Investigating the Prediction of aFRR Activated Volume and Price Using Machine Learning

Claire LAMBRIEX*, Felix PREUSCHOFF, Denise BANGKELING, Albert MOSER

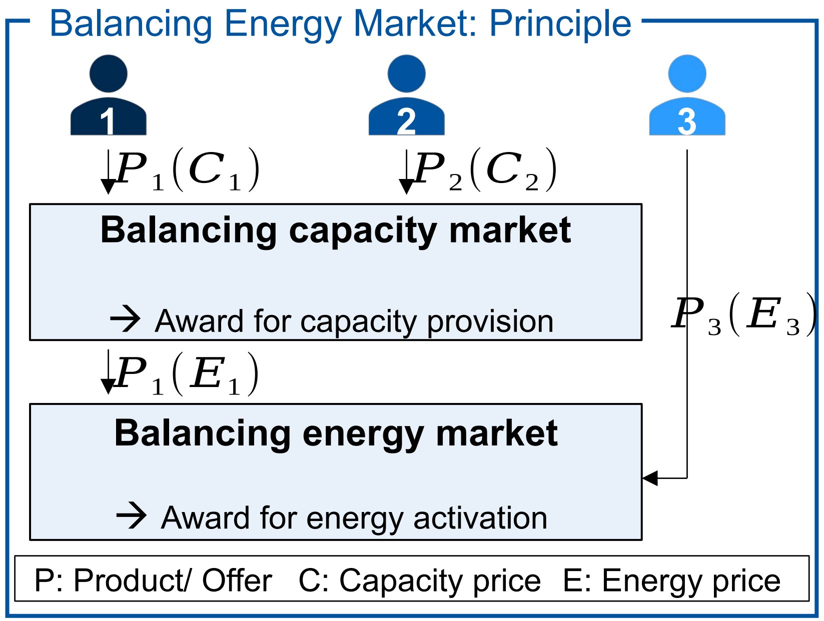
18. Symposium Energieinnovation, 15.02.2024, Graz

IAEW Elektrische Anlagen & Netze, Digitalisierung & Energiewirtschaft | RWTH AACHEN UNIVERSITY

Background and Motivation

- **Balancing reserves**: compensation of short-term imbalances in electricity grid
- **Remuneration** of standard balancing reserve products **aFRR[1] and mFRR[2]** contains:
  - Capacity price for reservation of balancing capacity
  - Energy price for the actual provision of energy when activated
- Electricity Balancing Guideline (EB GL): introduction of **separate balancing energy market**
  - Participation in an energy auction without having been successful in previous capacity auction
  - More short-term trading of balancing energy possible

  → Introduction of separate balancing energy market for aFRR and mFRR in Germany in November 2020
- Balancing energy market is a **new trading opportunity for market participants**
- **Performance of prediction models** used to maximize profits could be **influenced by the new market**



Goal: Investigate the prediction of aFRR activated volumes and prices in Germany since the introduction of the balancing energy market using machine learning methods

[1]aFRR: automatic Frequency Restoration Reserve
[2]mFRR: manual Frequency Restoration Reserve

Methodology

Collection of Input Data → Input Data Generation and Transformation → Hyperparameter Tuning and Model Training → Model Evaluation

Collection of publicly available data

In 15-minute resolution for May 2021 to April 2023

- **Electricity generation**
  - Forecasted generation for renewable energy sources (RES)
  - Actual generation for all energy sources
- **Electricity consumption** (forecasted and actual): total grid load and load from hydro pumped storages
- **Balancing capacity** (positive and negative): procured volumes and capacity prices

Methodology

Collection of Input Data → **Input Data Generation and Transformation** → Hyperparameter Tuning and Model Training → Model Evaluation

Input data generation (feature engineering)

- **Generation ramps**: difference between generation at time steps and
- **Consumption ramps**: difference between consumption at time steps and
- **Forecast errors**
  - RES generation: difference between actual and forecasted generation
  - Consumption: difference between actual and forecasted consumption

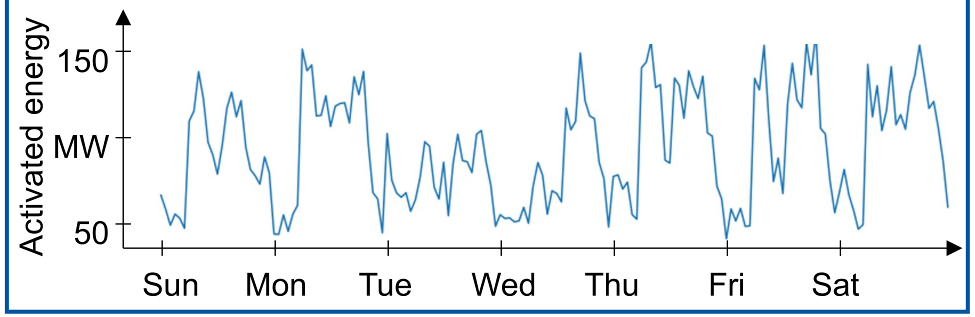
Input data transformation

Transformation of **categorical features**

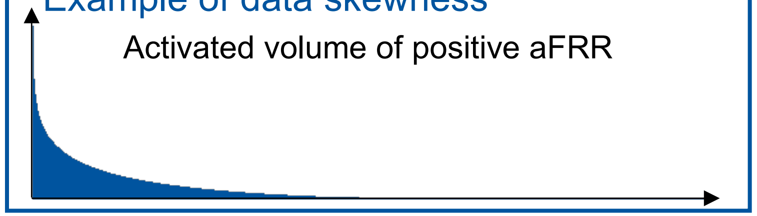
- Hour
- Time of day
- Day of week
- Month
- Season

Transformations to **improve algorithms' learning ability** (e.g. handling of skewness)

Average hourly activated volume of positive aFRR



Example of data skewness



Methodology

Collection of Input Data → Input Data Generation and Transformation → **Hyperparameter Tuning and Model Training** → Model Evaluation

Hyperparameter tuning and model training

- **Supervised learning** with **four target variables: positive and negative aFRR activated volume and price**
- Machine learning methods used: **Gradient Boosting (GB), Random Forest (RF), XGBoost (XG) and LightGBM (LG)**
- **Hyperparameter tuning**: optimization of certain parameters before the training process using Random Search
- **Model training**:
  - Random separation of input data in train and test sets with ratio 80:20
  - Evaluation of features' importance to find the optimal number of features
  - Investigation of different input data combinations

IAEW Elektrische Anlagen & Netze, Digitalisierung & Energiewirtschaft | RWTH AACHEN UNIVERSITY

Methodology

Collection of Input Data → Input Data Generation and Transformation → Hyperparameter Tuning and Model Training → **Model Evaluation**

Model evaluation

- Different input data combinations varying use of actual and forecast values and handling of skewness

Combination	Generation and consumption data used	Max no. of features	Skewness threshold
1	Only forecast values	19	1.5
2	Forecast and actual values	59	1.5
3	Forecast and actual values	59	1
4	Forecast and actual values	59	No transformation for skewed distributions

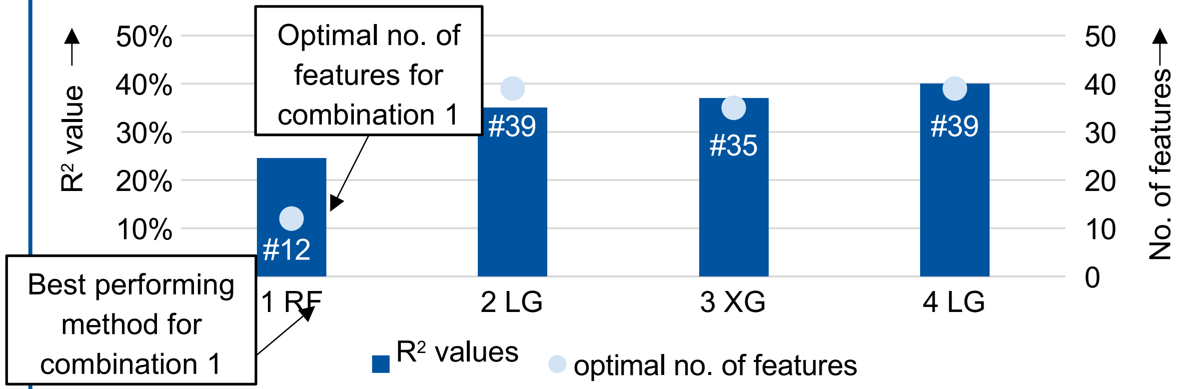
- Identification of **best performing method** and **optimal number of features** for each input data combination
- **Evaluation of model performance** for each combination and target variable by **coefficient of determination R^2**

IAEW Elektrische Anlagen & Netze, Digitalisierung & Energiewirtschaft
RWTH AACHEN UNIVERSITY

Results

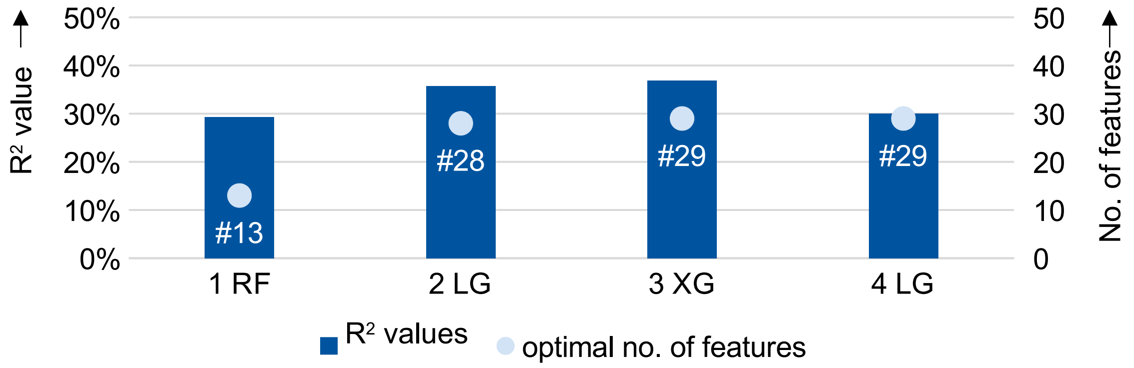
Activated volume of aFRR

Postive aFRR volume



- Combinations **with use of actual generation and consumption data** (2-4) perform **better** than combination **without use of actual data** (1)
- Best performance by combination 4 with R^2 of 40.0%
- **Performance generally not sufficient**
- Most important feature for combination 1: **RES generation**
- Most important features otherwise: **hydropower-related**

Negative aFRR volume

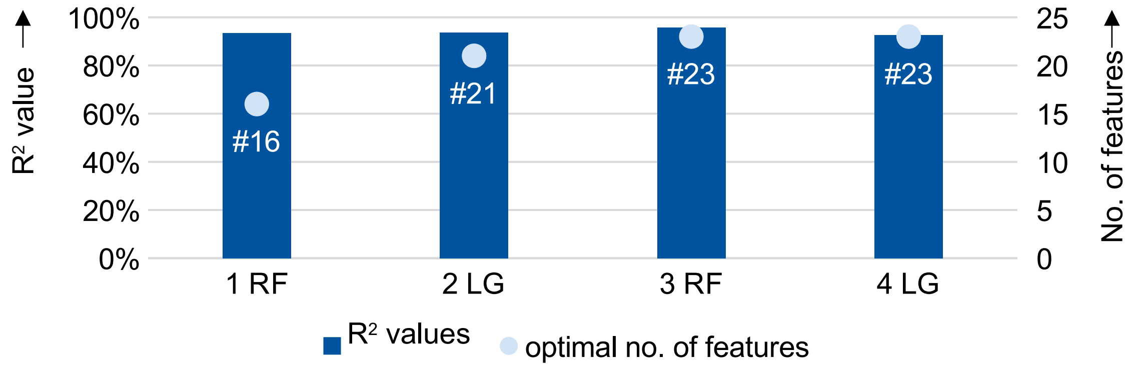


- Combinations **with use of actual generation and consumption data** (2-4) perform **better** than combination **without use of actual data** (1)
- Model performances worse than for positive volume
- Best performance by combination 3 with R^2 of 36.9%
- Most important feature for combination 1: **RES generation**
- Most important features otherwise: **hydropower-related**

Results

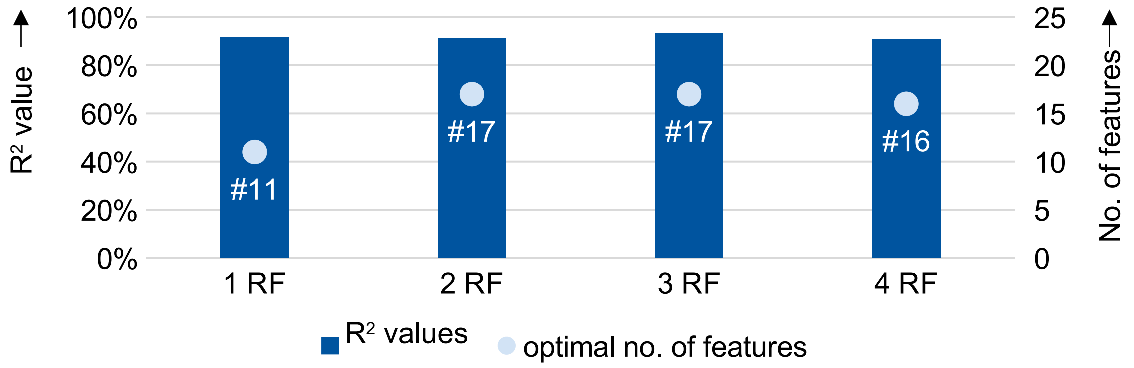
Energy price of aFRR

Postive aFRR energy price



- **All methods** achieve **R^2 values of more than 90%**
- Best performance by combination 3 with R^2 of 95.8%
- Dominating important features:
  - **Capacity price of negative aFRR**
  - **Volume of positive aFRR capacity procured**
- Time-related feature month has an effect as well

Negative aFRR energy price



- **Best performance** reached by **Random Forest for all combinations**
- Best performance by combination 3 with R^2 of 93.5%
- **Lower optimal no. of features** than for all other target variables
- Most important features differ in all combinations

→ **Data transformations influence feature importance**

IAEW Elektrische Anlagen & Netze, Digitalisierung & Energiewirtschaft | RWTH AACHEN UNIVERSITY

Summary

Background and Motivation

- New balancing energy market for aFRR introduced in Germany in 2020 → new trading opportunity for market participants
- Balancing energy market possibly changes the performance of prediction models used to maximize profits

→ Goal: Investigating the prediction of aFRR activated volumes and prices in Germany since the introduction of the balancing energy market using machine learning methods

Methodology

- Use of different machine learning methods and input data combinations

Results

- No machine learning method performed best for all target variables and input data combinations
- Models for activated aFRR volume performed poorly
  - Some market parameters changed during the analyzed period (e.g. introduction of the platform PICASSO)
  - If it was predictable, would balancing energy be needed?
- Models for aFRR energy prices performed good → prediction possible with appropriate input data combination and method

IAEW Elektrische Anlagen & Netze, Digitalisierung & Energiewirtschaft | RWTH AACHEN UNIVERSITY

Thank you for your attention!

Claire Lambriex
RWTH Aachen University
Institut für Elektrische Anlagen & Netze,
Digitalisierung und Energiewirtschaft
Schinkelstraße 6, 52056 Aachen

c.lambriex@iaew.rwth-aachen.de
www.iaew.rwth-aachen.de