Electricity price forecasts in agent-based energy system simulations

Felix Nitsch, Christoph Schimeczek

WAW Maschinelles Lernen 6
Price forecasts in agent-based electricity market modelling

- Multiple competing agents need price forecast
- Competition disrupts simple forecast
- Goal: integrate expected bidding behaviour
The idea of a learning forecast agent

- Forecast agent learns bidding behaviour

- Architecture:
  - Feed-forward model
  - LSTM model

- Inputs:
  - Previous prices
  - Previous residual load
  - (Future residual load)

- Output:
  - Forecast for at least next 24 hours
Electricity prices

In simulations

- **Without flexibility options:** price as function of residual load

![Electricity price without flexibility options](chart.png)
Electricity prices

In simulations

- **Without flexibility options:** price as function of residual load

- **With flexibility options:** more complex, time-dependent relation between residual load and prices

Fig. 4: Electricity price with significant capacities of flexibility options
Feed-forward model I

• Map residual load on day-ahead price

• Artificial scenario with no storage capacity

• Therefore no unforeseen deviations

• Architecture:
  • Input: Residual_load(t)
  • Output: Price(t)
  • 3 hidden layers [100, 50, 30]
  • 48 epochs
  • batch size of 32

• Fit:
  • R2 0.9999
  • MAE 0.26 EUR/MWh
  • Max. abs. error 2.39 EUR/MWh
Feed-forward model II

- Map residual load on day-ahead price
- Artificial scenario with extended storage capacity,
- Leads to various unforeseen deviations due to storage dispatch
- Architecture:
  - Input: Residual_load(t)
  - Output: Price(t)
  - 3 hidden layers [100, 50, 30]
  - 48 epochs
  - batch size of 32
- Fit:
  - R2 0.9482
  - MAE 1.52 EUR/MWh
  - Max. abs. error 58.66 EUR/MWh
Long-short term model (LSTM)

- Artificial scenario with extended storage capacity,
- LSTM should account for time-dependent deviations due to storage operation and therefore correct the FF prediction

- Architecture:
  - Input: Past_simulated_prices(t-24, ..., t-1), Delta_from_FF(t-24, ..., t-1)
  - Output: Price(t)
  - 3 hidden layers [100, 50, 30]
  - 72 epochs
  - batch size of 32
- Fit:
  - R2 0.9945
  - MAE 2.25 EUR/MWh
  - Max. abs. error 48.92 EUR/MWh

Fig.9: Predicted prices against simulated prices from FF network

Fig.10: Predicted prices against simulated prices from LSTM network using FF predictions and simulated prices as input
Comparison of predictions

Fig. 11: Comparison of simulated prices (black), FF prediction (grey dotted), FF&LSTM prediction (red dashed) and storage dispatch over time
Conclusion & outlook

• Price forecasts in energy system models must consider competition amongst market actors

• Provide forecasts using multi-stage neural networks to integrate bidding behavior of actors:
  • Basic estimate: Feed forward model
  • Time-dependent corrections: LSTM

• First results look promising

• Questions on deployment and training:
  • Generalization of training data (e.g. different power plant park)?
  • Many specialized sub-models vs. comprehensive general model?

Contact: Felix Nitsch, Christoph Schimeczek
German Aerospace Center (DLR), Institute of Engineering Thermodynamics, Department of Energy Systems Analysis, Curiestraße 4 | 70563 Stuttgart, felix.nitsch@dlr.de
Appendix
Retrospective: INREC 2019

- Analysis of commercial day-ahead price forecast
- Identification of key error components
  - Merit Order gradient
  - 24h cycle characteristic (e.g. PV & demand)
  - Autocorrelation
  - Random fluctuations
- Construction of artificial day-ahead price forecasts
- Application in agent-based electricity market model AMIRIS (Deissenroth et al., 2017)
- Enabling of modelling more realistic agent-behaviour due to similar error characteristics as found in the industry

Fig.2: Summary of presentation at INREC 2019 (Schimeczek and Nitsch, 2019)
Forecasts in energy system simulations

- **Background:** agent-based model AMIRIS developed at DLR Stuttgart (Deissenroth et al., 2017) simulating German electricity market

- **Supply:**
  - Conventional power plants bid with marginal costs (operation, fuel, CO$_2$, etc.)
  - Renewables follow provided generation profiles
  - Flexibility options rely on price forecasts for optimizing operational strategy

![Schematic model overview of the agent-based model AMIRIS](chart13)

Fig.1: Schematic model overview of the agent-based model AMIRIS
Extract flexibility option signal

Fig.13: Simulated electricity price (red) and FF prediction delta (blue) in sample period of 300 hours

- Task: predict delta for forecasted price deviation of FF network to account for time-dependent dispatch by flexibility options

- Prediction delta (and past simulated electricity price) should be used as input for LSTM