Model in model: Electricity price forecasts in agent-based energy system simulations

Felix Nitsch, Christoph Schimeczek

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DLR

German Aerospace Center
Institute of Engineering Thermodynamics
Energy Systems Analysis
Curiestraße 4, 70563 Stuttgart

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

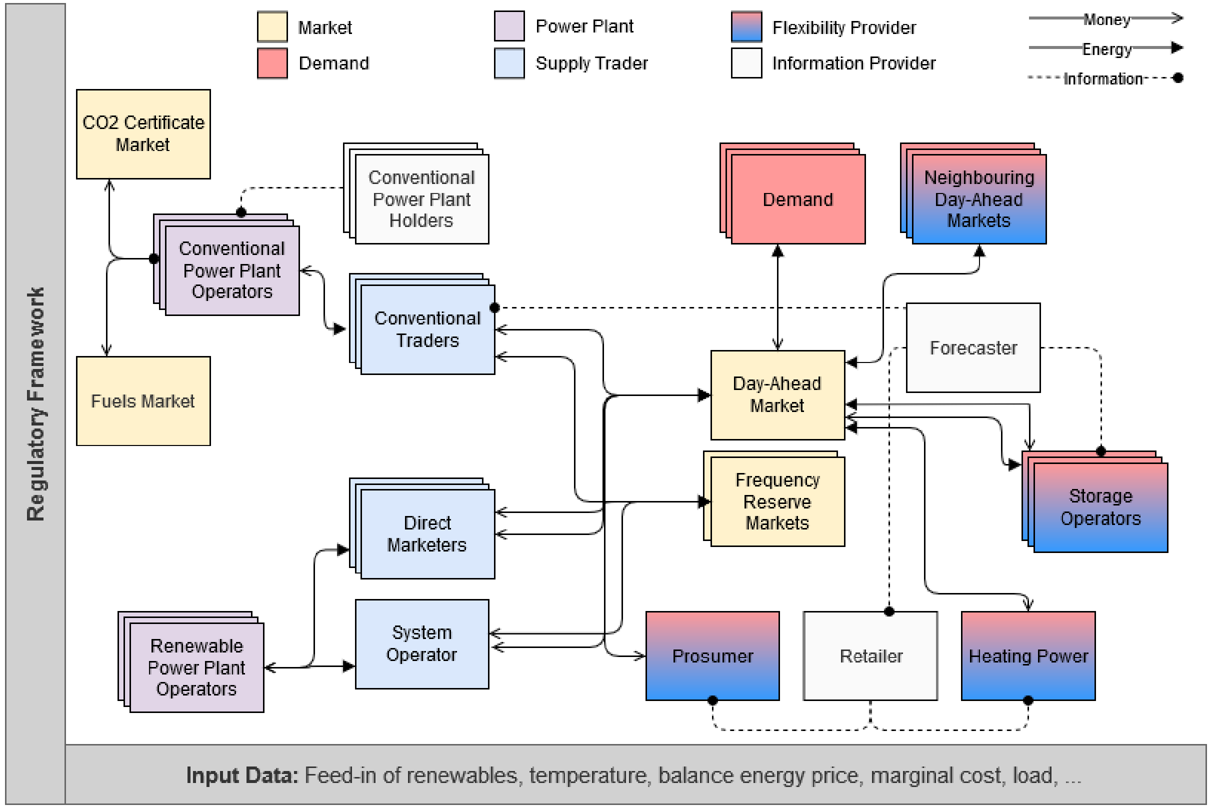

Fig.1: Schematic model overview of the agent-based model AMIRIS

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

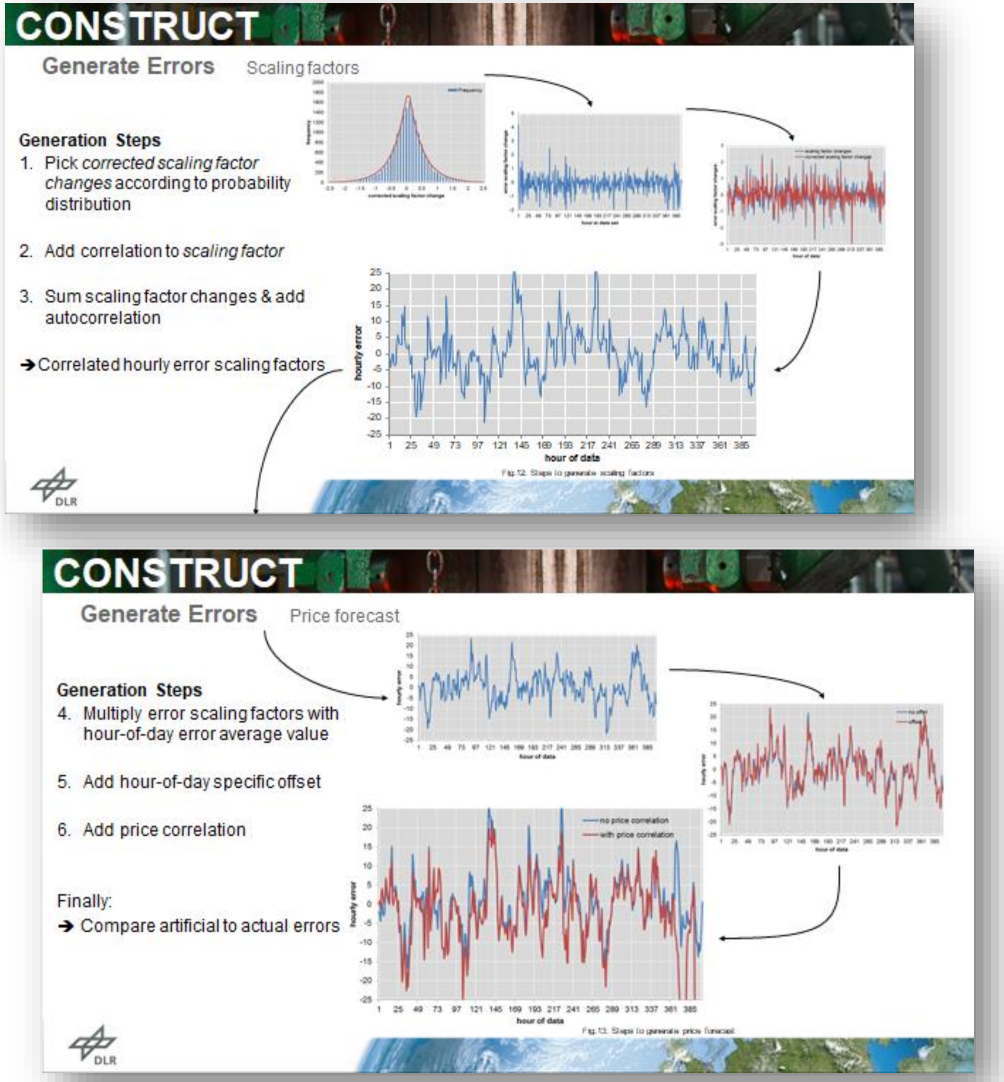

Fig.2: Summary of presentation at INREC 2019 (Schimeczek and Nitsch, 2019)

Providing forecasts for flexibility option agents

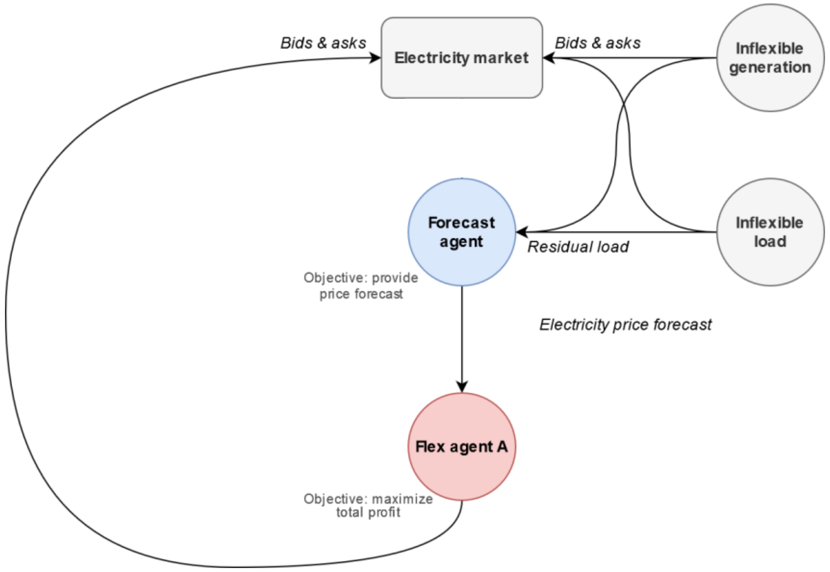

Fig.3: Agent providing forecasts for a **single** flexibility option

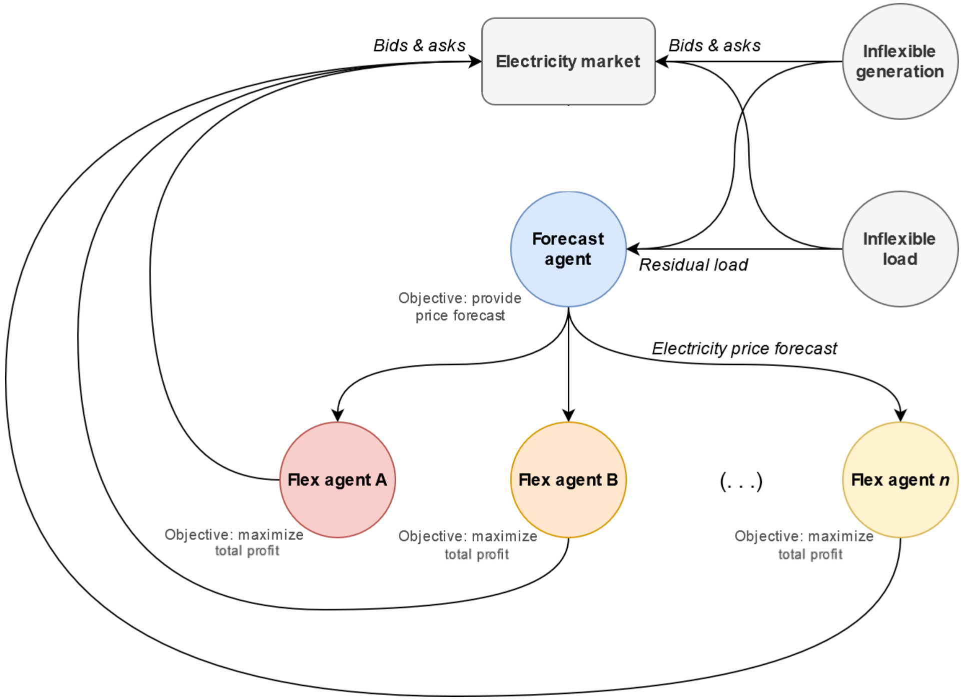

Fig.4: Agent providing forecasts for **multiple** flexibility options

- Perfect price forecast which for **single** agent
- No competition
- Perfect optimization of operational strategy

- **Multiple** flexibility agents receive price forecast
- Forecast errors due to competition
- Disrupts optimization of operational strategies

How-to provide accurate forecasts for multiple agents?

- Goal: integrate expected bidding behaviour of flexibility agents

- Common approach:
  - Finding equlilibrium for flexibility operators using game theory
  - High computational effort

- Alternative approach:
  - Forecast agent is equipped with neural network:
    - Estimate bidding behaviour of flex agents
    - Use data from previous and future hours of simulation
  - Technical details:
    - Combine multiple NN
    - Feed-forward network & Long Short-Term Memory (LSTM)
    - Training on data from previous simulations
    - Implementation in agent-based electricity model (‚Model-in-model' approach)

The idea of a learning forecast agent

- Central forecast agent is learning bidding behaviour of flexibility options and their impacts on prices
- Architecture:
  - Feed-forward model
  - LSTM model
- Inputs:
  - Previous prices
  - Previous residual load
  - (Future residual load)
- Output:
  - Forecast for at least next 24 hours

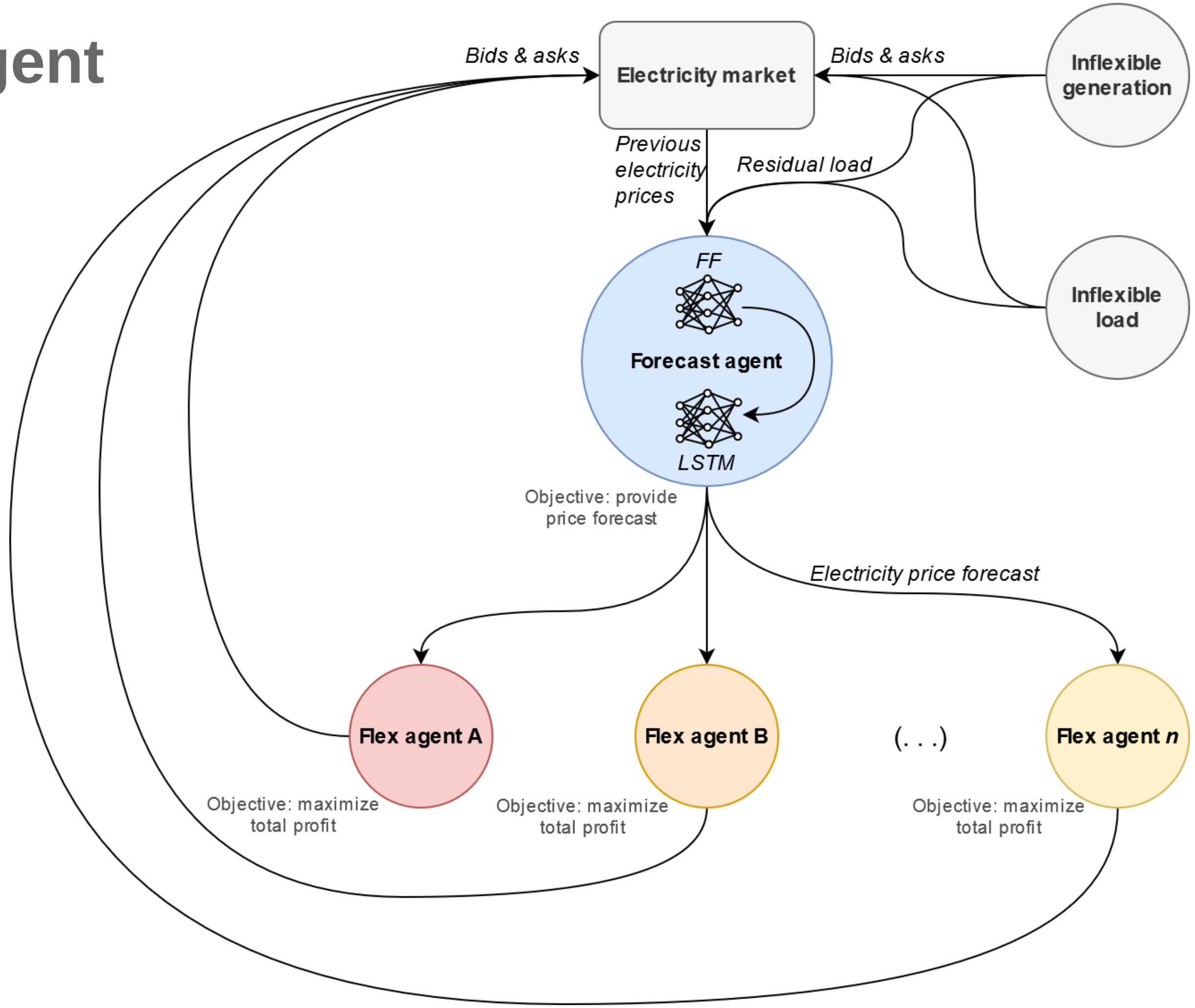

Fig.5: Forecast agent equipped with neural networks providing forecasts for multiple flexibility options

Merit Order Model

- Conventional power plants bid with marginal costs (according to theory)

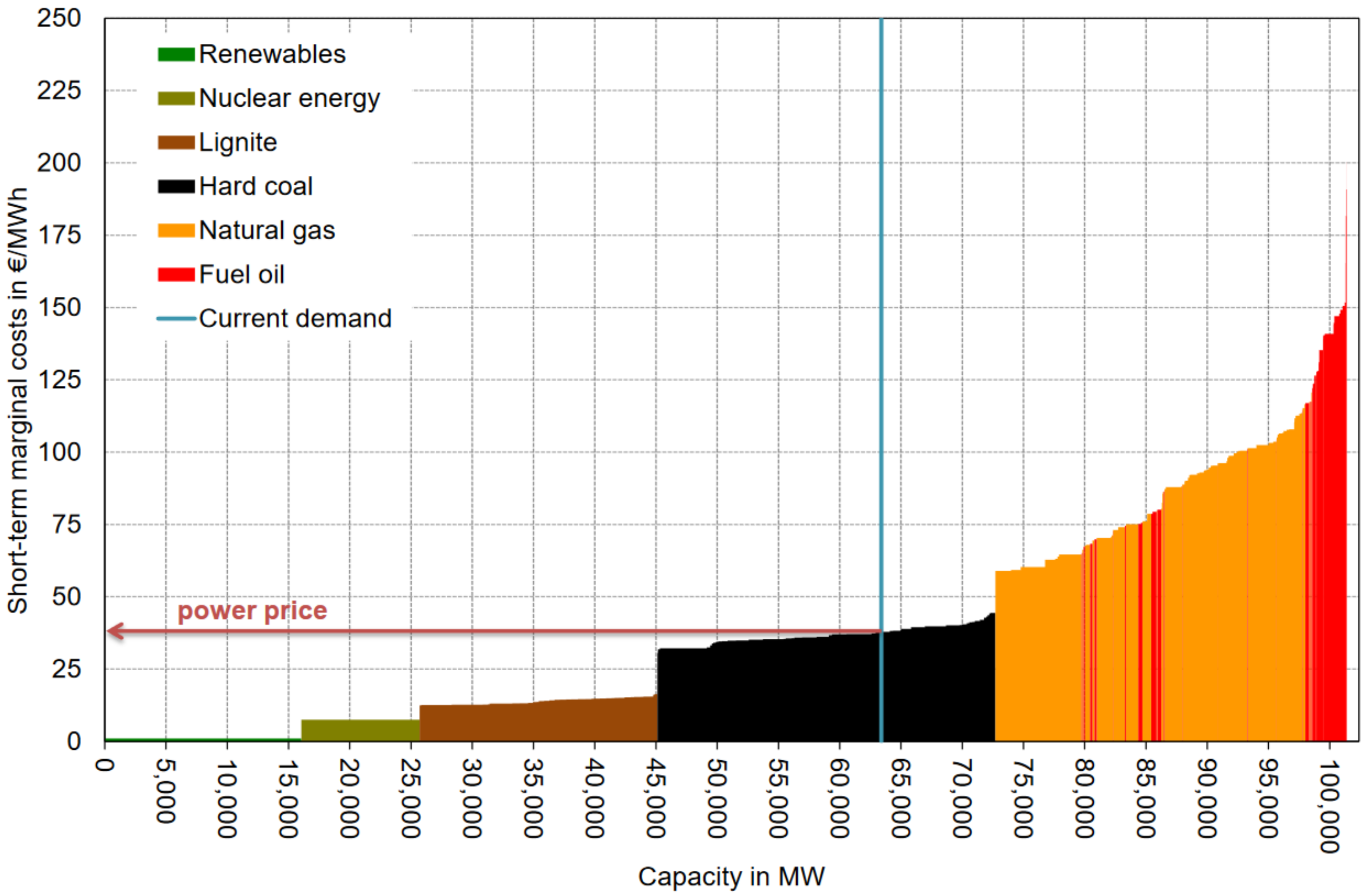

Fig.6: Stylized merit order curve (Cludius et al., Energy Economics 44, 2014)

Merit Order Model

- Conventional power plants bid with marginal costs (according to theory)

In simulations

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

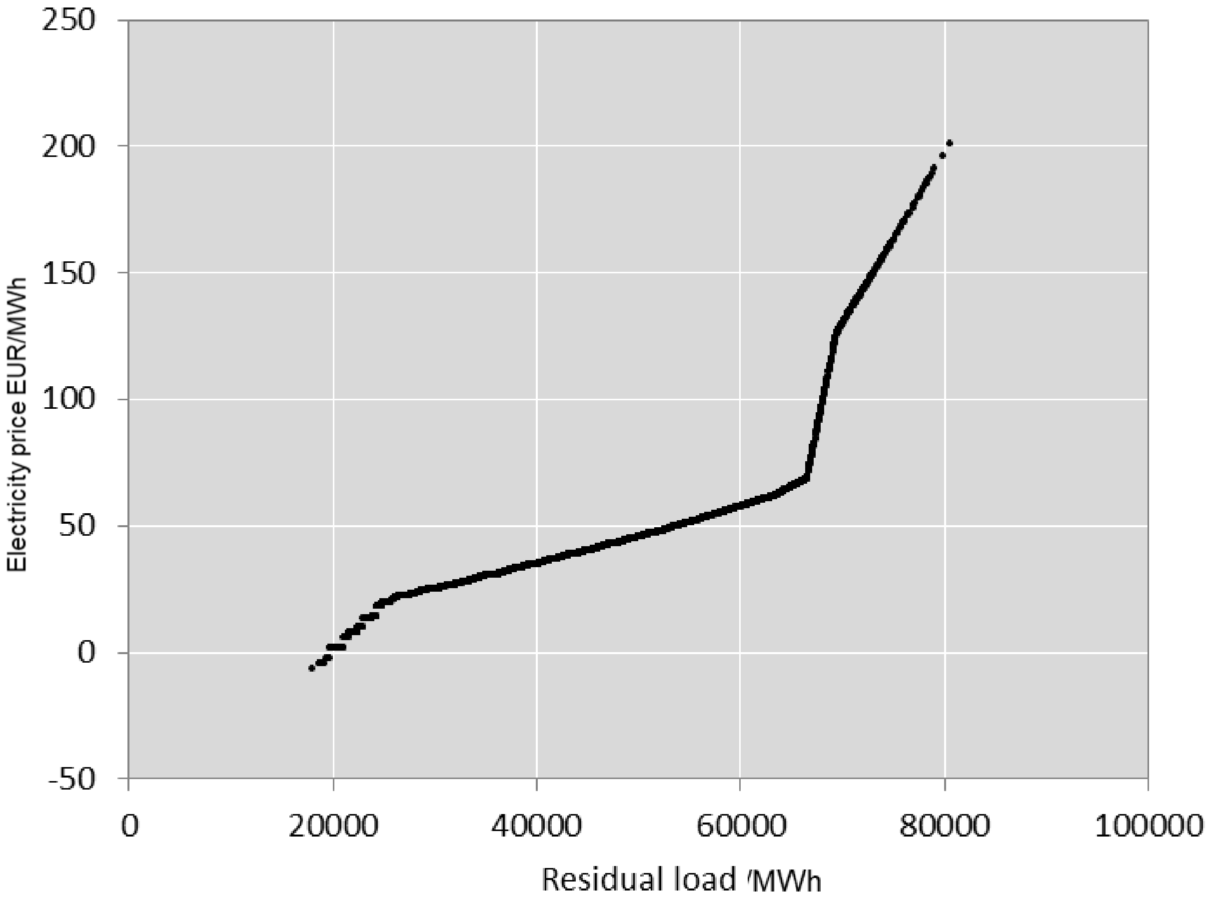

Fig.7: Modelled merit order curve without flexibility options

Merit Order Model

- Conventional power plants bid with marginal costs (according to theory)

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

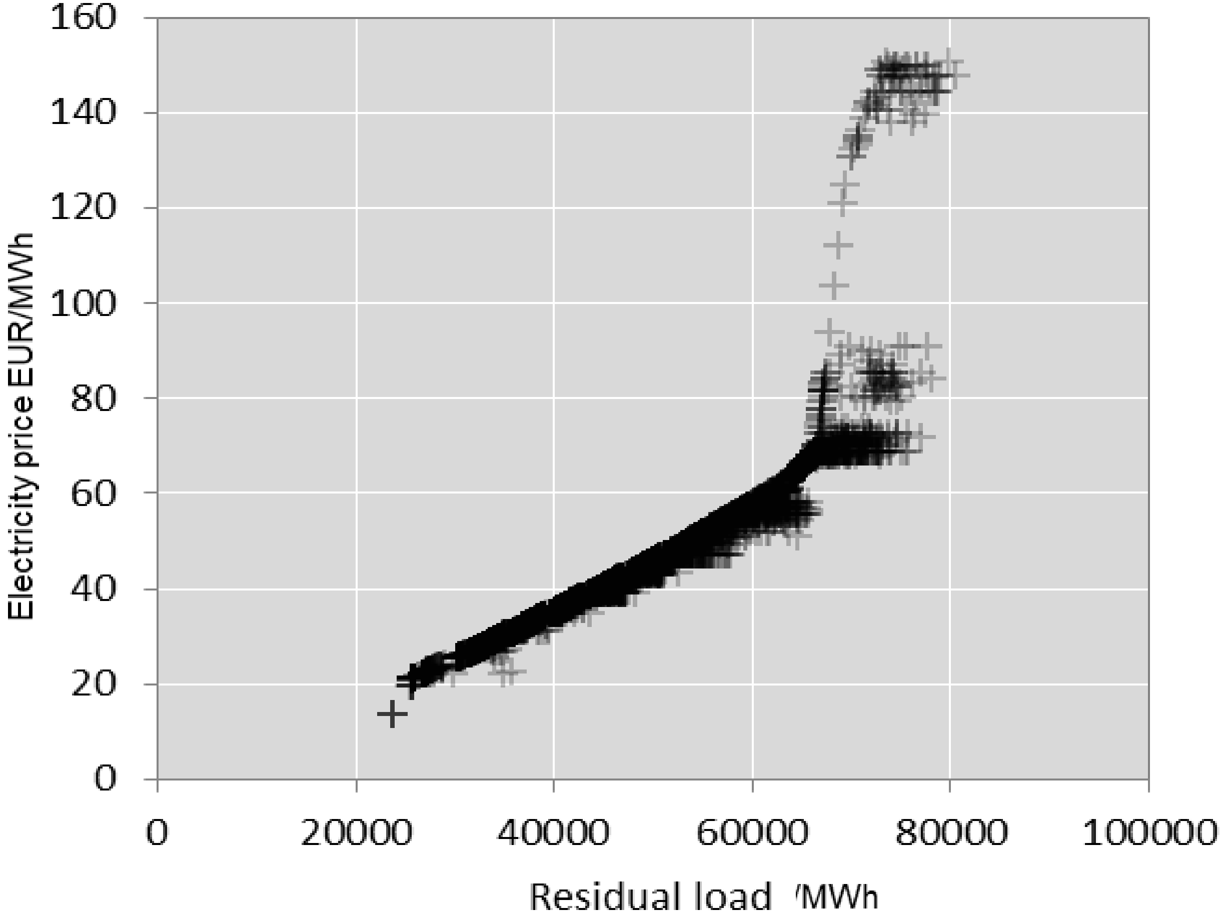

Fig.8: Modelled merit order curve with significant capacities of flexibility options

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

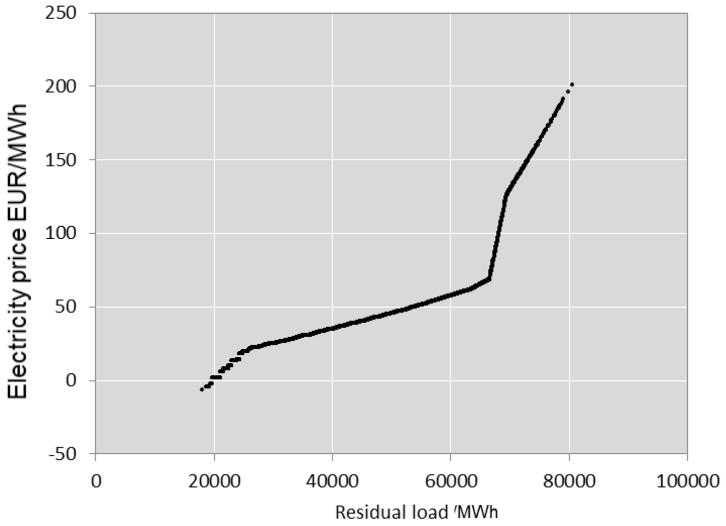

Fig.9: Residual load in scenario with no storage capacity

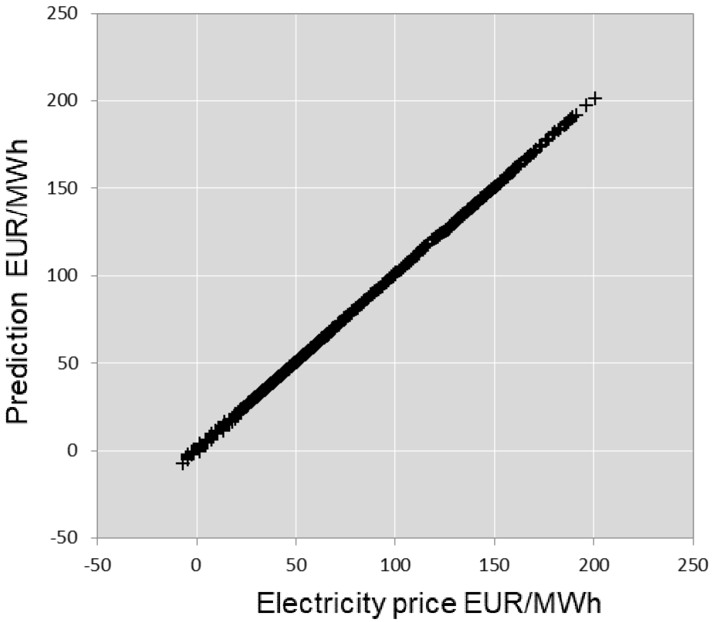

Fig.10: Predicted prices against simulated prices

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

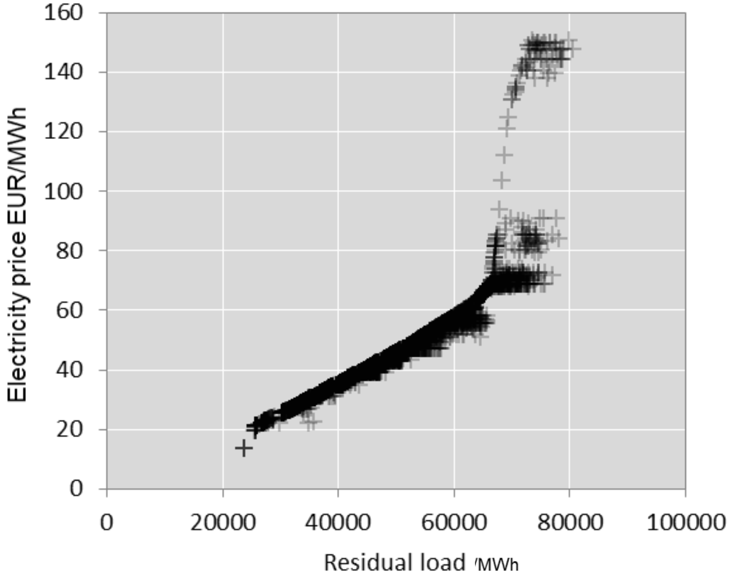

Fig.11: Residual load in scenario with extended storage capacity

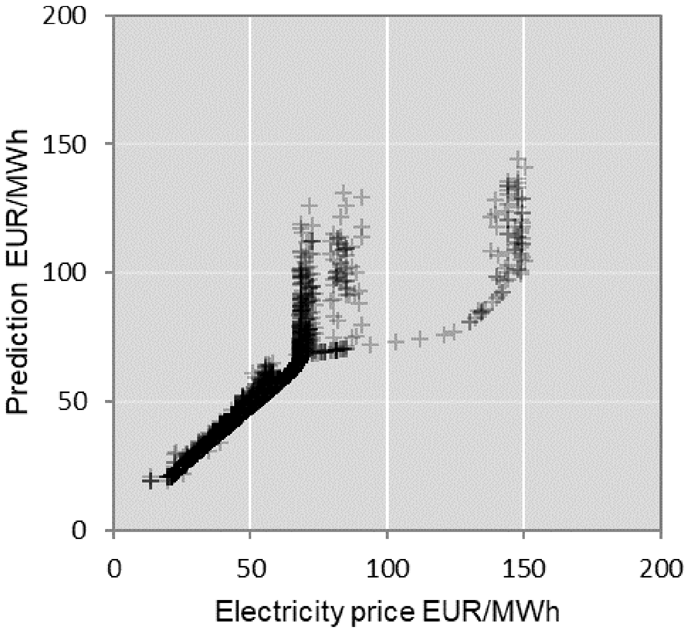

Fig.12: Predicted prices against simulated prices

Extract flexibility option signal

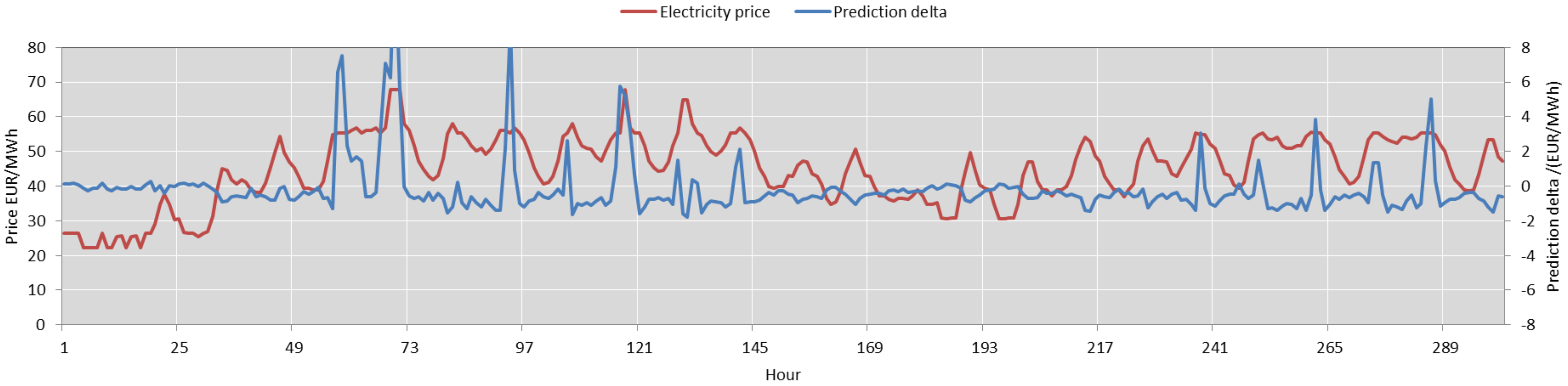

Fig.13: Simulated electricity price (red) and FF prediction delta (blue) in sample period of 300 hours

- 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

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

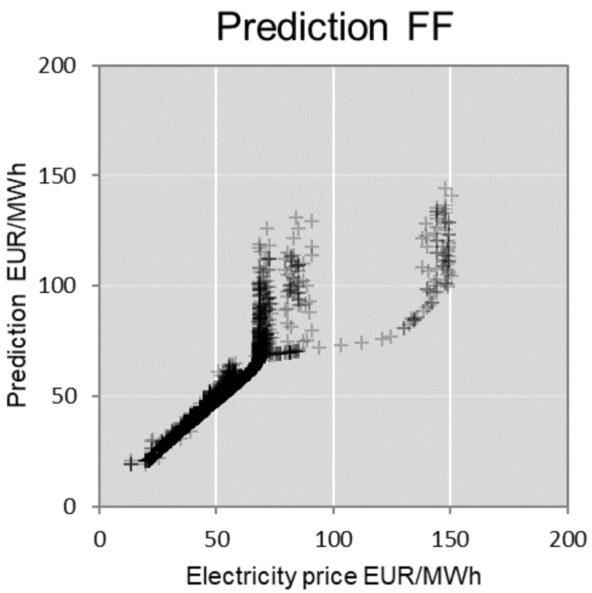

Fig.14: Predicted prices against simulated prices from FF network

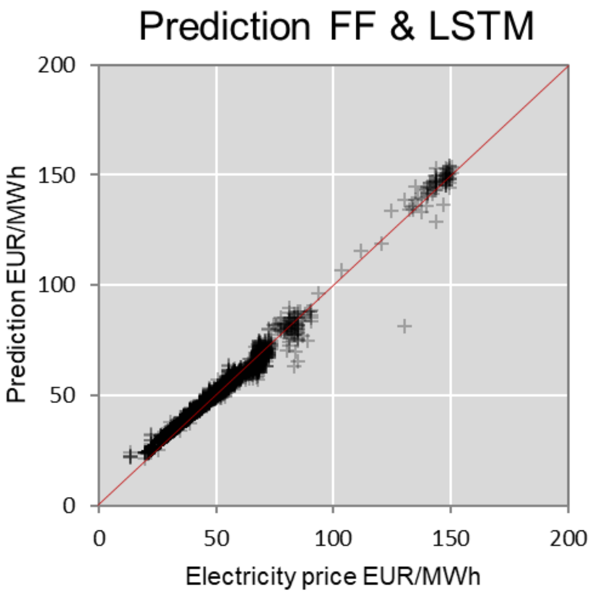

Fig.15: Predicted prices against simulated prices from LSTM network using FF predictions and simulated prices as input

Comparison of predictions

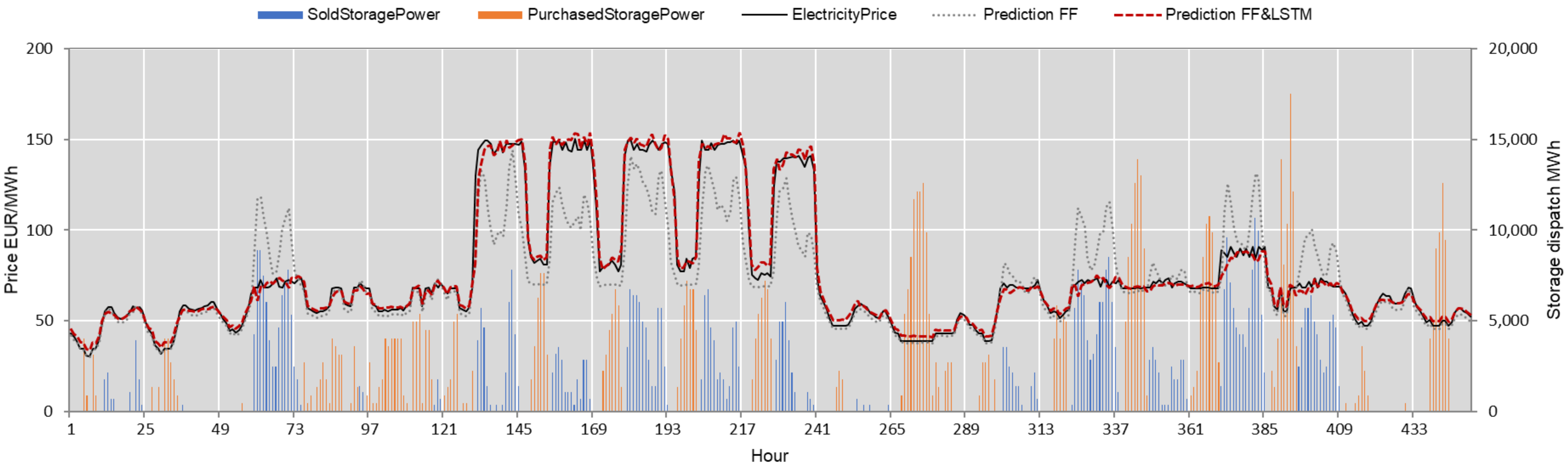

Fig.16: Comparison of simulated prices (black), FF prediction (grey dotted), FF&LSTM prediction (red dashed) and storage dispatch over time

Discussion

- Generalization of FF possible or training for each specific scenario setup necessary?
  - Power plant park
  - Operational costs (prices, emission allowances, etc.)

- Generalization of LSTM possible or training for different flexibility option setups necessary?
  - Different technologies (Pumped hydro vs. Li-Ion vs. H_2 vs. P2X2P storage)
  - Different capacities

- Deploying individually trained sub-networks, e.g. for in simulation?
  - Accounting for time-segment specific characteristics (each hour of day)

Conclusion

- Price forecasts in agent-based energy system models need to be adapted to account for competition amongst multiple flexibility options
- Game theory no preferred method due to high computational effort
- Forecast agent equipped with neural networks to integrate flexibility agents bidding behaviour
  - Feed forward to account for residual load
  - LSTM to model price impact by flexibility options
- Results demonstrate feasibility of idea to integrate model-in-model approach in ABM
- Still open questions on deployment and training

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