Electricity price forecasts in agent-based energy system simulations

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Price forecasts in agent-based electricity market modelling

- Multiple competing agents need price forecast
- Competition disrupts simple forecast

- Goal: integrate expected bidding behaviour

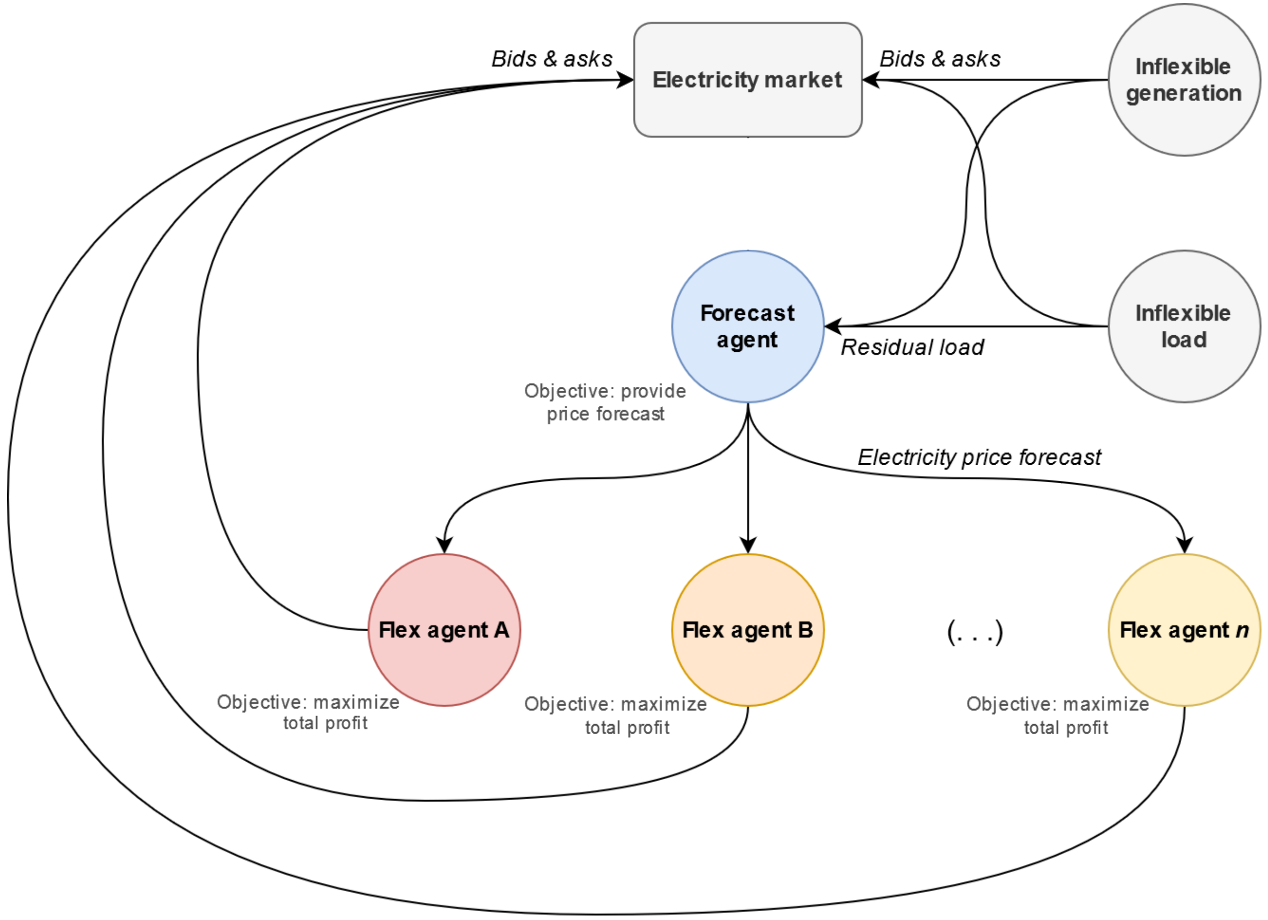

Fig.1: Agent providing forecasts for multiple flexibility options

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

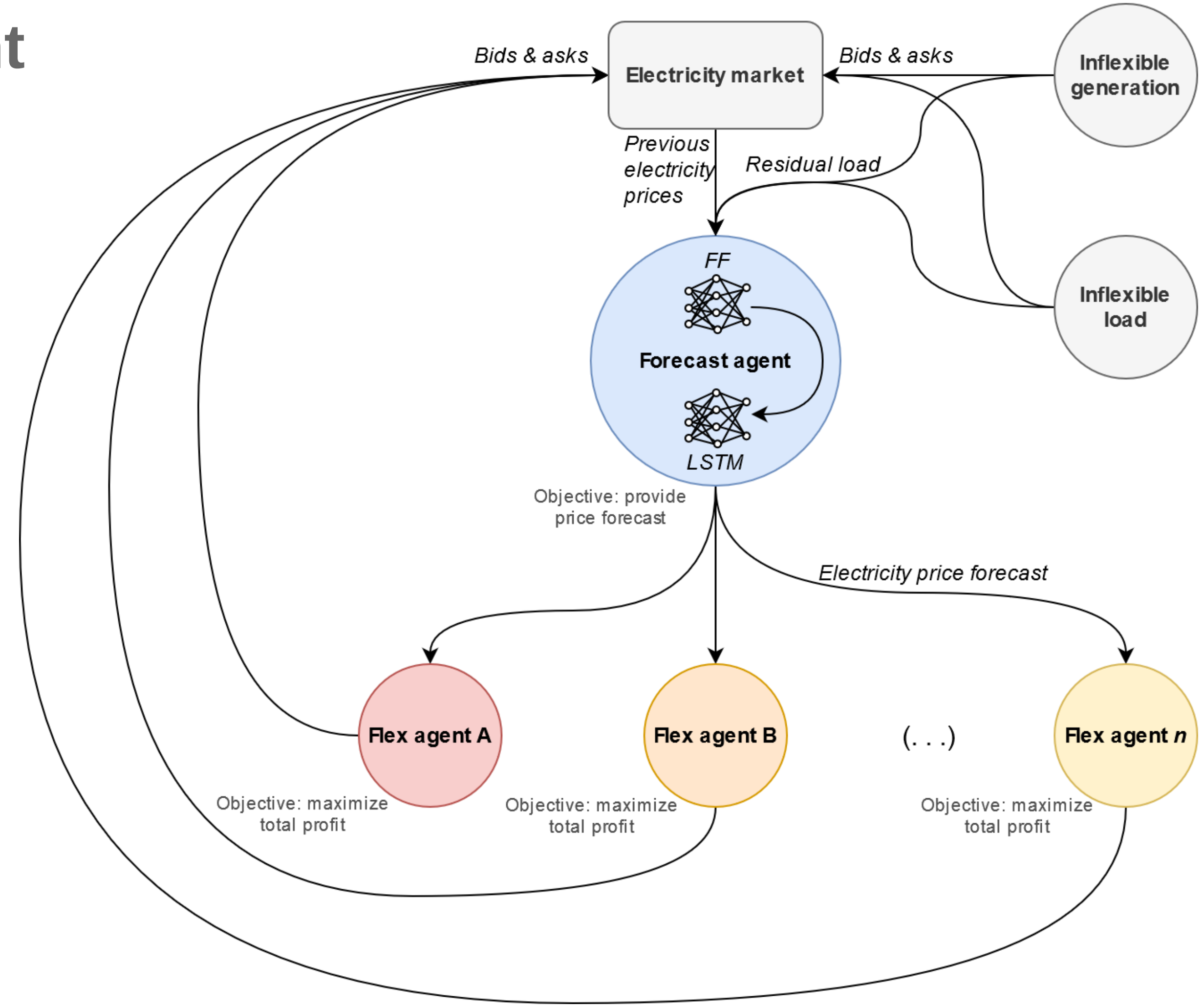

Fig.2: Forecast agent equipped with neural networks providing forecasts for multiple flexibility options

Electricity prices

In simulations

- Without flexibility options:
  price as function of residual load

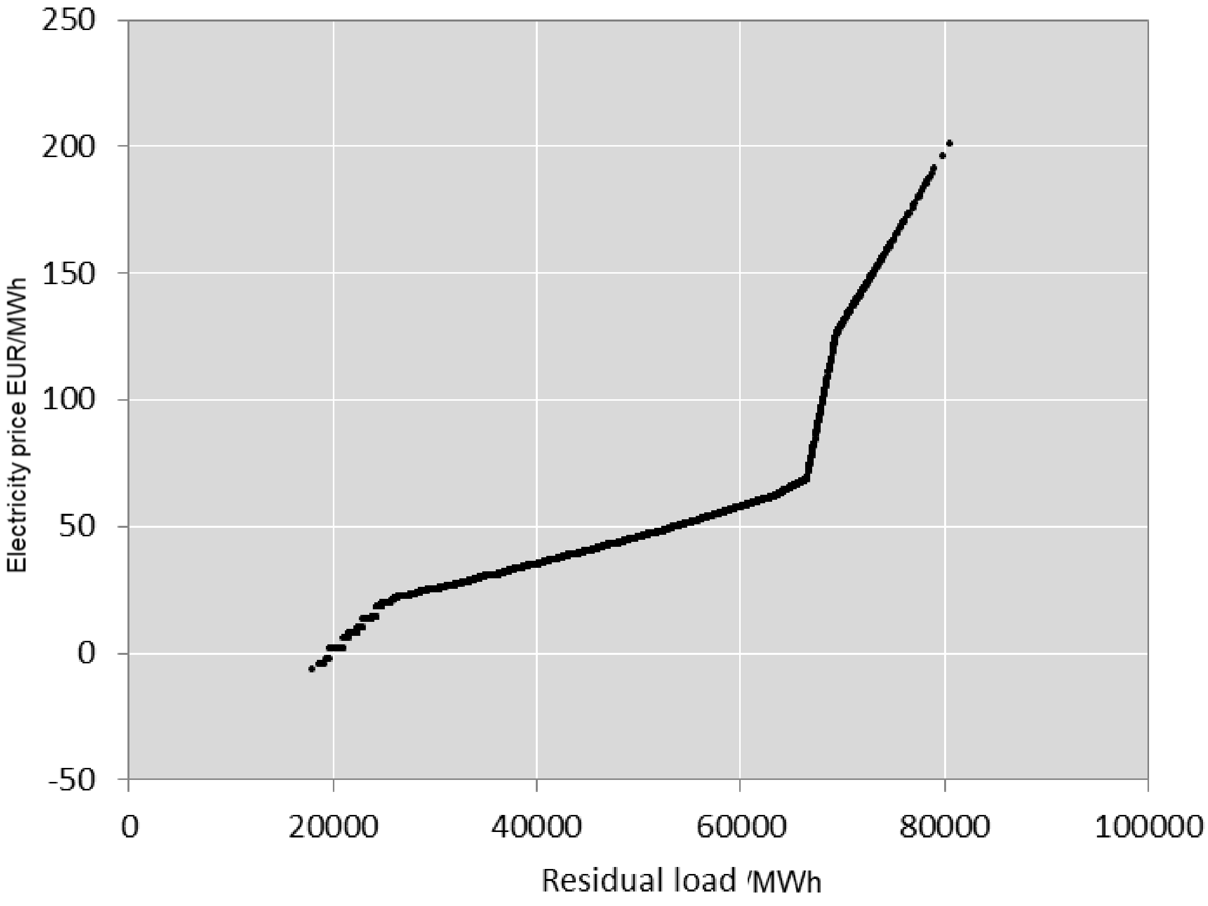

Fig.3: Electricity price without flexibility options

Electricity prices

In simulations

- <u>Without flexibility options:</u>
  price as function of residual load

- <u>With flexibility options:</u>
  more complex, time-dependent relation between residual load and prices

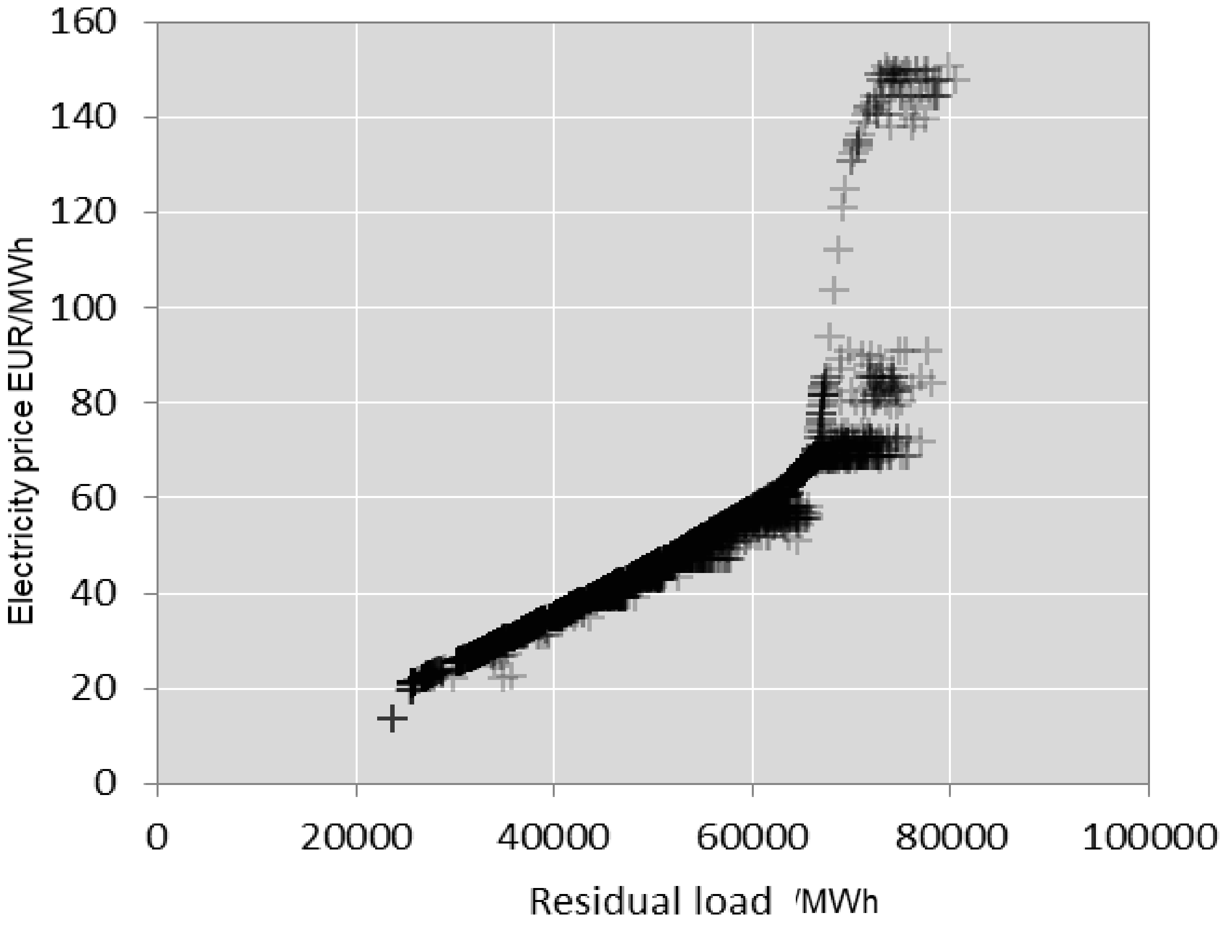

Fig.4: Electricity price with significant capacities of flexibility options

Feed-forward model I

- Map residual load on day-ahead price
- Artificial scenario with <u>no storage </u>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

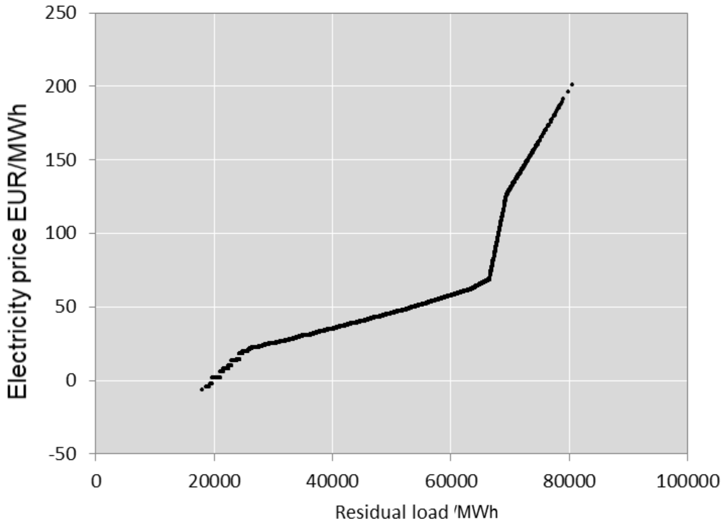

Fig.5: Residual load in scenario with no storage capacity

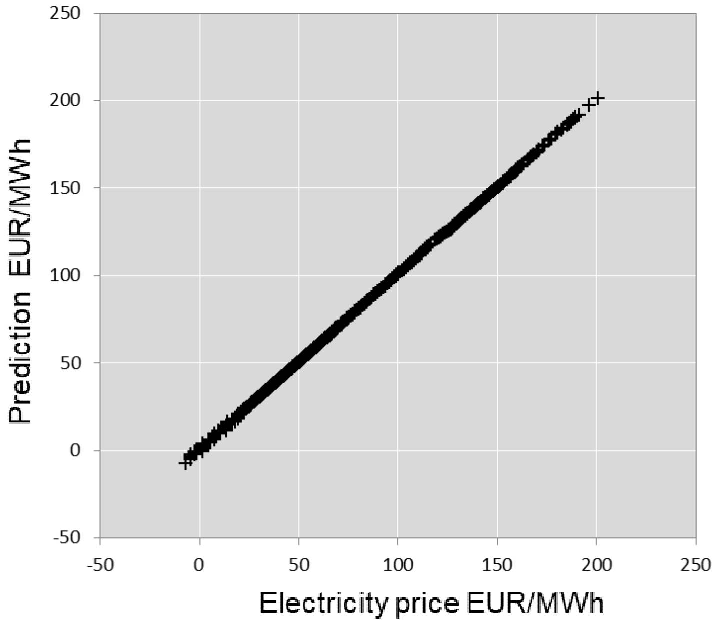

Fig.6: Predicted prices against simulated prices

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

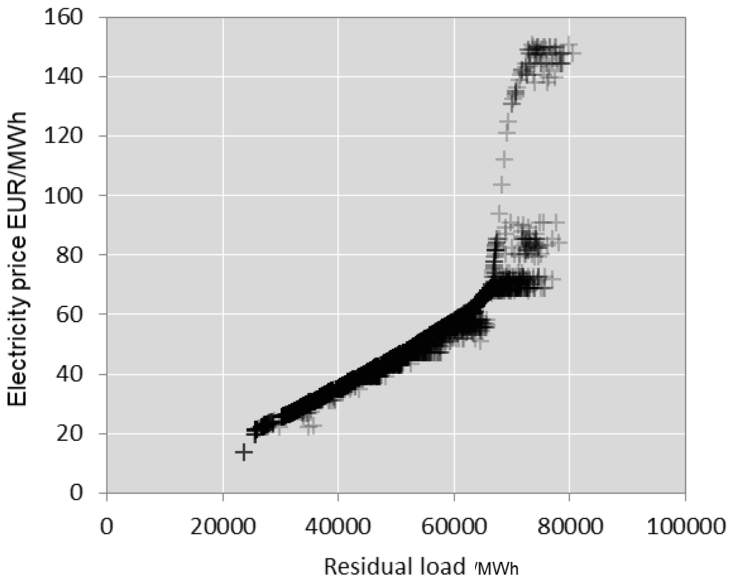

Fig.7: Residual load in scenario with extended storage capacity

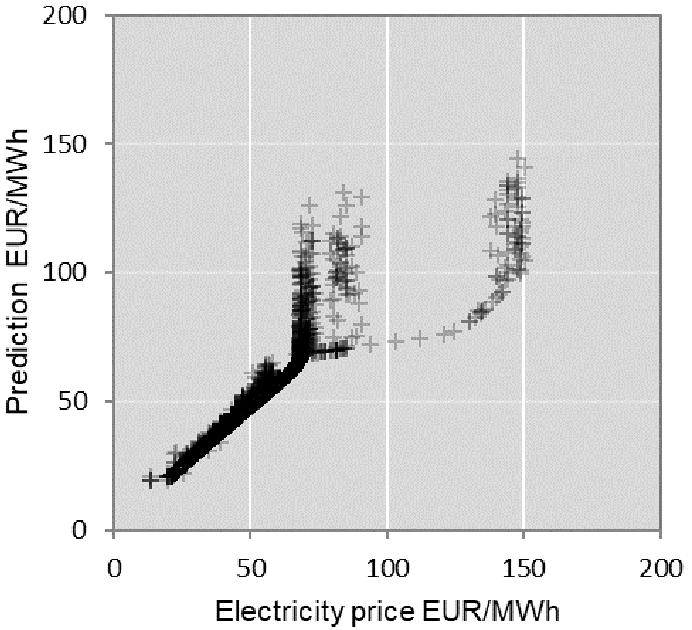

Fig.8: Predicted prices against simulated prices

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

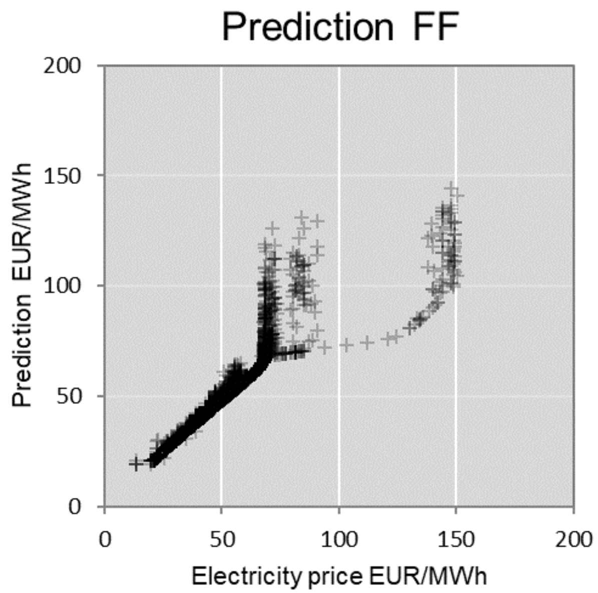

Fig.9: Predicted prices against simulated prices from FF network

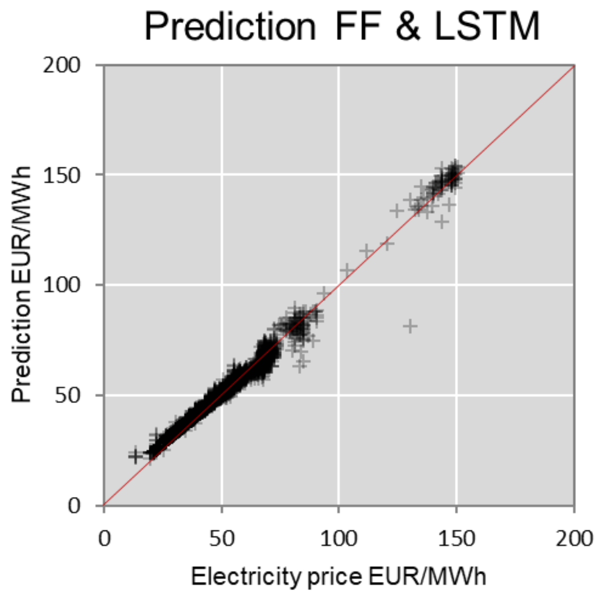

Fig.10: Predicted prices against simulated prices from LSTM network using FF predictions and simulated prices as input

Comparison of predictions

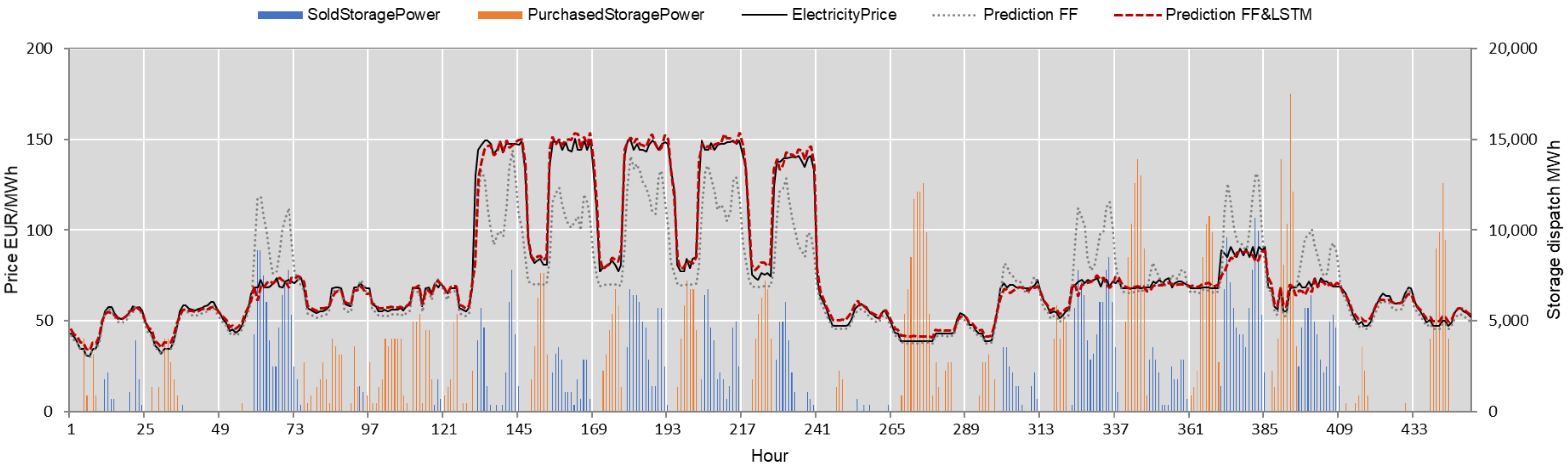

Fig.11: Comparison of simulated prices (black), FF prediction (grey dotted), FF&LSTM prediction (red dashed) and storage dispatch over time

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?

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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

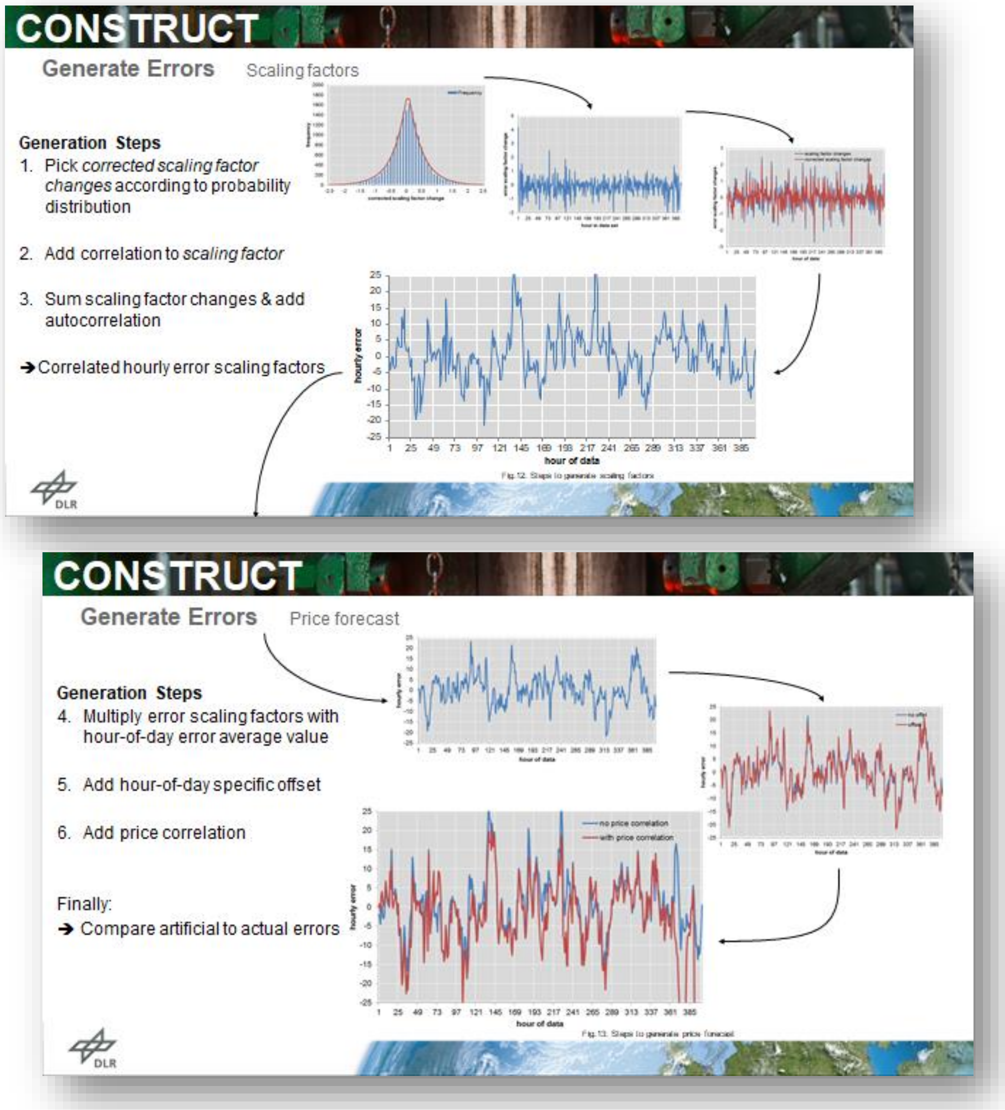

Fig.2: Summary of presentation at INREC 2019 (Schimeczek and Nitsch, 2019)

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

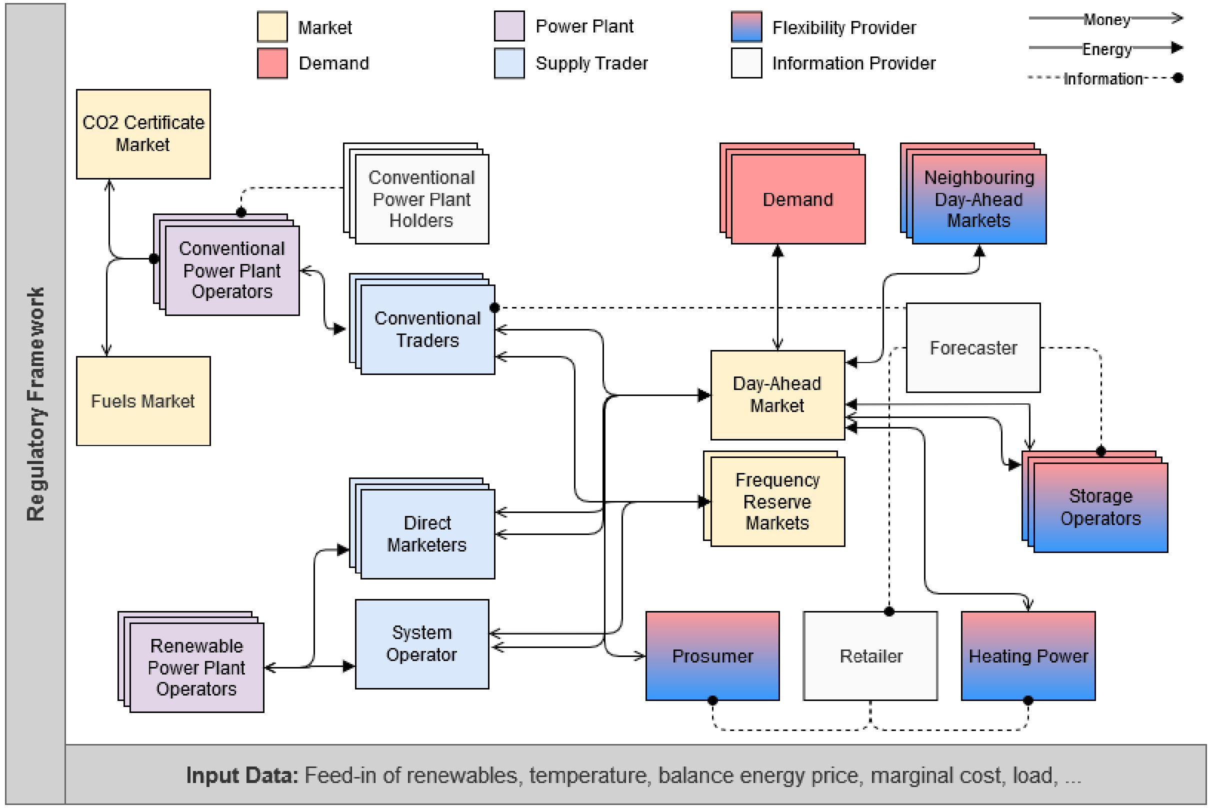

Fig.1: Schematic model overview of the agent-based model AMIRIS

Extract flexibility option signal

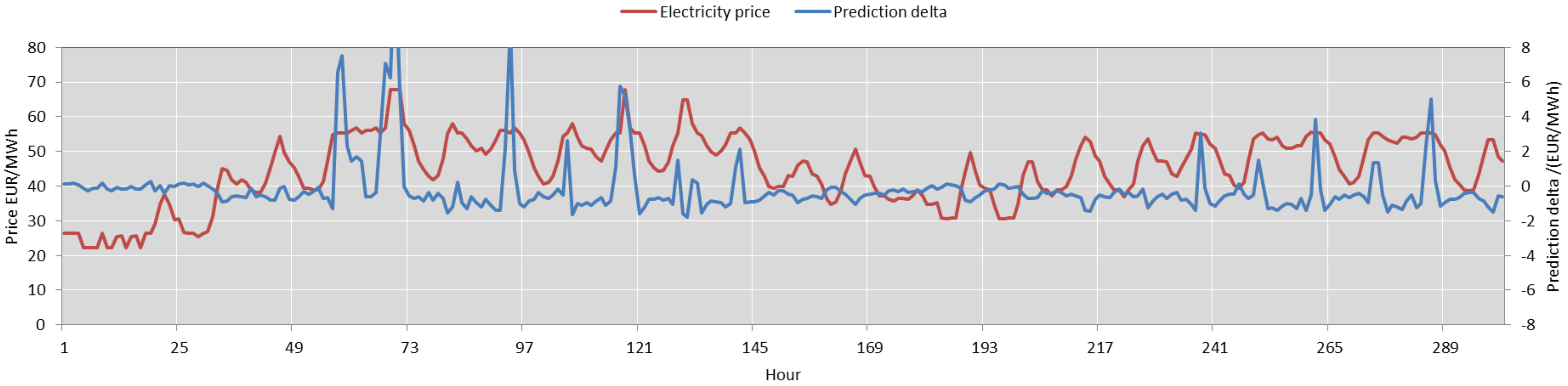

Fig.13: Simulated electricity price (red) and FF prediction delta (blue) in sample period of 300 hours

- 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