# COMPARISON OF ELECTRICITY PRICE FORECASTING METHODS FOR USE IN AGENT-BASED ENERGY SYSTEM MODELS

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# Motivation

- Timeseries: Important inputs in energy system models (ESM)
- Challenge: Timeseries forecasting
- Requirements for forecasts in ESM:
  - Reliable
  - Fast
  - Convenient

- Promising advances in machine learning; How are they applicable in ESM?

- Today: Case study on price timeseries forecasting

# Simulating Electricity Markets with AMIRIS

## Input
- RE feed-in
- Load
- Power plant park
- Efficiencies
- Plant availabilities
- Fuel & $CO_2$ costs

## Output
- Electricity prices
- Power plant dispatch
- Storage dispatch
- Market values
- Emissions
- System costs

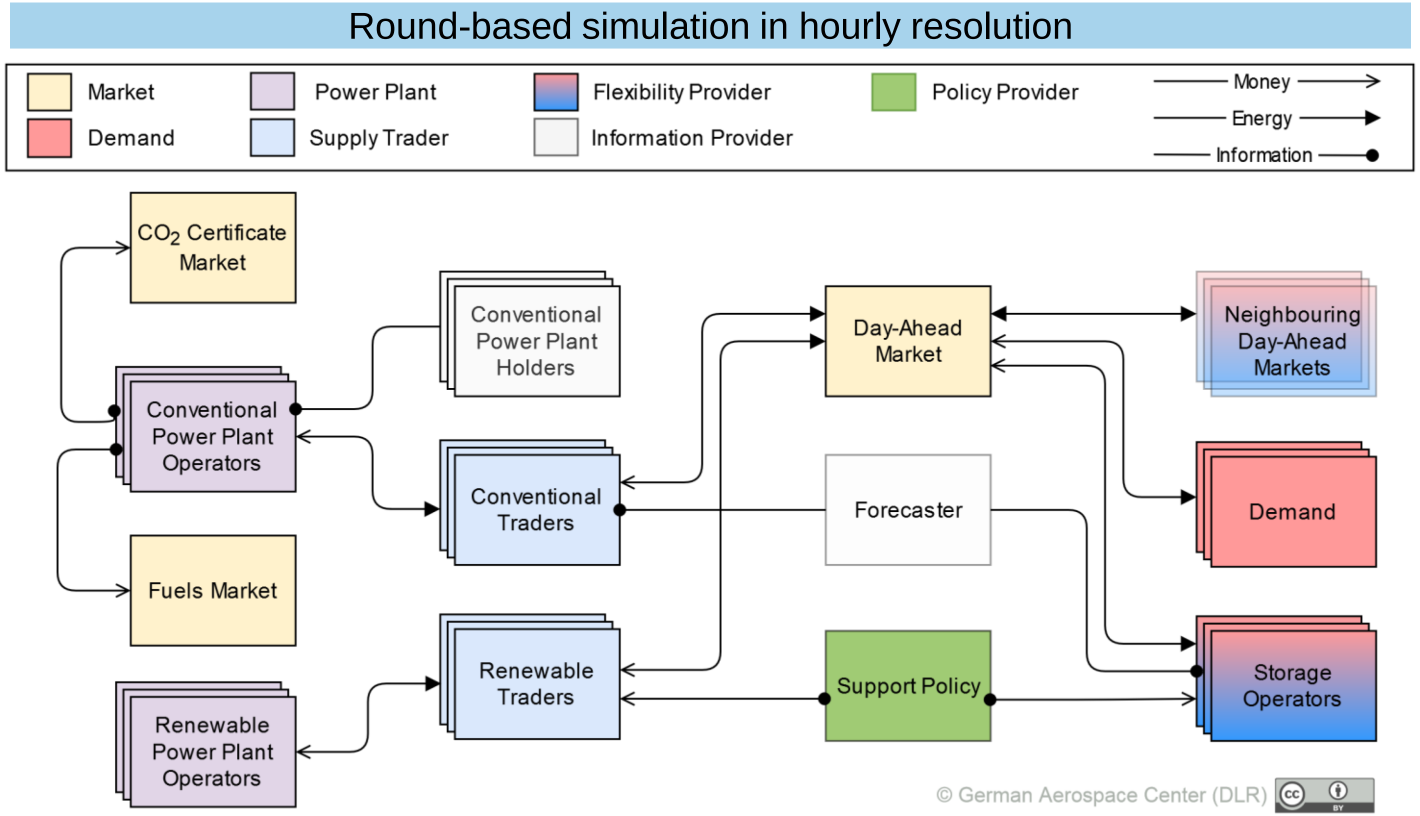


*Fig.: AMIRIS model architecture*

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See also https://dlr-ve.gitlab.io/esy/amiris/home/

# Idea: the Price Forecasting Agent

## Aim

- Central forecast agent
- Price forecasts for >=24h
- Feeds schedule optimization of agents

## Available Inputs

- Previous prices
- Previous residual load
- Future forecasted (residual) load
- Future forecasted EE generation

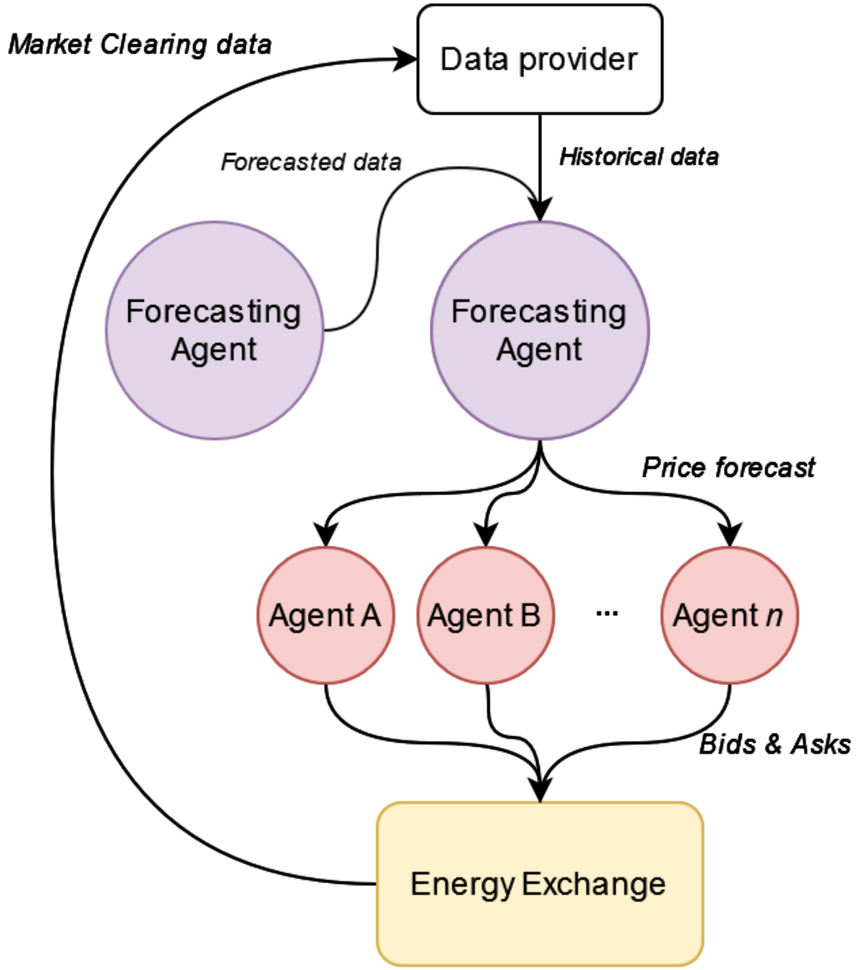



*Fig.: Concept of new Price Forecasting Agent in AMIRIS*

# Methodology

## Naïve Methods

- t+1, t+24, naïve drifts

*Serving as benchmarks*

## Regression Methods

- Linear Reg., LightGBM[1], Exponential Smoothing

*Common statistical approaches*

## Machine Learning Methods

- NBeats[2], TemporalFusionTransformer[3], DeepAR[4]

*State-of-the art machine learning methods*

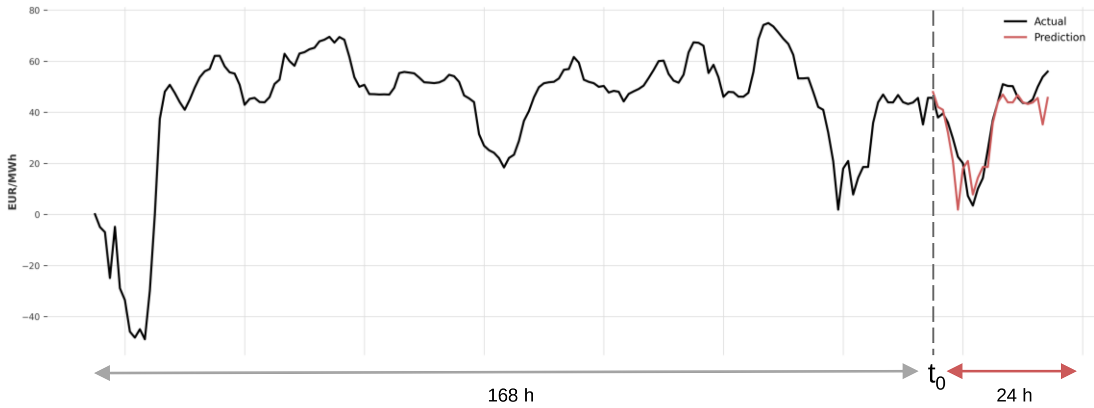
## Data

- Timespan 2003 – 2019
- EEX:
  - Day-ahead auction prices

[1] Ke G. et al. (2017): https://papers.nips.cc/paper/6907-lightgbm-a-highly-efficient-gradient-boosting-decision-tree
[2] Oreshkin B. et al. (2019): https://doi.org/10.48550/arXiv.1905.10437
[3] Lim B. et al. (2021): https://doi.org/10.1016/j.ijforecast.2021.03.012
[4] Salinas D. et al. (2020): https://doi.org/10.1016/j.ijforecast.2019.07.001

# Results Naïve
## t+24

## Exemplary predictions



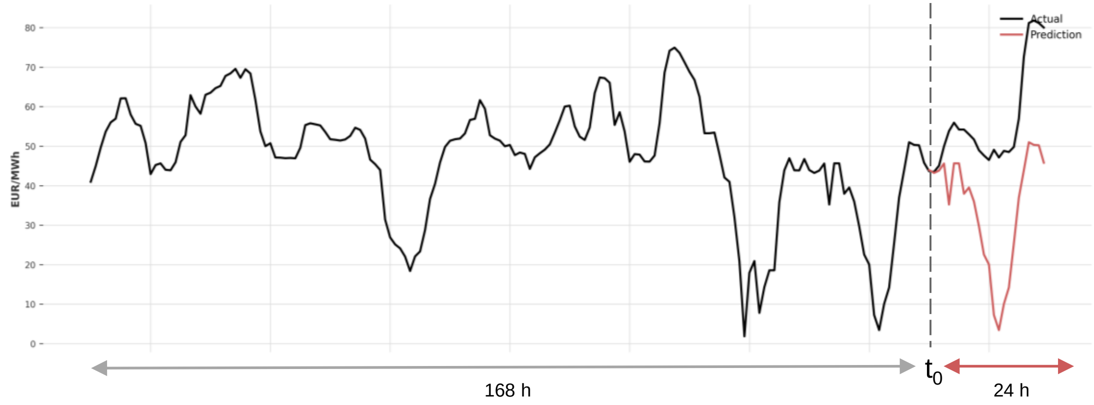
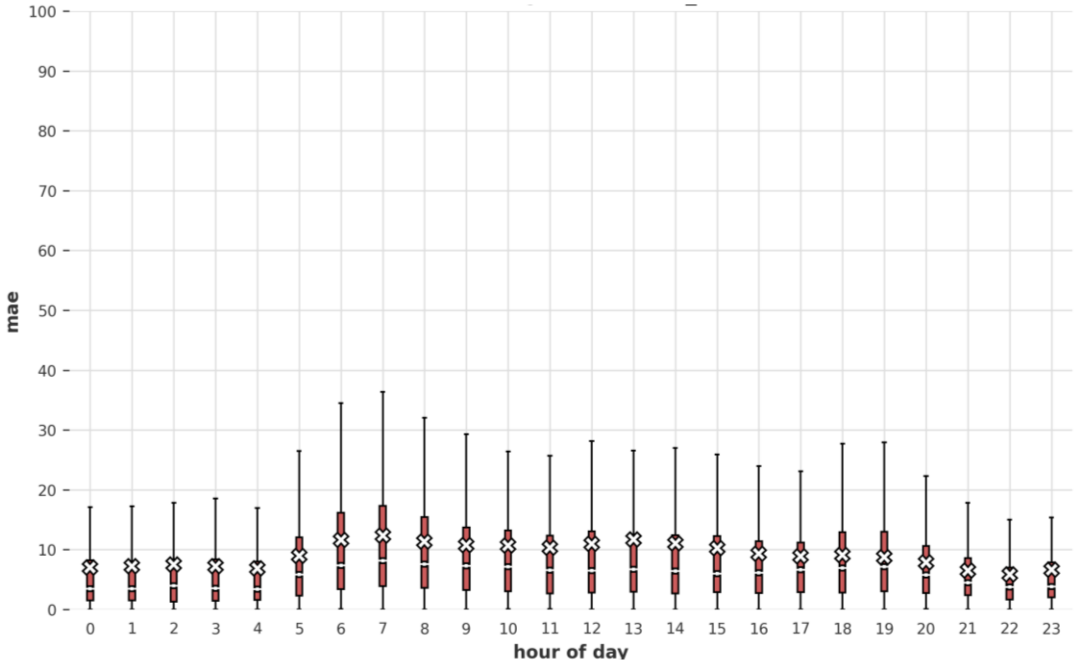




*Fig.: Timeseries of historical prices (black) and forecasted prices (red)*

## Performance overview

*Tab.: Mean Absolute Error (MAE) in €/MWh for each hour in year*



# Results Regression
## Exponential Smoothing

### Exemplary predictions

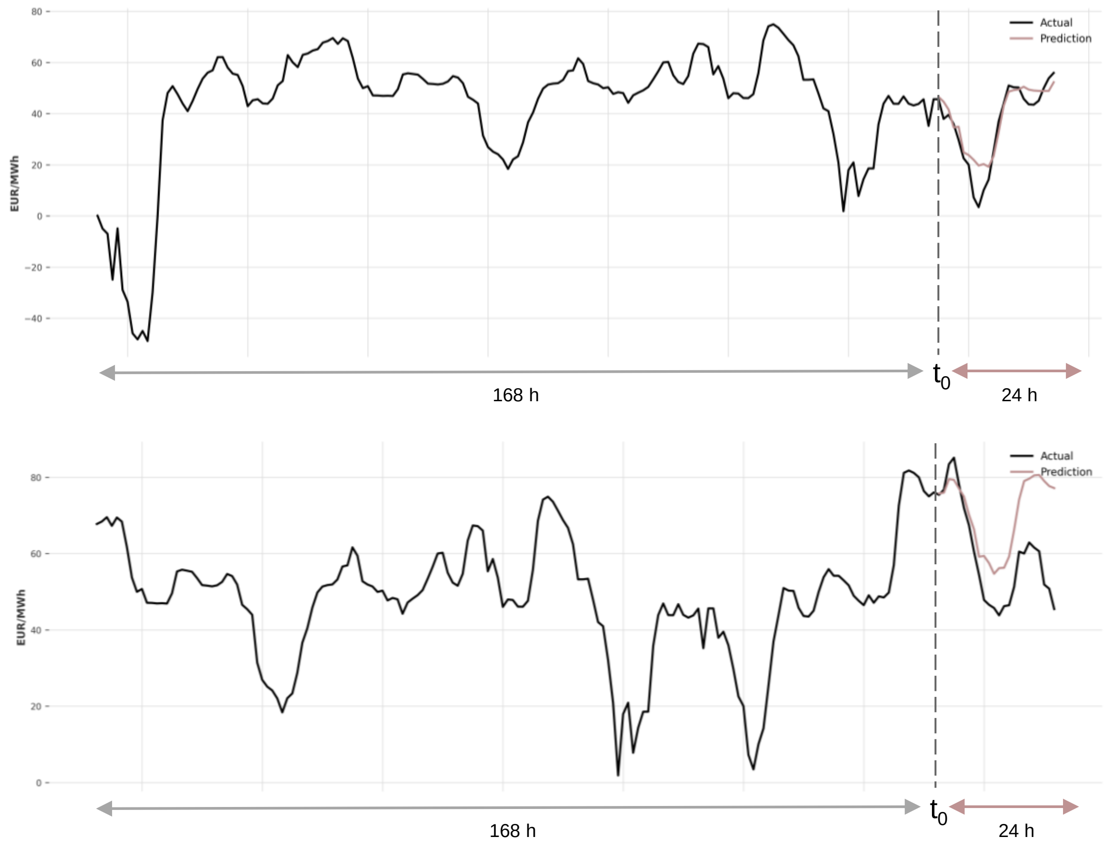
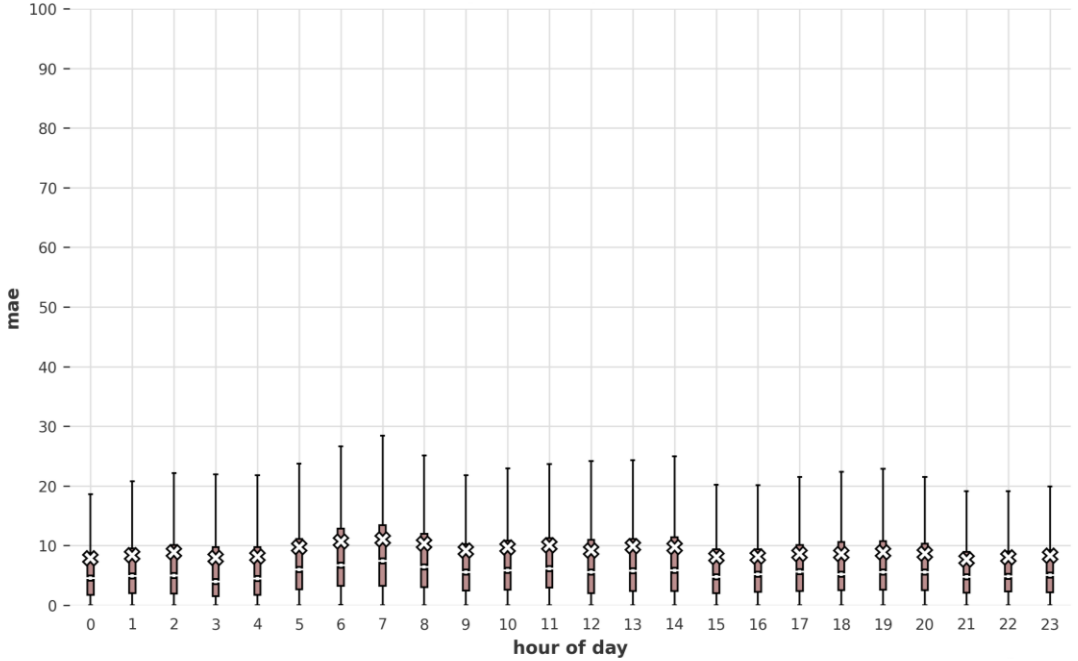



*Fig.: Timeseries of historical prices (black) and forecasted prices (coral)*

### Performance overview

*Tab.: Mean Absolute Error (MAE) in €/MWh for each hour in year*



# Results Machine Learning
## NBeats

### Exemplary predictions

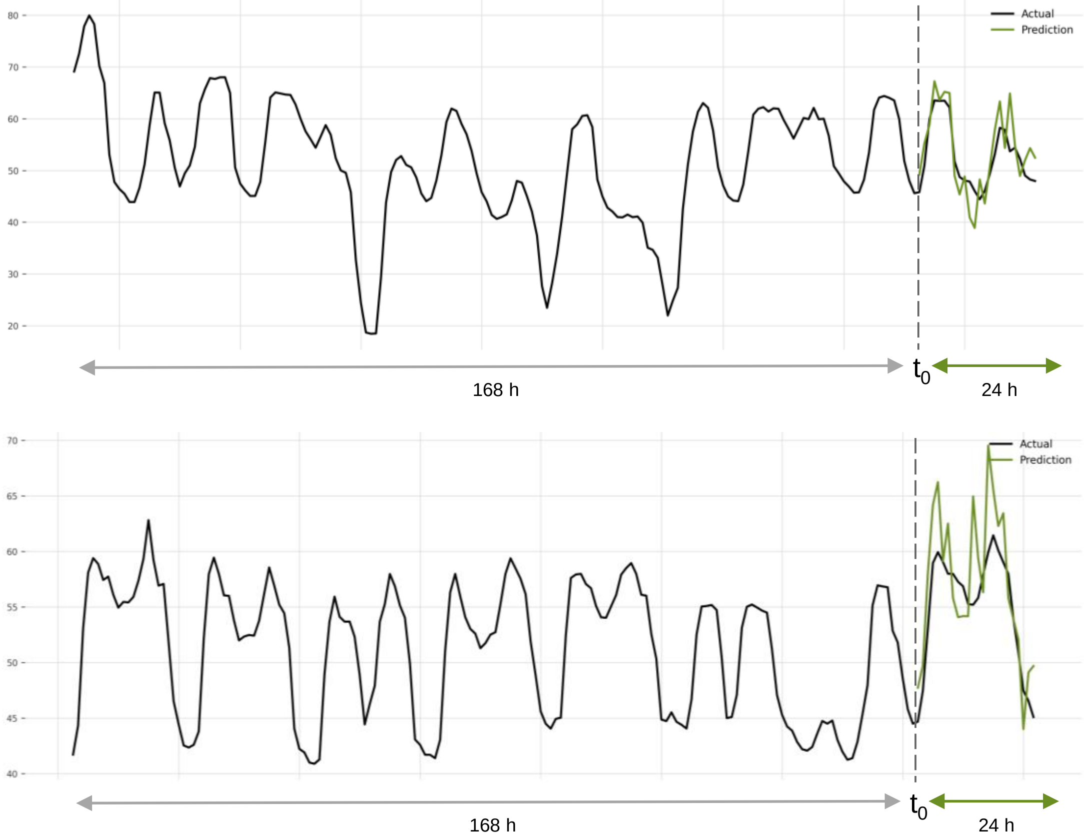
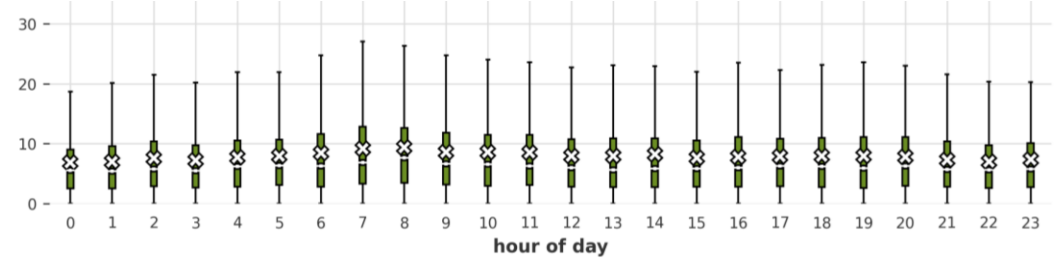



*Fig.: Timeseries of historical prices (black) and forecasted prices (green)*

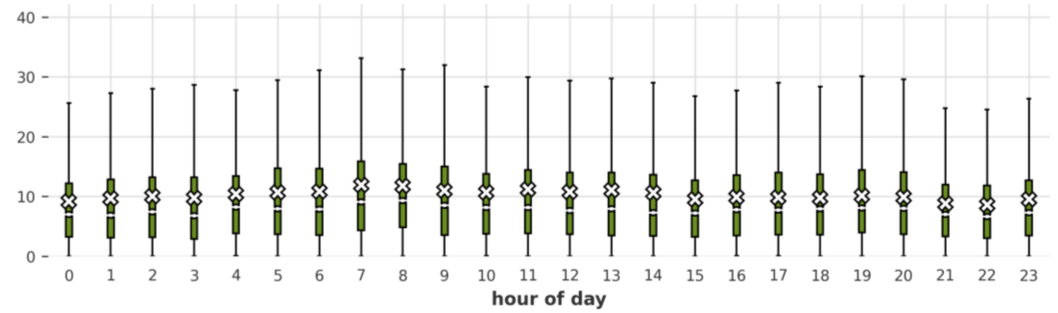
### Performance overview

*Tab.: Mean Absolute Error (MAE) in €/MWh for each hour in year*

**Test** 2018




**Validation** 2019



# Results
## NBeats with Additional Input Data

### Data

- Open power system data[1]
  - Load (forecasted & actual)
  - Installed RE Capacities
  - Actual RE Generation

- EEX:
  - $CO_2$ prices

*Table: MAE in €/MWh for NBeats model with different input data (best in* **bold***)*

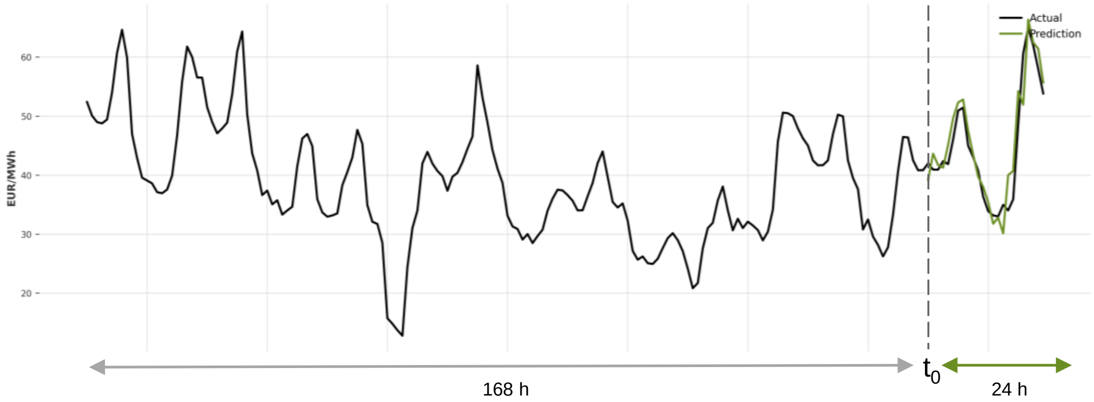
| Run | Input Data | Test 2018 | Validation 2019 |
|---|---|---|---|
| 1 | Historical Prices (P) | 7.90 | 10.22 |
| 2 | P + Dummy Hour (H) | 9.36 | 10.00 |
| 3 | P + Dummy All* (D) | 8.00 | 9.48 |
| 4 | P + $CO_2$ | 8.21 | 16.00 |
| 5 | P + Load (L) | 8.27 | 9.39 |
| 6 | P + Residual Load (RL) | 4.93 | 8.73 |
| 7 | **P + Renewable Energy Generation (RE)** | **4.66** | **8.55** |
| 8 | P + D + L + RL + RE + $CO_2$ | 5.05 | 15.62 |
| 9 | P + D + L + RL + RE | 4.70 | 13.11 |
| 10 | P + D + RE | 7.74 | 9.97 |

[1] https://doi.org/10.25832/time_series/2020-10-06

* Dummy Variables are Hour, Day Of Week, Holiday

# Results Machine Learning
## NBeats II (P + RE)

### Exemplary predictions



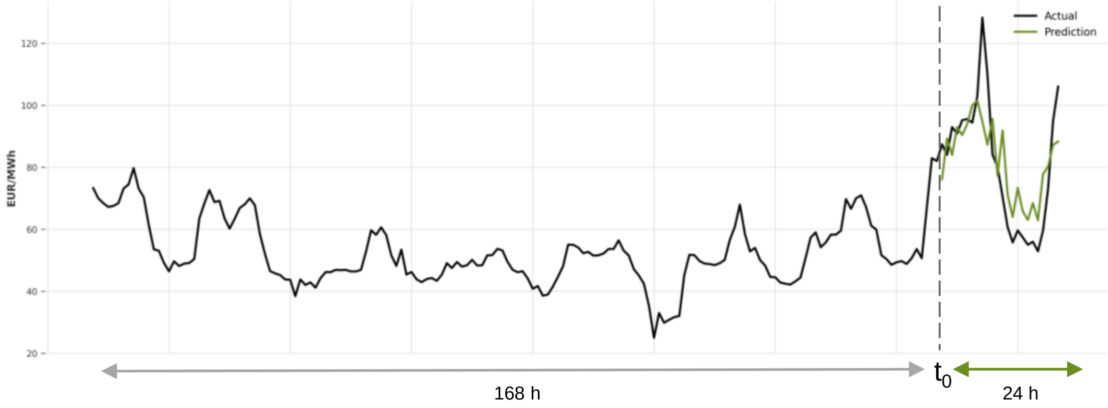
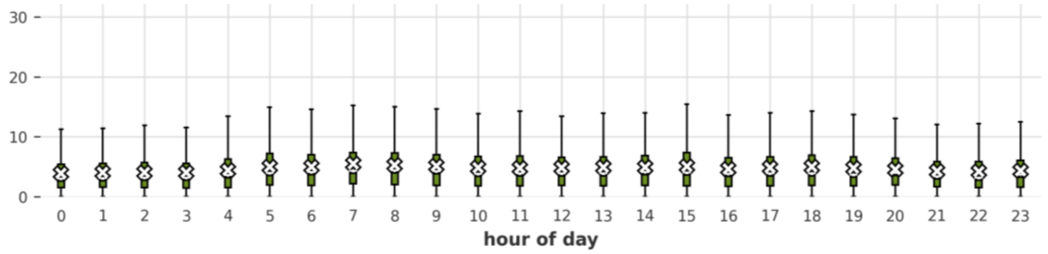




*Fig.: Timeseries of historical prices (black) and forecasted prices (green)*

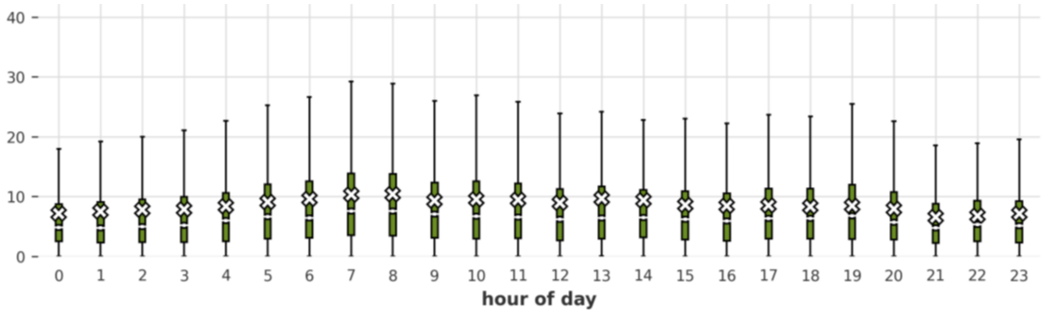
### Performance overview

*Tab.: Mean Absolute Error (MAE) in €/MWh for each hour in year*

**Test** 2018




**Validation** 2019



# Discussion

- Which errors are good enough?
- How are ESM results impacted by forecast performance? [1]
- How to retrieve information of uncertainty?
- How general are these models?
- How to train in future scenarios?

[1] Fraunholz C. et al. (2021): https://doi.org/10.1016/j.apenergy.2021.116688

# Conclusion

- Motivation: Timeseries forecasting in energy system models
- Method: Comparison of methods (naïve, regression, machine learning)
- Results: ML outperforms other methods depending on input data
- Discussion: Challenging integration in energy system models

# Outlook

- Further analysis in FEAT project, see https://www.mlsustainableenergy.com/
- Apply learnings to AMIRIS to provide electricity price forecasts
- Python package focapy to reproduce presented analysis to be published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# BACKUP

# Current price forecasting mechanism in AMIRIS

1. Power plant operators send future bids to forecast agent
2. Forecast agent calculates forecasted price
3. Forecasts are sent to one Flex-option agent
4. Flex-option agent optimizes its operational strategy
5. All traders send final bids to Energy Exchange
6. Energy Exchange calculates final electricity price

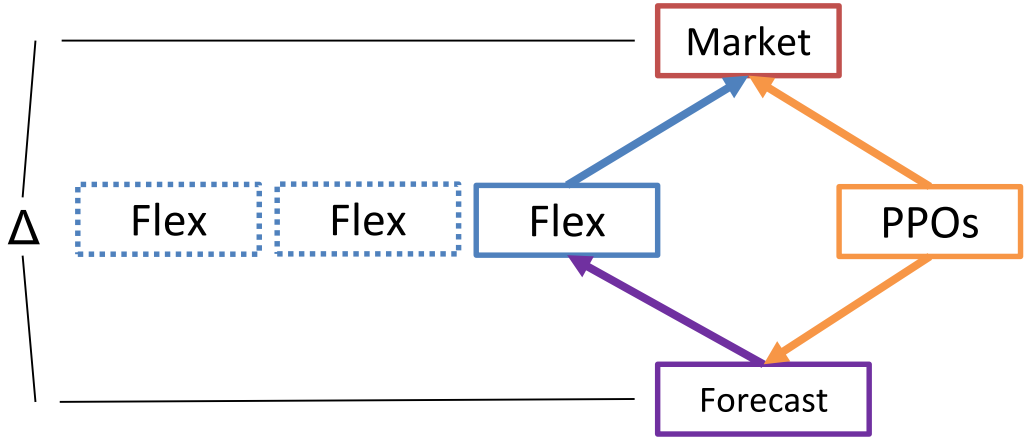


*Fig.: Current Forecasting Procedure in AMIRIS*

Final and forecasted price difference caused by flex-option agent actions
*(i.e. charging → „higher price“, discharging → „lower price“)*

**Challenge:**
<u>Multiple</u> flex-option agents mutually distort their forecasts due to their competitive actions
→ Significant impacts on the accuracy of the price forecast

# AMIRIS: parameterization and validation

**Motivation**
- Convenient parameterization
- Highest scientific standards

**Methodology**
- Collecting open data*
- Parameterization of agents
- Fitting day-ahead prices

**Outcome**
- Two sets for Germany & Austria
- Validation against historical prices
- Published under CC-BY-4.0 license
  https://gitlab.com/dlr-ve/esy/amiris/examples

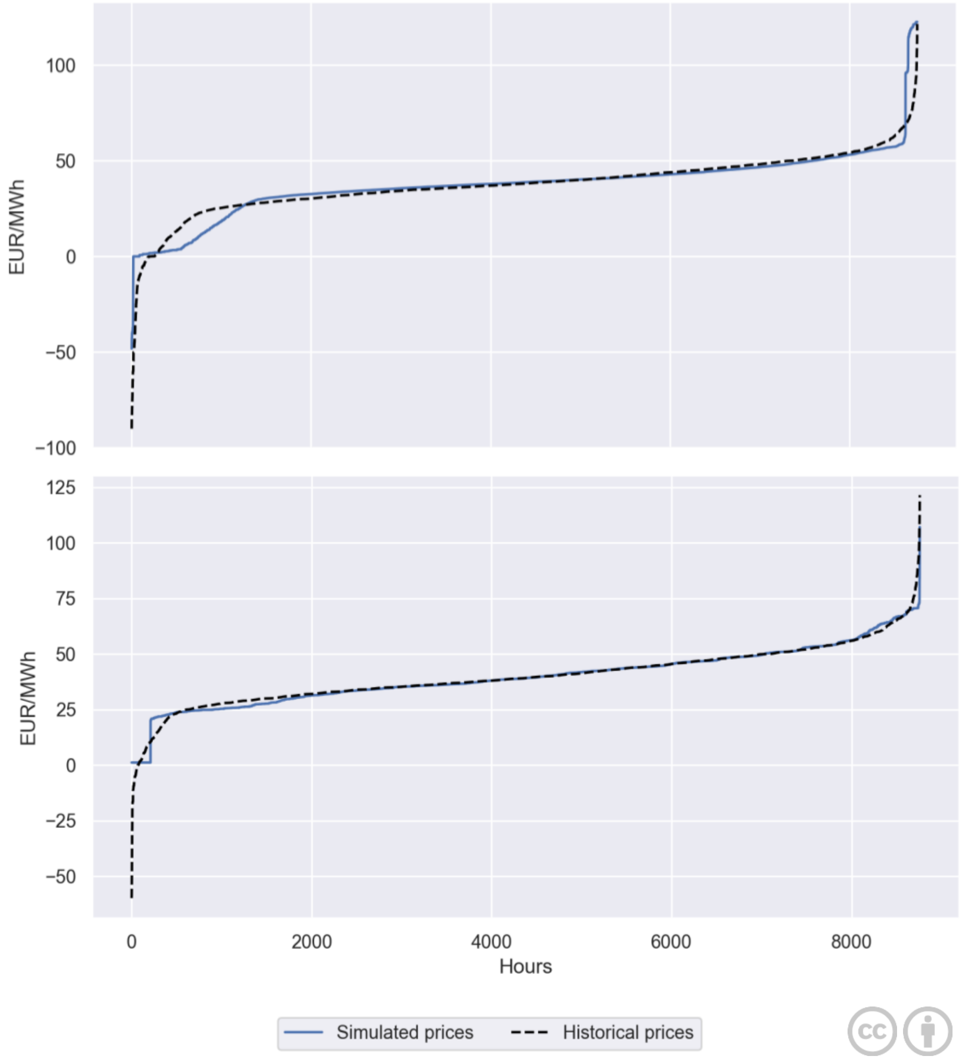


*Fig.: Price duration curves for Germany in 2019 (top) and Austria in 2019 (bottom)*

* Sources: SMARD Strommarktdaten, E-CONTROL, APG, EEX, Destatis
Nitsch et al. (2021a). https://doi.org/10.1016/j.apenergy.2021.117267
Nitsch et al. (2021b). https://doi.org/10.5281/zenodo.5726738

# Results Machine Learning
## NBeats

### Historical Prices (P) only



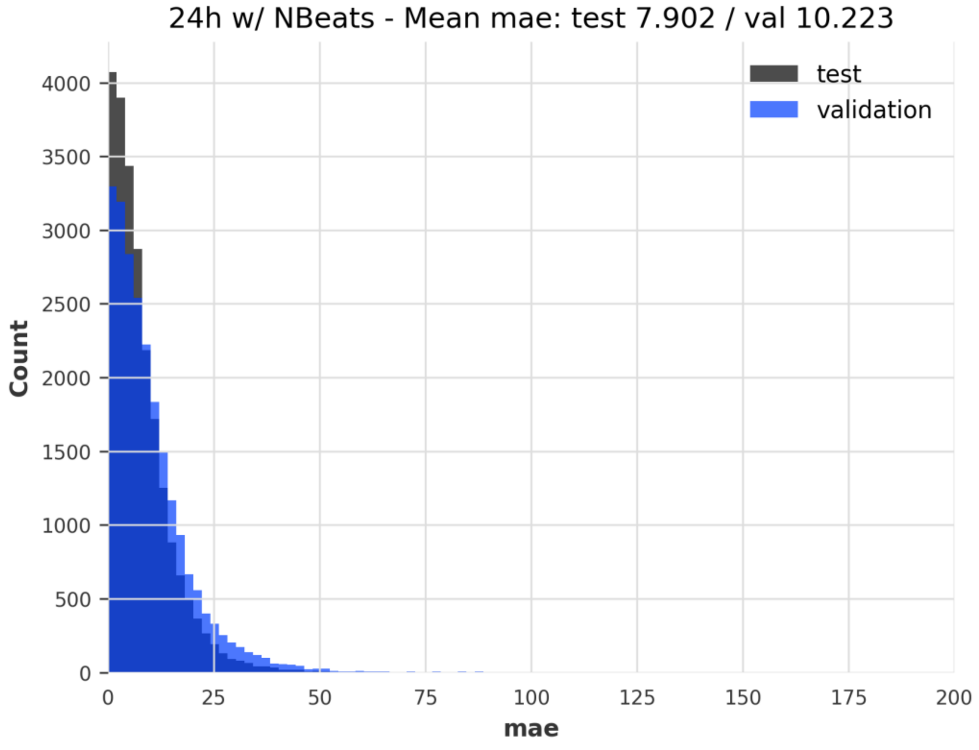


*Fig.: Test and validation histogram*

### P + Renewable Energy Generation (RE)



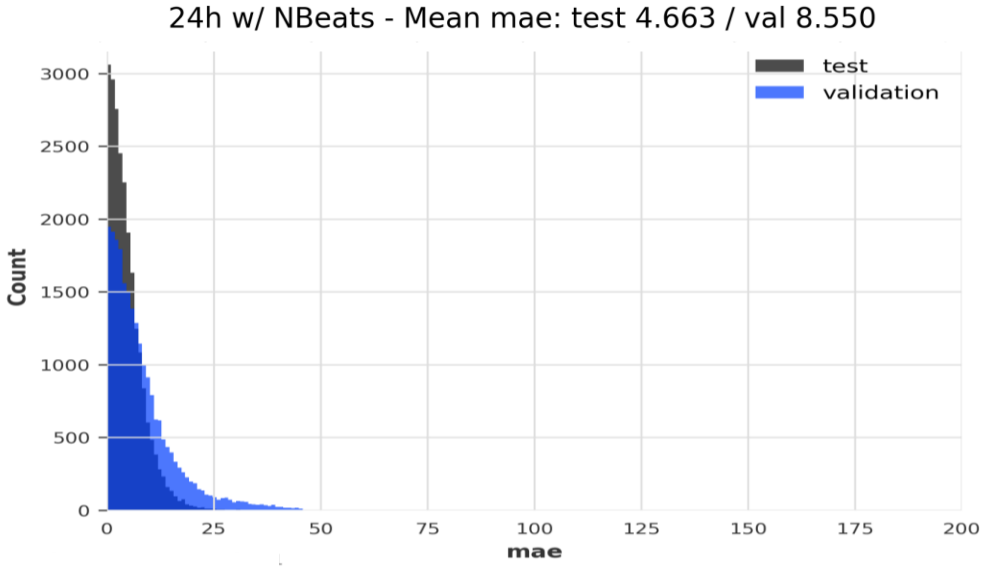


*Fig.: Test and validation histogram for NBeats run with Historical Prices and Renewable Energy Generation as Input*

# Imprint

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|---|---|
| Topic: | Comparison of electricity price forecasting methods for use in agent-based energy system models |
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| Institute: | Institute of Networked Energy Systems |
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