# Orderbook-based electricity price forecasting with neural networks

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# Orderbook-based electricity price forecasting with neural networks

- German Day-Ahead Market
- Orderbook-based forecasting method
- Application of neural networks

# I am interested in applications of financial mathematics and data science in (energy) industry

- Fraunhofer Society: between university and industry, 27000 people, > 70 research institutes
- Fraunhofer Institute for Industrial Mathematics ITWM is the world-biggest research institute for industrial mathematics (32 Mio. EUR budget, 280+ people)
- financed by about 50 % through industrial projects
- close connection to Technical University of Kaiserslautern (Germany)

- Financial Mathematics Department (20+ people)
- financial mathematics and data science applications in finance, energy, and other industries



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# Ask questions

# We adress the forecast of electricitiy prices using orderbooks and neural networks

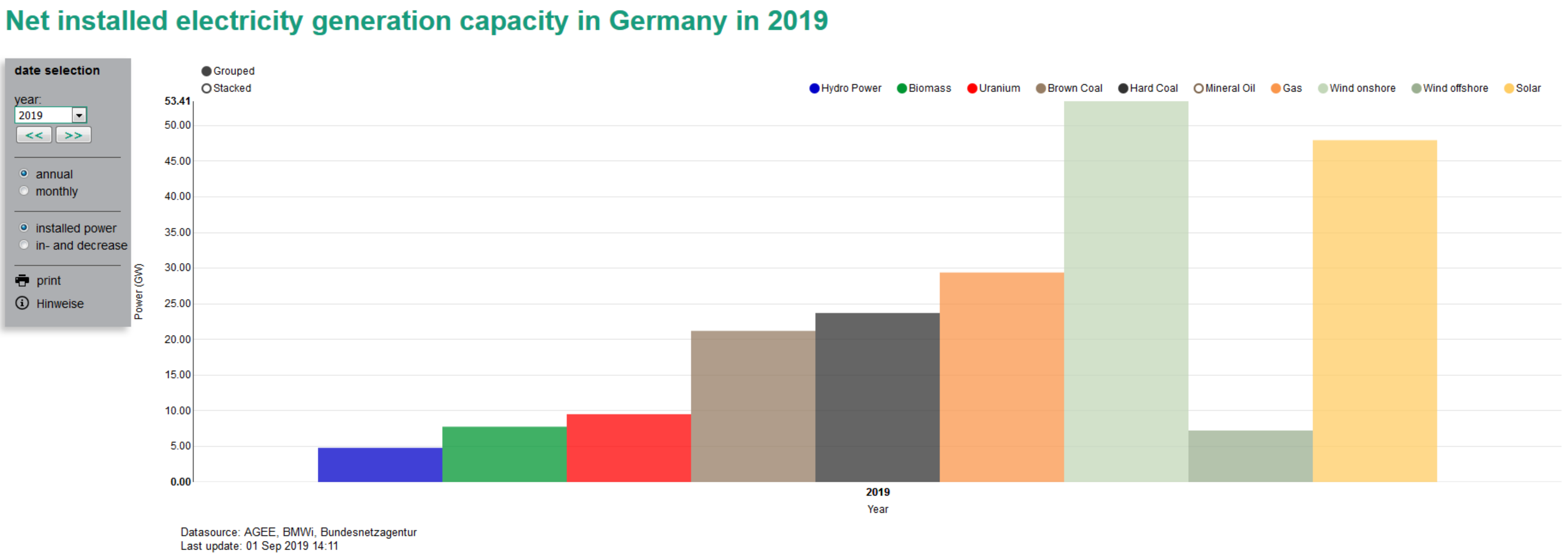
## Orderbook-based electricity price forecasting with neural networks

- Focus on German EPEX Day-Ahead market
- orderbook-based forecasting methods show good performance
- calibration is complicated
- simplification using machine learning possible?

## Research questions:

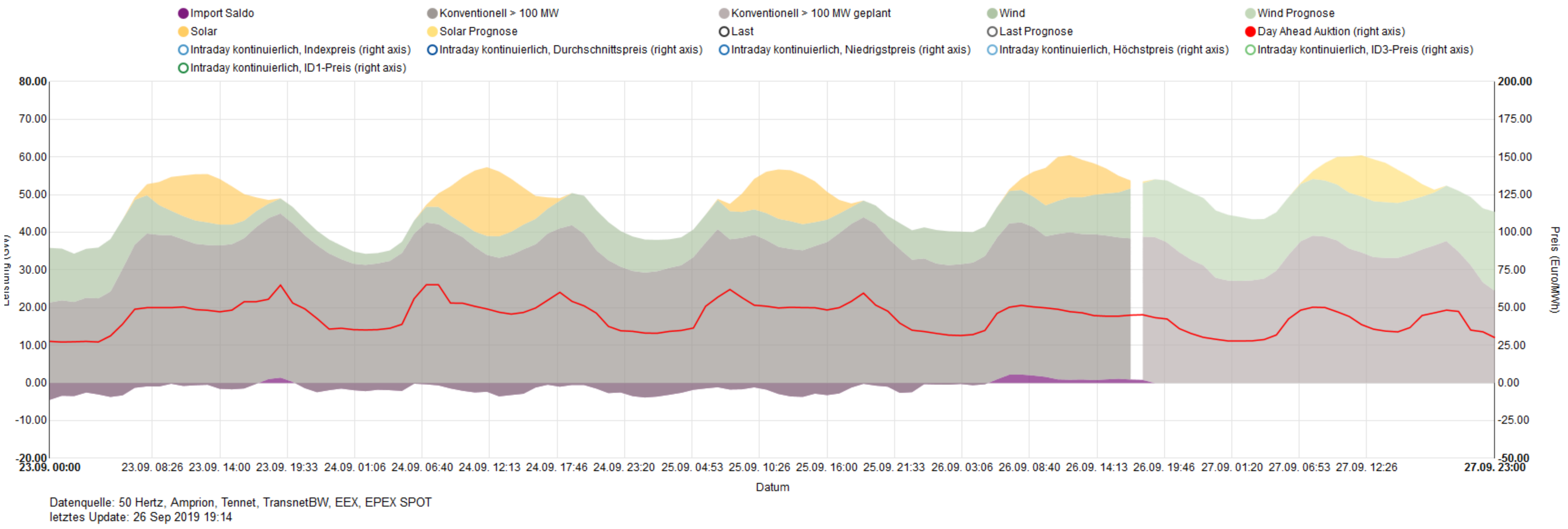
- How can orderbooks from electricity markets be included in machine learning algorithms?
- How can orderbook-based spot price forecasts be improved using machine learning?

# Germany has 105 GW installed wind and solar capacity, share of renewables on total production is above 45 %



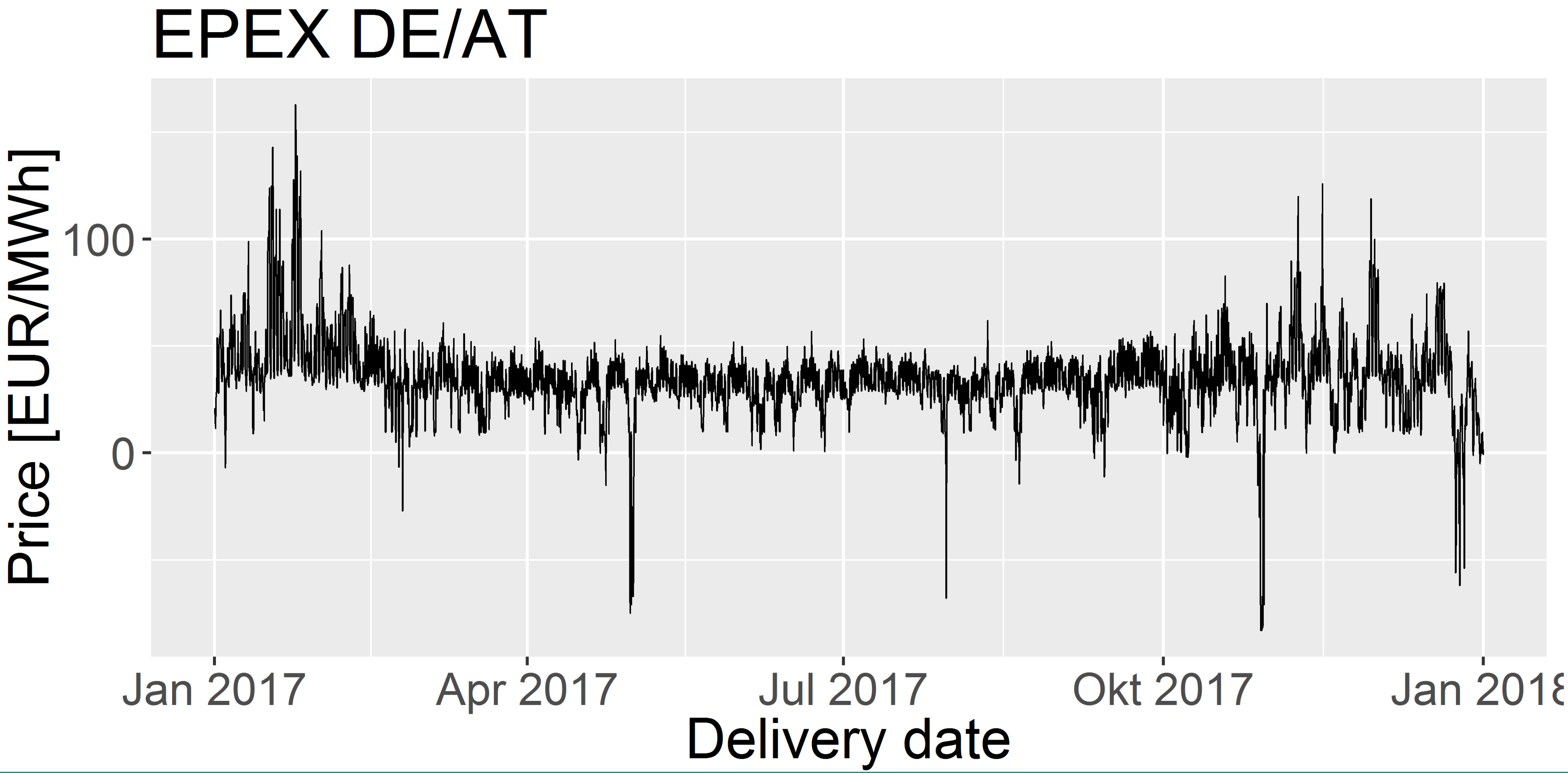

https://www.energy-charts.de/

# Prices are set by conventional generation, renewable infeed decides how much conventional production is needed

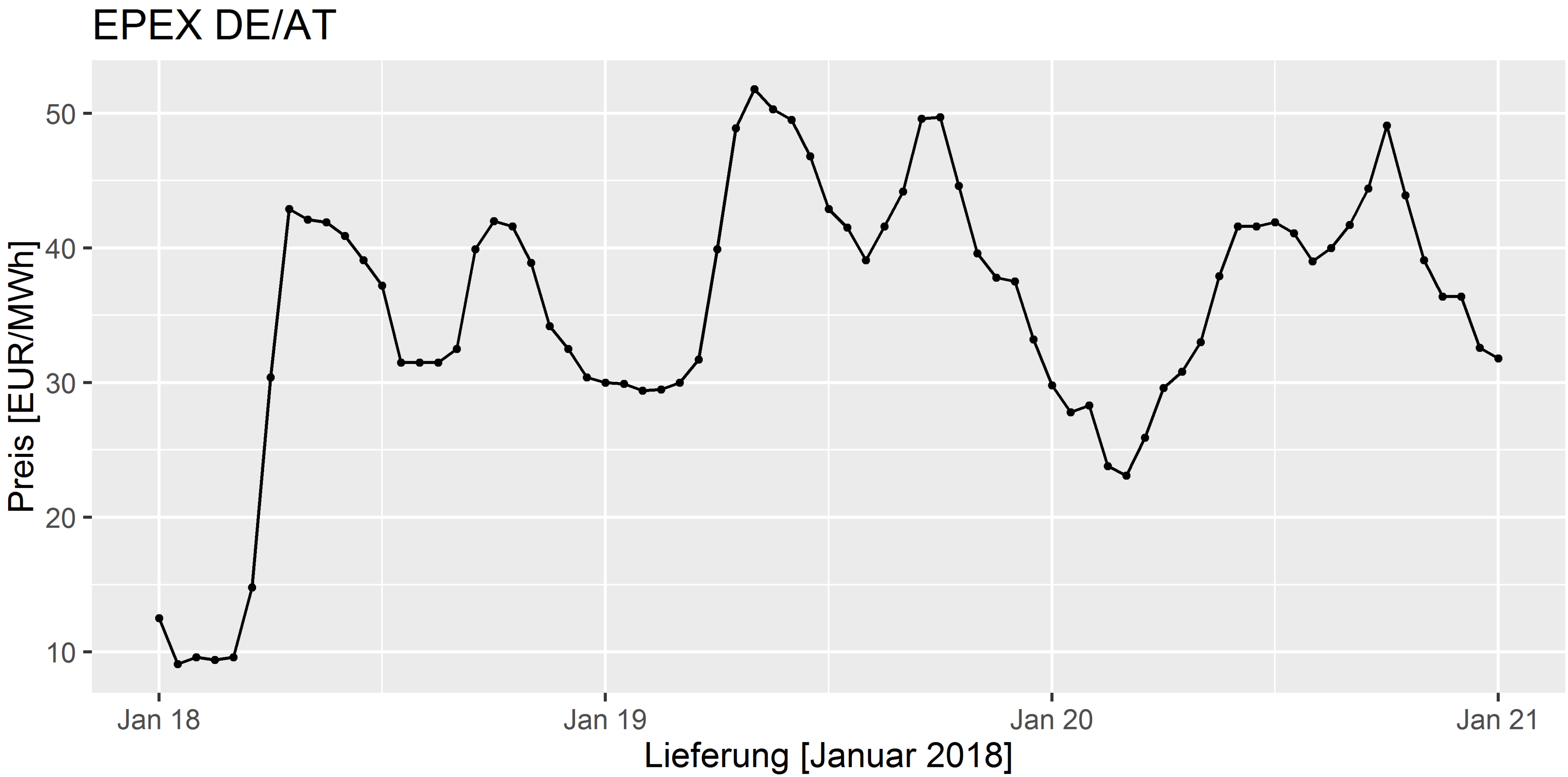



https://www.energy-charts.de/

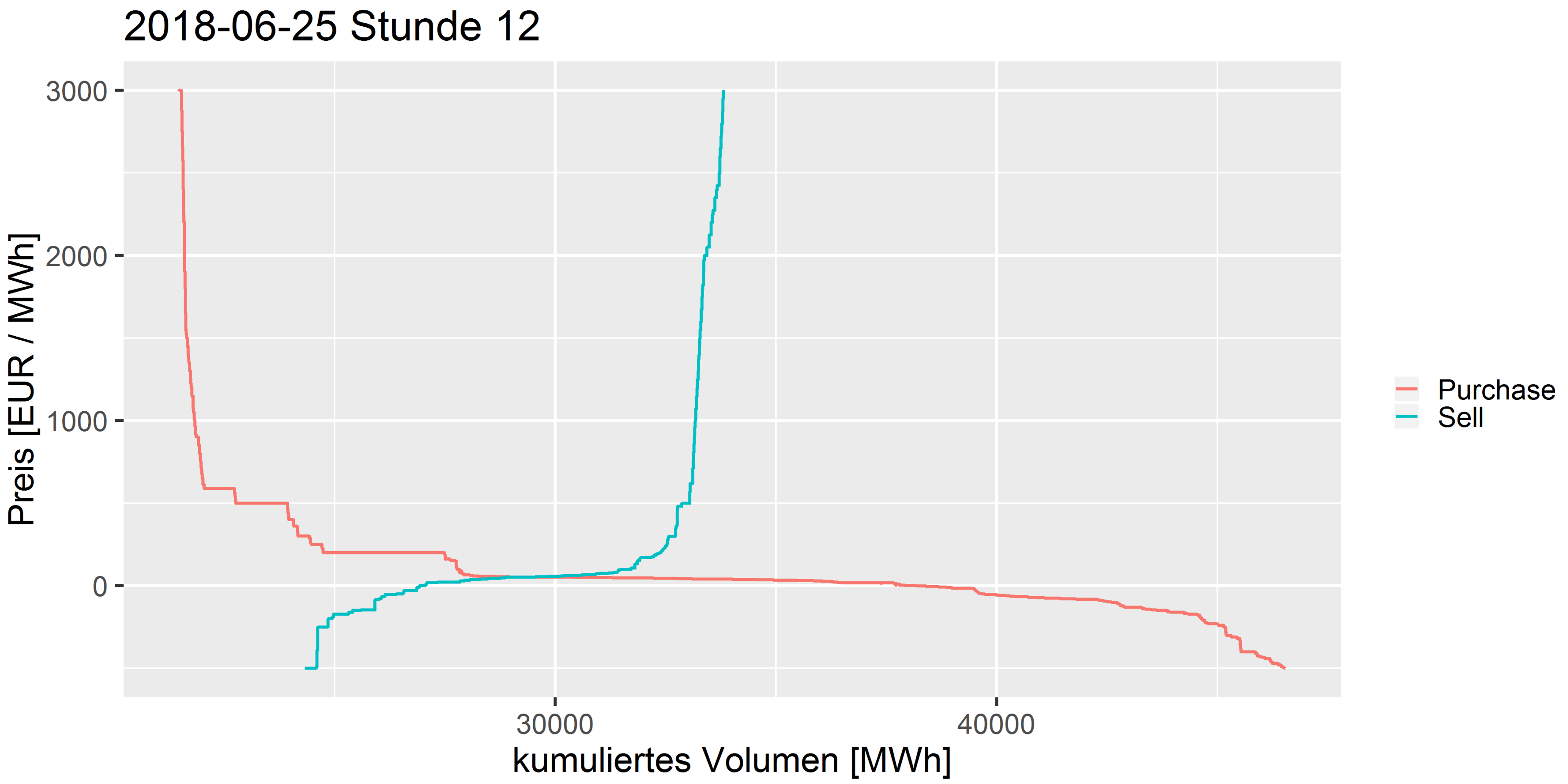
# Prices are seasonal, spiky and may become negative

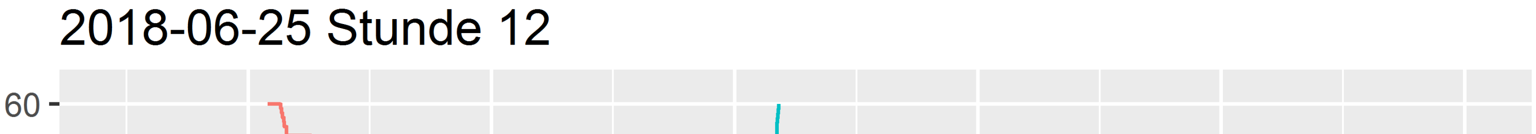


# There is one price for each delivery hour



# Each price results from an auction and is the intersection of the bid (purchase)- and ask (sell) curve





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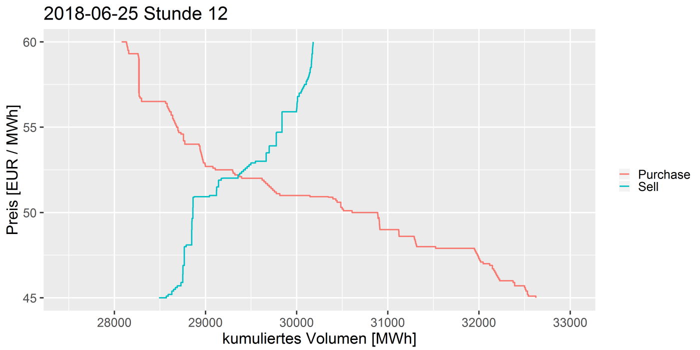
# There is a wide range of approaches to price forecasting in literature

**Different approaches**

| fundamental | | time-series |
|---|---|---|
| mixed-integer optimization | bid-curve based, ARIMAX | SARIMA, NN, reference-day method |
| commercial models (Pöyry, Energy Brainpool), research institutes (HEMF Uni Duisburg-Essen, EWI Uni Köln, Fraunhofer ISI, ...) | W. (2014), Ziel, Steinert (2016), Carmona, Coulon (2014) | Weron (2014, 2018), Nogales (2002), Conejo (2005), Lora (2007) |

# Our forecast is based on orderbooks of the previous day and forecasts on renewable infeed

orderbook

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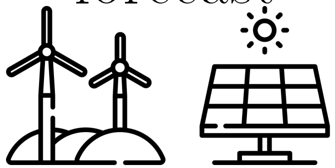
renewable infeed forecast



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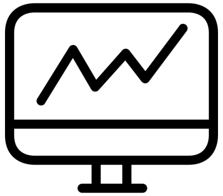
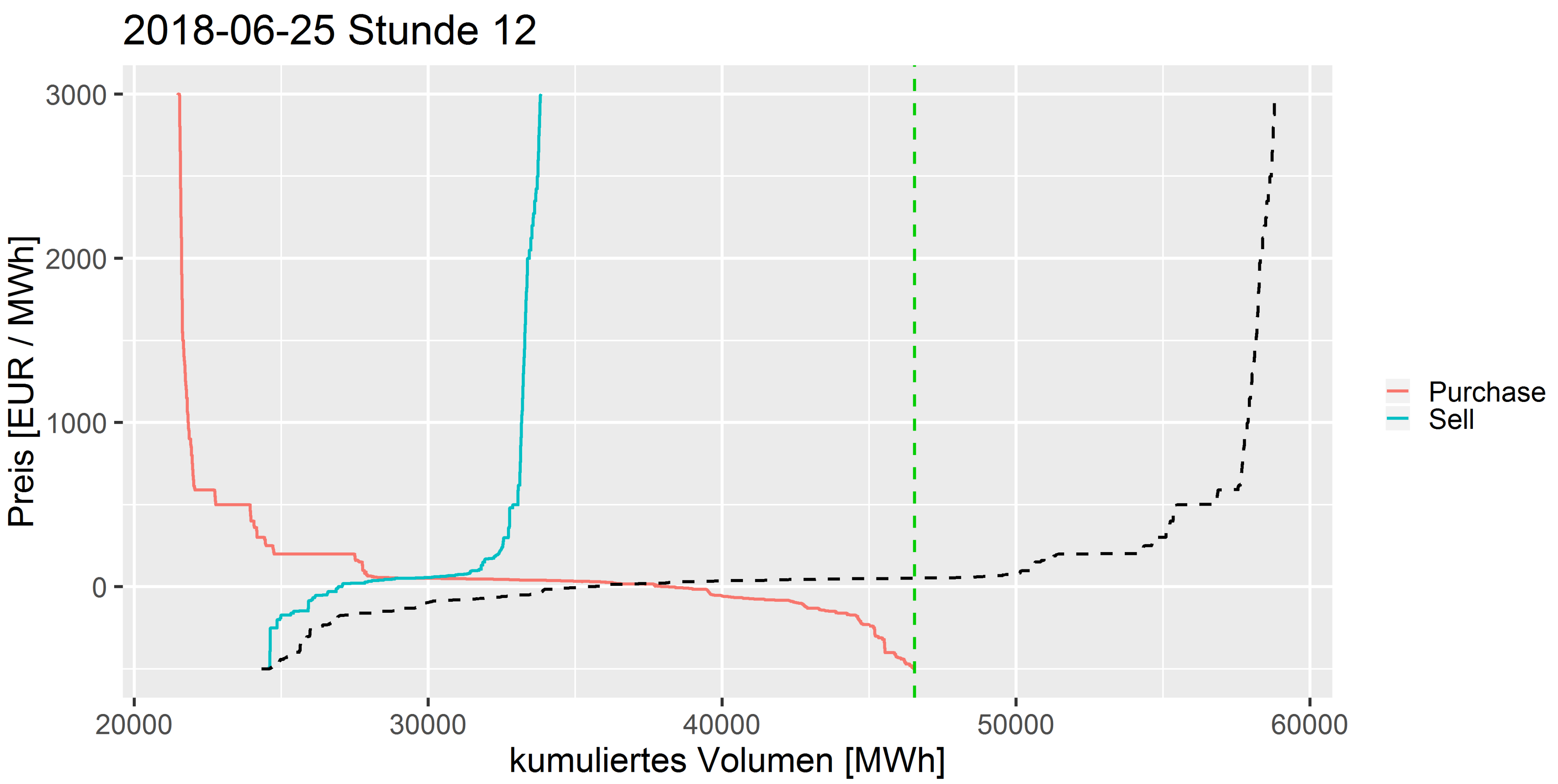
price forecast



# We transform the bid/ask curves to a merit-order and price-inelastic demand





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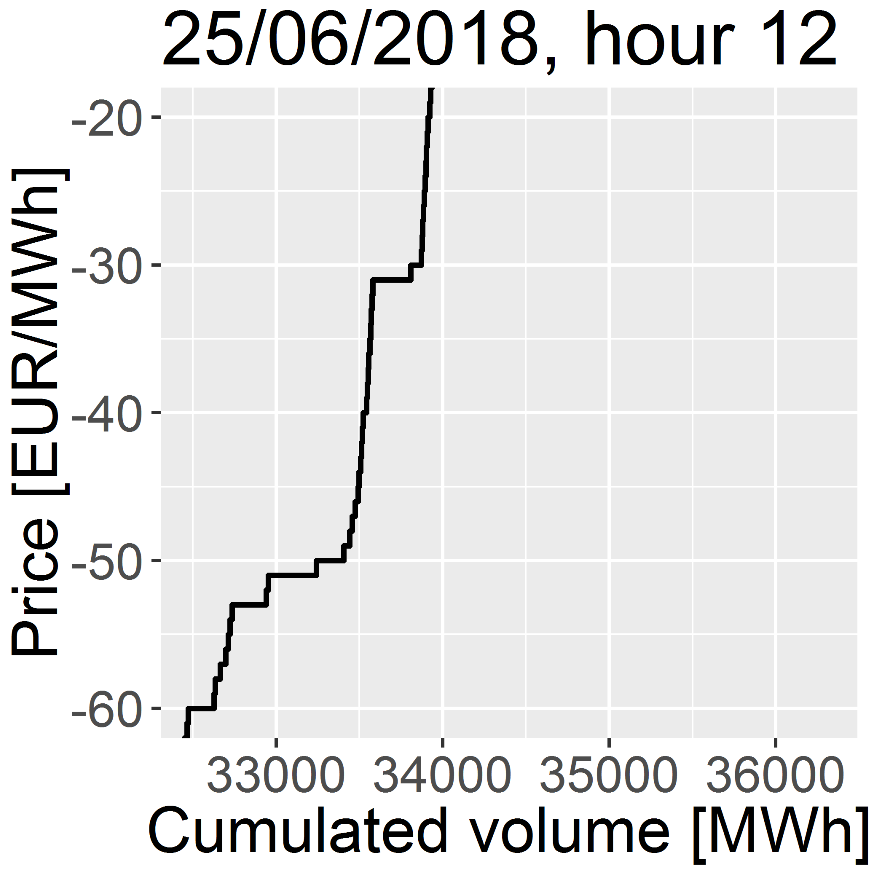
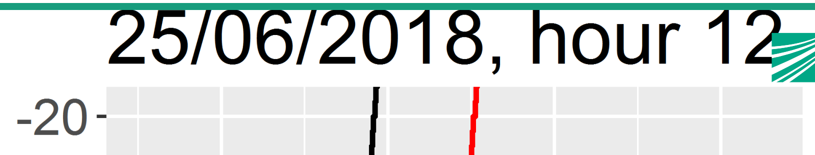
# We shift renewable volumes at the corresponding price levels according to forecasts

- Merit-order is shifted according to forecasts
- New intersection with (inelastic) demand
- Forecast results from the new intersection
- Finding the price levels is a lot of statistical (data-analysis) work
- Simplify with supervised learning? Our approach



# We want to replace the manual shifting of the merit order by neural networks

## Steps:

1. find a suitable representation of the orderbook
2. set up feature vector
3. define network architecture and find optimal hyper parameters

# Feature vector contains merit order curve and fundamental data for reference and forecast day

## Components of feature vector

- Merit-order curve is seperated into about 80 price intervals (based on constant volume intervals)
- inelastic demand
- calender information:
  - transform hour and month on a cyrcle

$$\begin{Bmatrix} \sin \\ \cos \end{Bmatrix} \left( \frac{2 * \pi * h_i}{24} \right)$$

  - year, type-of-day (One-hot encoding)
- Forecast data of wind- and photovoltaic infeed

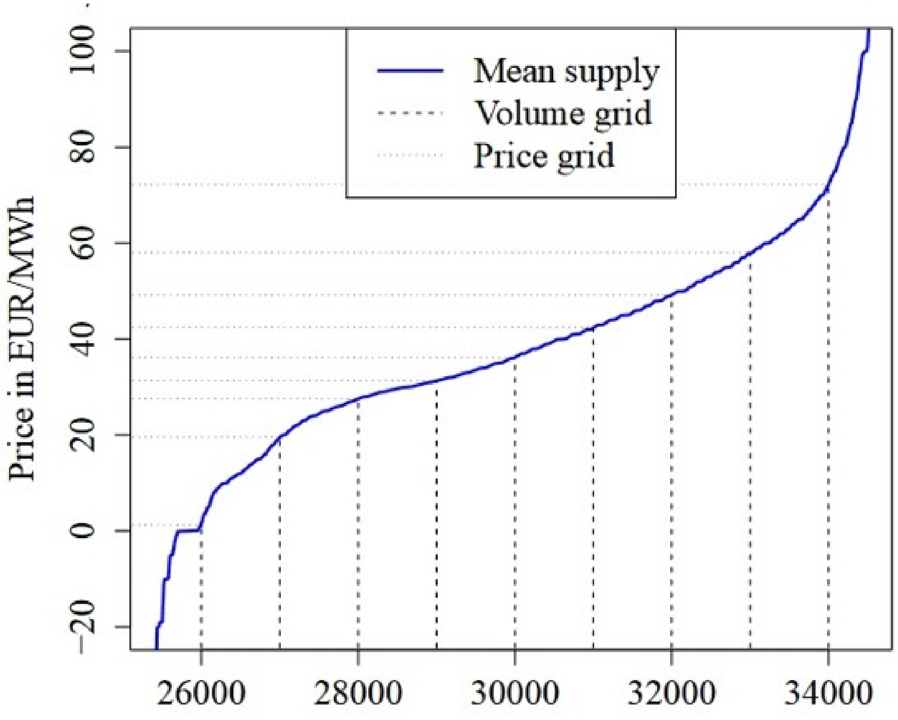



Figure from Ziel, Steinert 2016

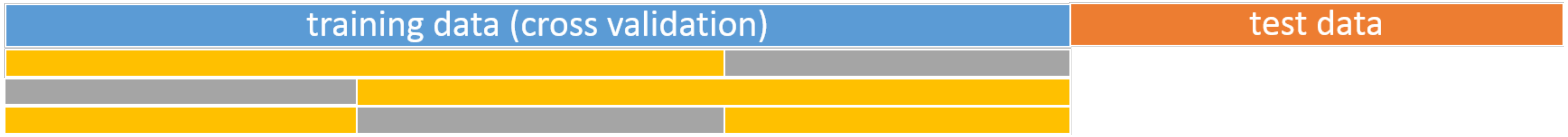
reference day order-book (80 price intervals,demand)

Fundamentals reference (calendar, wind, PV)

Fundamentals forecast (calendar, wind, PV)

# Using cross-validation we optimize architecture and hyperparameters

- data set: 1.2.2015 to 30.9.2018 (= 32.111 hours)
- test data from 6.1.2018

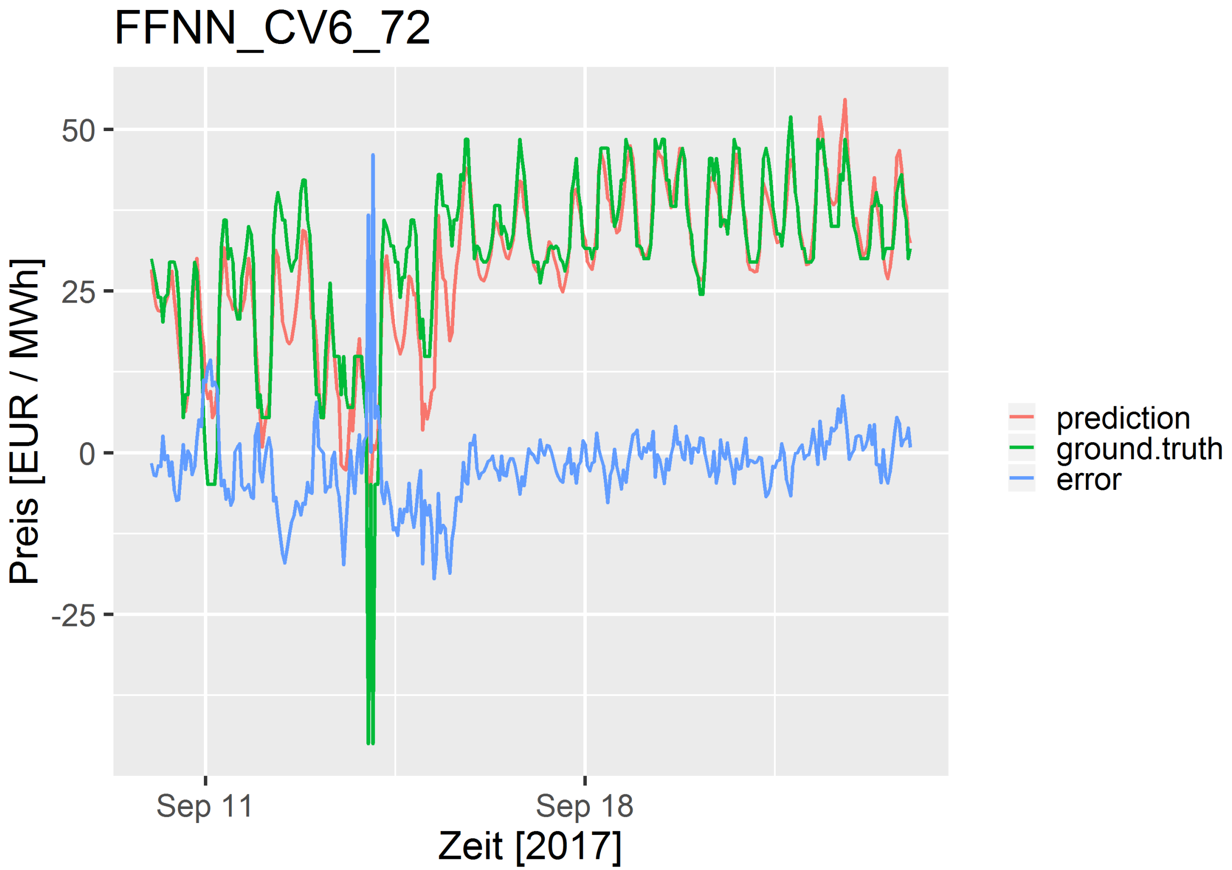



- parameters under consideration/optimization
  - architecture: LSTM or FFNN
  - forecast 1 price / forecast 24 prices (whole day)
  - number of layers and neurons / layer
  - activating function
  - optimizier
  - Drop-out
  - reducing dimension of feature vector (random forest, PCA)

| | std.test.error | test.error | train.error | nn__activation | nn__batch_size | nn__dropout_prob | nn__epochs | nn__n_hidden | nn__optimizer | nn__output_activation |
|---|---|---|---|---|---|---|---|---|---|---|
| 116 | 1.999204e-04 | 0.0005749586 | 0.0003554792 | tanh | 256 | [0, 0.1] | 100 | [10, 10, 10] | Adam | linear |
| 43 | 8.817970e-05 | 0.0005763444 | 0.0003048862 | tanh | 128 | [0, 0.1] | 100 | [10, 10, 10] | rmsprop | linear |
| 61 | 2.600061e-04 | 0.0006019773 | 0.0003539623 | tanh | 128 | [0, 0.2] | 50 | [10, 10, 10] | rmsprop | linear |
| 142 | 2.221261e-04 | 0.0006031170 | 0.0003740133 | tanh | 256 | [0, 0.2] | 100 | [25, 25, 25] | Adam | linear |
| 115 | 1.559292e-04 | 0.0006094105 | 0.0003885659 | tanh | 256 | [0, 0.1] | 100 | [10, 10, 10] | rmsprop | linear |
| 71 | 1.719773e-04 | 0.0006186637 | 0.0002602797 | tanh | 128 | [0, 0.2] | 100 | [50, 25, 10] | rmsprop | linear |
| 118 | 2.121828e-04 | 0.0006271222 | 0.0003318525 | tanh | 256 | [0, 0.1] | 100 | [25, 25, 25] | Adam | linear |
| 310 | 2.012744e-04 | 0.0006336037 | 0.0005558937 | linear | 128 | [0, 0] | 100 | [25, 25, 25] | Adam | linear |
| 68 | 2.024666e-04 | 0.0006342373 | 0.0002978133 | tanh | 128 | [0, 0.2] | 100 | [10, 10, 10] | Adam | linear |
| 352 | 2.082766e-04 | 0.0006364834 | 0.0005374449 | linear | 128 | [0, 0.2] | 50 | [25, 25, 25] | Adam | linear |
| 360 | 2.307997e-04 | 0.0006405951 | 0.0005364056 | linear | 128 | [0, 0.2] | 100 | [50, 25, 10] | Adam | linear |
| 95 | 1.294804e-04 | 0.0006448784 | 0.0002820392 | tanh | 256 | [0, 0] | 100 | [50, 25, 10] | rmsprop | linear |
| 135 | 2.323990e-04 | 0.0006449217 | 0.0004849614 | tanh | 256 | [0, 0.2] | 50 | [25, 25, 25] | rmsprop | linear |
| 336 | 2.038787e-04 | 0.0006452603 | 0.0005272062 | linear | 128 | [0, 0.1] | 100 | [50, 25, 10] | Adam | linear |
| 326 | 2.438585e-04 | 0.0006455844 | 0.0005359410 | linear | 128 | [0, 0.1] | 50 | [10, 10, 10] | Adam | linear |
| 212 | 7.747586e-05 | 0.0006455875 | 0.0003129788 | relu | 128 | [0, 0.2] | 100 | [10, 10, 10] | Adam | linear |
| 402 | 2.691034e-04 | 0.0006513953 | 0.0005570466 | linear | 256 | [0, 0.1] | 50 | [50, 25, 10] | Adam | linear |
| 308 | 2.009271e-04 | 0.0006517306 | 0.0005398851 | linear | 128 | [0, 0] | 100 | [10, 10, 10] | Adam | linear |
| 65 | 2.725988e-04 | 0.0006533027 | 0.0003529057 | tanh | 128 | [0, 0.2] | 50 | [50, 25, 10] | rmsprop | linear |
| 302 | 2.063677e-04 | 0.0006533203 | 0.0005426409 | linear | 128 | [0, 0] | 50 | [10, 10, 10] | Adam | linear |
| 408 | 2.144154e-04 | 0.0006541339 | 0.0005503601 | linear | 256 | [0, 0.1] | 100 | [50, 25, 10] | Adam | linear |
| 406 | 2.057292e-04 | 0.0006547971 | 0.0005412881 | linear | 256 | [0, 0.1] | 100 | [25, 25, 25] | Adam | linear |

# Out-of-sample results are competitive to other methods in literature

| Method | RMSE |
|---|---|
| reference day | 12.68 |
| random forest | 11.92 |
| FFNN: [5,5,5] | 9.59 |
| FFNN feature reduction: [25]*25 | 9.41 |
| FFNN Keles et al. 2016 architecture | 14.87 |
| FFNN Lago et al.. 2018 architecture | 21.05 |
| EXAA | 5.23 |
| Results on other datasets for comparison | |
| Conejo et al. 2005 | 10.72 |
| Keles et al .2016 | 9.53 |
| Ziel et al. 2015 | 6.46 |



# Orderbook features can also be used to get insights for classical bid-curve forecasting

- random forests
- target: wind infeed
- results show, at which price levels wind infeed is bid into the market

Feature Importance
(Random Forest, Gini)

| Rang | Feature |
|---|---|
| 1 | [-80,-79) |
| 2 | [-76,-75) |
| 3 | [-70,-71) |
| 4 | [-71,-70) |
| 5 | [-81,-80) |
| 6 | [-65,-64) |
| ... | ... |

# Results are competitive, but still involve a lot of HI (human intelligence)

## Key Learnings:

- Orderbooks can be used in ML-algorithms using the volume-discretisation
- Reducing the dimension of the feature vector generally improved results
- Definition of feature vector and search for the best NN needs significant ressources
- There cannot be enough data

## Future work:

- Use load forecasts and a modified selection of reference day
- Train network to generate hourly price forward curves
- Include market coupling: include other markets' bid curves (France, Netherland, ...)
- Apply to the DE-market (German / Austria market split in Oct-2018)

# Literature (1)

- bid-curve based models
  - Ziel, Steinert 2016: Electricity price forecasting using sale and purchase curves: The X-Model, Energy Economics, 59, 435-454
  - Carmona, Coulon 2014: A survey of commodity markets and structural models for electricity prices, Quantitative Energy Finance, 41-83
  - Wagner 2014: Residual demand modeling and application to electricity pricing, The Energy Journal, 45-73
- Forecasting (surveys)
  - Aggarwal et al 2009: Electricity price forecasting in deregulated markets: A review and evaluation
  - Weron 2014: Electricity price forecasting: A review of the state-of-the-art with a look into the future, International Journal of forecasting, 30(4), 1030-1081.
  - Ziel, Weron 2018: Day-ahead electricity price forecasting with high-dimensional structures: Univariate vs. multivariate modeling frameworks, Energy Economics, 70, 396-42
- Forecasting (other methods)

# Literature (2)

- Nogales et al 2002: Forecasting Next-Day Electricity Prices by Time Series Models, IEEE Transactions on power systems, 17(2)
- Conejo et al 2005: Day-Ahead Electricity Price Forecasting Using the Wavelet Transform and ARIMA Models, IEEE transactions on power systems, 20(2)
- Lora et al 2007: Electricity Market Price Forecasting Based on Weighted Nearest Neighbors Techniques, IEEE Transactions on Power Systems, 22(3)

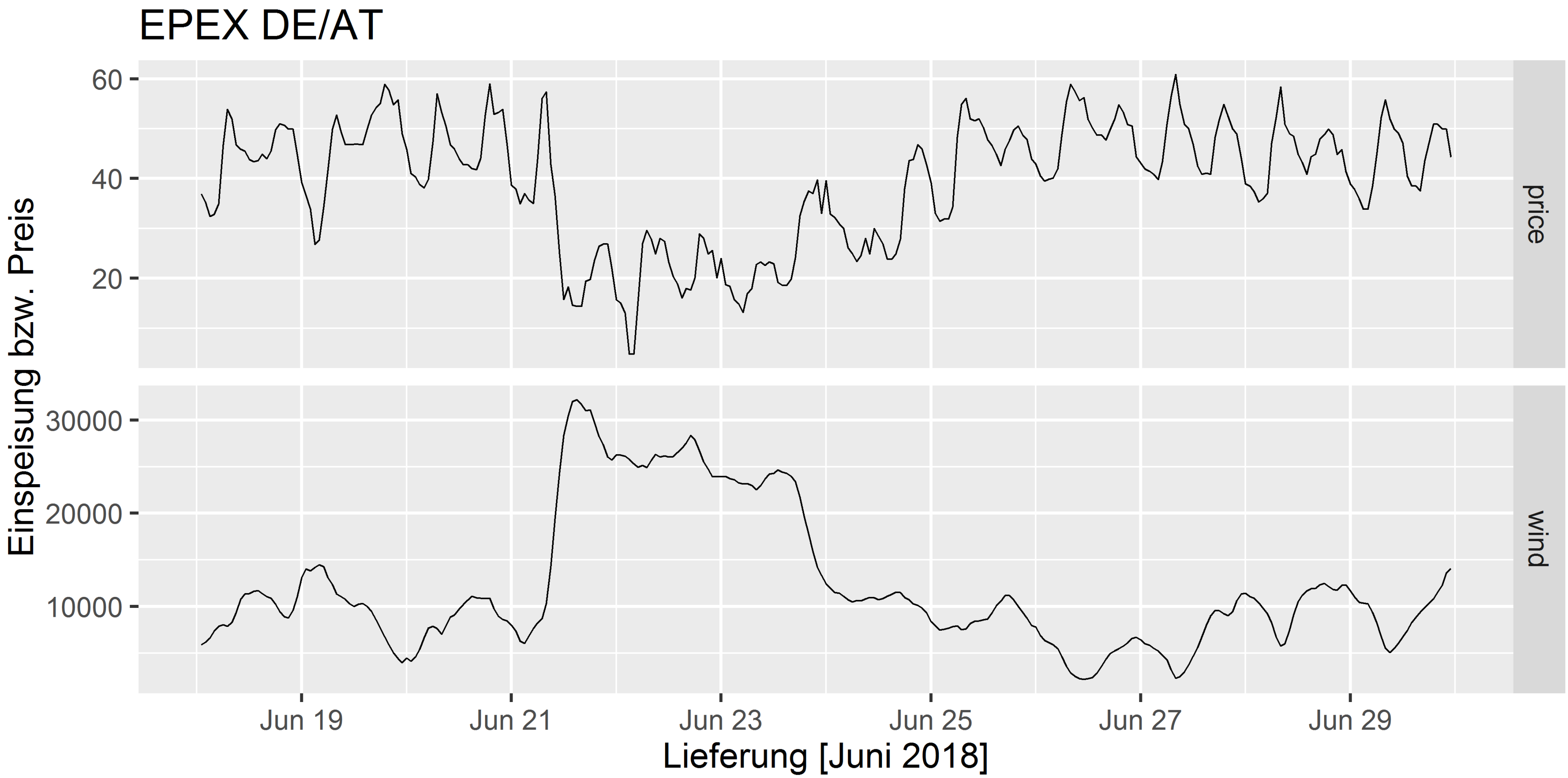
- Forecasting (ML)
  - Chen et al 2012: Electricity Price Forecasting With Extreme Learning Machine and Bootstrapping, IEEE Transactions on Power Systems, 27(4)
  - Mosbah, El-Hawary 2016: Hourly Electricity Price Forecasting for the Next Month Using Multilayer Neural Network, Canadian Journal of Electrical and Computer Engineering, 39(4), 283-291
  - Keles et al 2016: Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks, Applied energy, 162, 218-230

# Literature (3)

- Lago et al 2018: Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms, Applied Energy, 221, 386-405
- Marcjasz et al 2018: On the importance of the long-term seasonal component in day-ahead electricity price forecasting with NARX neural networks, International Journal of Forecasting (in press)

# Backup

# Wind infeed lowers spot prices ...



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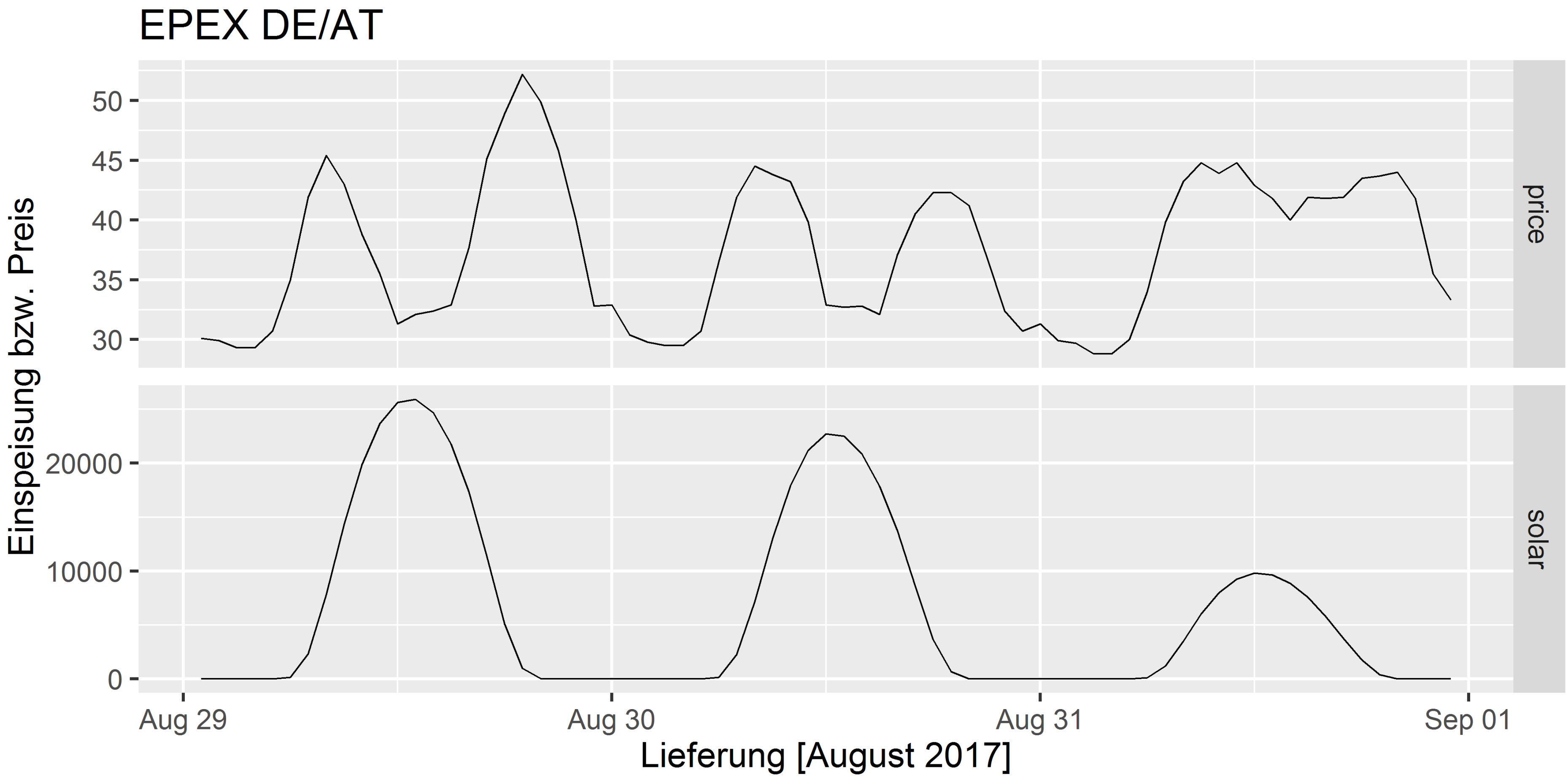
# … solar does the same







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