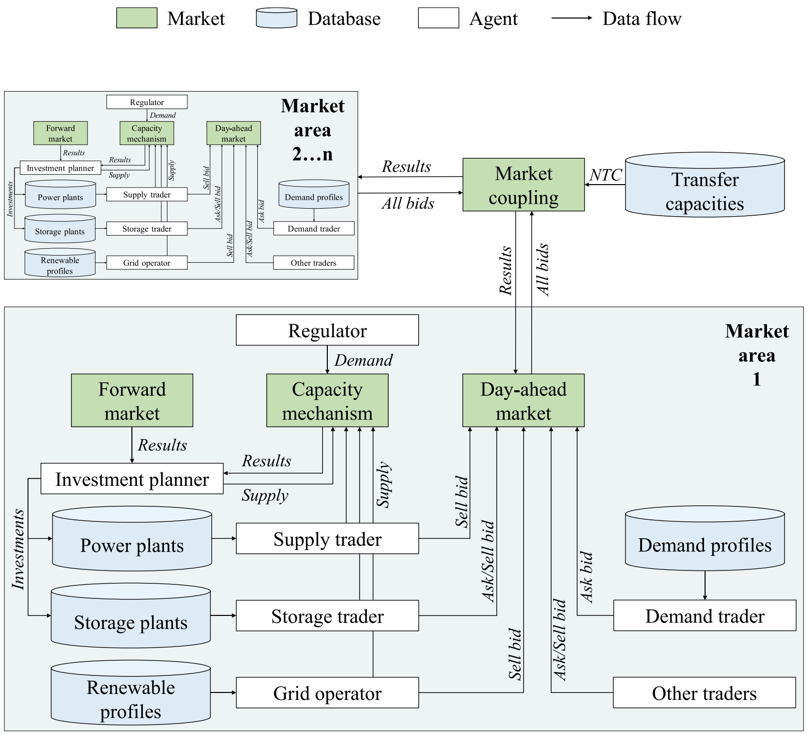
Introduction to PowerACE: Overview



Characteristics

- Agent-based electricity market simulation model
- Time horizon: 2015–2050 at hourly resolution (8760 h/a)
- Day-ahead market simulation: coupling of the national markets to maximize welfare
- Investment decisions: iterative determination of a Nash-equilibrium

Input

- Power plant fleets of the base year
- Fuel and carbon prices
- Hourly electricity demand and renewable feed-in
- Net transfer capacities between the market areas

Output

- Hourly day-ahead market prices
- Hourly dispatch of power plants and storages
- Investment decisions for power plants and storages

Introduction to PowerACE: Day-Ahead Market

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Simulation in four major steps

Agent-level	*Agent-level*	*System-level*	*Agent-level*
Price forecasting	**Bidding**	**Market clearing**	**Dispatch**
Agents create price forecast for the day-ahead market	Agents prepare bids (volume, price) for their generation units	Central market operator matches supply bids and demand bids	Agents plan the dispatch of their generation units

➔ Day-ahead market procedure is carried out every simulation day over a time horizon of 2020–2050

Introduction to PowerACE: Day-Ahead Market

Bidding strategy

If, according to the price forecast, a medium- or peak-load power plant is in the market...

- in all hours:

$$b(h) = c_{\text{var}} \qquad \forall h$$

- in some hours (or never):

$$b(h) = c_{\text{var}} + \frac{c_{\text{start}}}{t_{\text{on}}} \qquad \forall h \in \boldsymbol{H}_{\text{on}}$$

$$b(h) = c_{\text{var}} + \frac{c_{\text{start}}}{\Delta t} \qquad \forall h \in \boldsymbol{H}_{\text{off}}$$

➔ Distribution of the start-up costs is strongly affected by the price forecast

Problem setup

- Price forecast drives the bidding behavior and therefore impacts the simulated electricity prices
- Mutual dependency between forecasts and market outcomes distinguishes the problem from a standard price forecast
- Accurate model-endogenous price forecasts are essential, yet non-trivial to establish in a setup with multiple interconnected countries

Basic idea

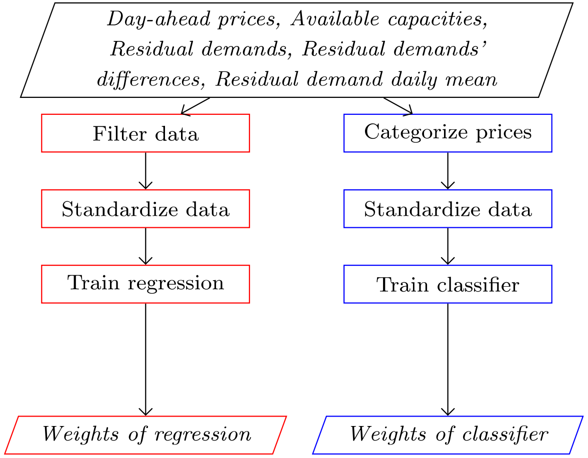
➔ Adaptive forecasting model, which uses information of already simulated day-ahead market outcomes to provide accurate price forecasts to agents

Methodology: Artificial Neural Network Model

General approach

- One price forecast module per market area, extendable to individual module for each trader (but: computational limits!)
- Combination of two feedforward networks
  - Regression (*red*): find relationships between inputs and simulated day-ahead electricity prices
  - Classification (*blue*): account for outliers (prices set by renewables or scarcity)
- Other independent variables like fuel prices could be integrated (but: typically constant over the course of a year in PowerACE)

Training procedure



Updates once per market area and simulation month over a period of 31 years (2020–2050)

➔ 31·12·10·2 = 7440 model trainings!

Methodology: Benchmark Models

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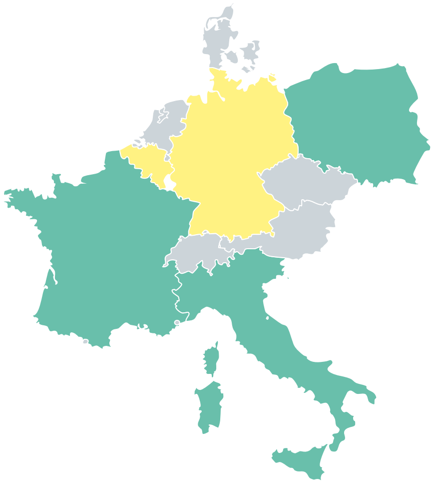
Naive price forecast	Linear regression model
▪ Price forecast = Simulated price of previous day/week (i.e., time lag of 24 or 168 hours) ▪ Very basic approach as lower bound ▪ Despite simplicity: good performance in the literature for exogenous price forecasting!	▪ Similar procedure as used for the ANN approach, but linear relationships ▪ Model complexity between naive and ANN ▪ Regression part: multiple linear regression ▪ Classification part: multinominal logistic regression

Definition of the Case Study

Regional scope and market design

Energy-only market	Strategic reserve
Capacity mechanism	



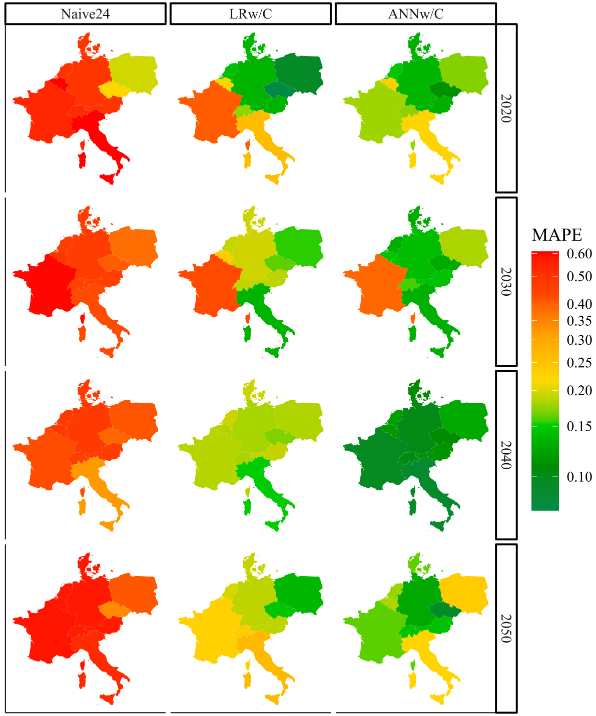
General simulation setup

- Ten interconnected European countries
- Time period 2020–2050 with resolution of 8760 h/a
- Renewable share of ~80% in 2050

Considered price forecasting approaches

- Naive forecast with lag of 24 hours (*Naive24*)
- Linear regression with logistic classifier (*LRw/C*)
- Feedforward neural network with feedforward neural network classifier (*ANNw/C*)
- Additional simulations without classifiers (not part of this presentation)

Results of the Case Study: Overview



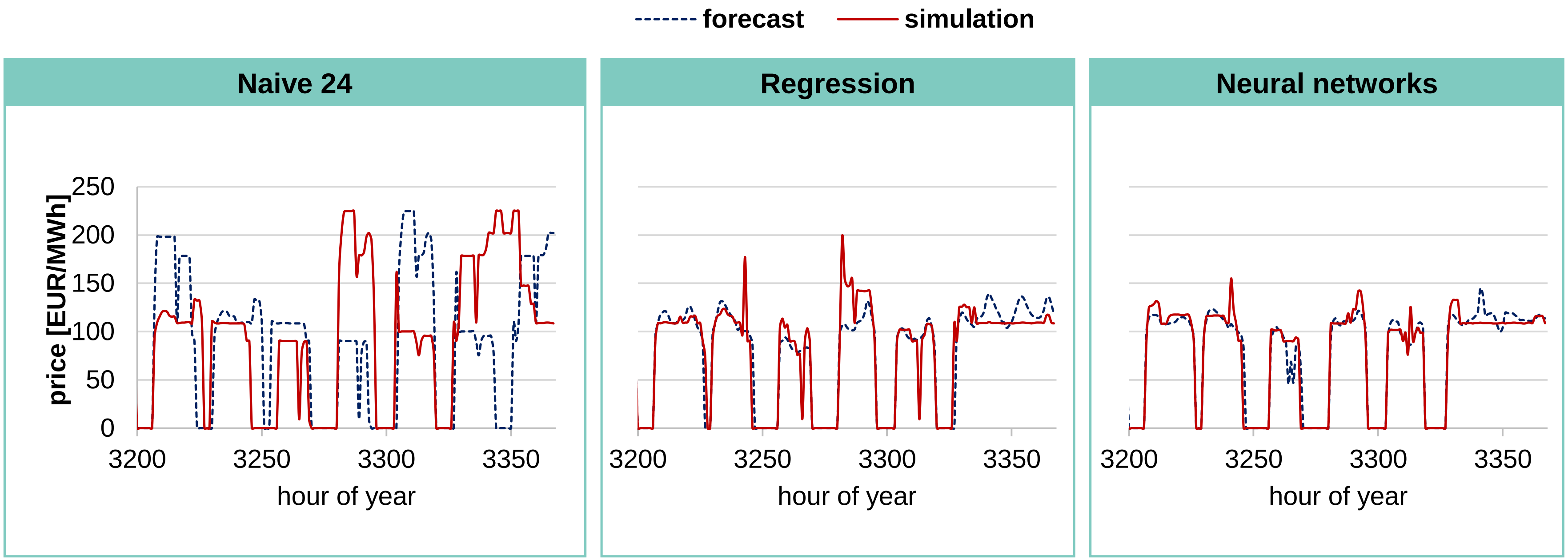
$$e_{s,m,y}^{\text{MAPE}} = \frac{1}{8760} \sum_{h=1}^{8760} \frac{|p_{s,m,y,h} - \hat{p}_{s,m,y,h}|}{\bar{p}_{s,m,y}}$$

with

p	realization (hourly)
$\hat{p}$	forecast (hourly)
$\bar{p}$	arithmetic mean (yearly)
s	scenario
m	market area
y	year
h	hour

➔ Linear regression (*LRw/C*) and even more so the artificial neural networks (*ANNw/C*) clearly outperform the naive forecast (*Naive24*)

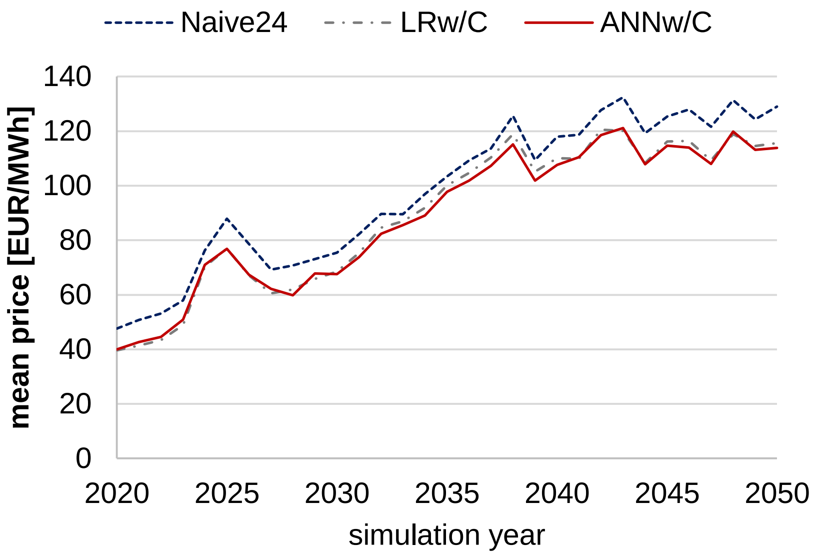
Results of the Case Study: Germany 2050*



*randomly chosen one-week period

Results of the Case Study: Simulated Prices

Volume-weighted mean day-ahead prices*



*Germany, similar results in other countries

Major findings

- Strong increase of the general price level over the simulation period (driven by model assumptions, e.g., renewable share of 80% and carbon price of 150 EUR/t_{CO_2} in 2050)
- Similar price curves for *LRw/C* and *ANNw/C*, while distorted bidding behavior under the *Naive24* method leads to an elevated price level
- Prices simulated under accurate price forecasts are likely to be closer to reality, since real-world electricity price forecasting is also rather accurate

Conclusion

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- Price forecasting technique using ANNs implemented in an agent-based electricity market simulation model
- Multi-country case study confirms importance of accurate model-endogenous price forecasts as well as suitability of the ANN approach
- In contrast to real-world electricity price forecasts, the naive approach performs very poorly when deployed model-endogenously
- Joint application of machine learning and agent-based modeling also beneficial in other research contexts?

Thank you for your attention!