# Day-ahead probability forecasting for redispatch 2.0 measures

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# Redispatch

„A request issued by the transmission system operator (TSO) to power plans to adjust the real power they input in order to avoid or eliminate congestion. This method can be applied within or between control areas. “ (Transnetbw)

This talk on Quantinar

# Relevance

- Grid Congestion Dynamics
- Challenges with Renewables
- Cost of Redispatch
- Legislative Adaptation

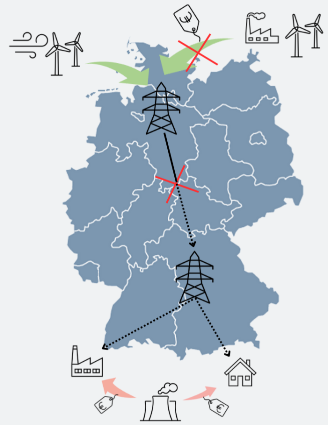
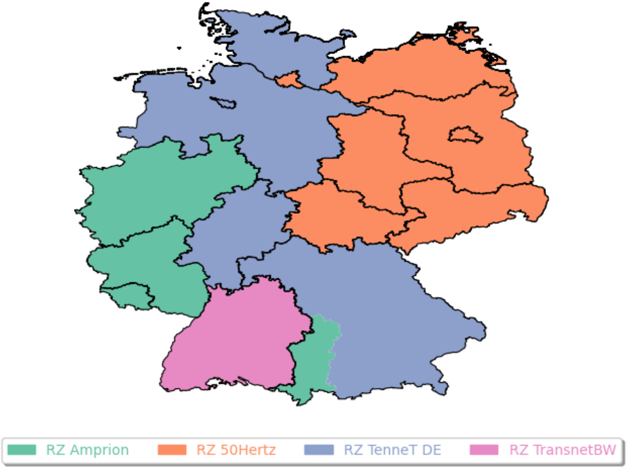


Figure 1: Redispatch Process

# TSO in Germany



# Electricity generation in Germany

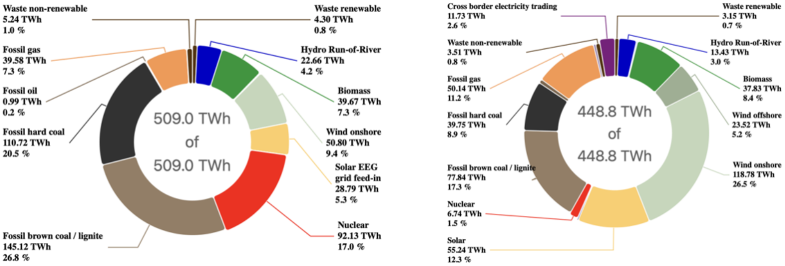



Figure 2: Public net electricity generation in Germany in 2013 (left) and 2023 (right), Source link

# State of the Art

- Zhou, Tesfatsion, and Liu, 2011
- Srivastava et al., 2021
- **Gürses-Tran, Flamme, and Monti, 2020**
  - use three versions of RNN-base probabilistic forecasting model with parametric and non-parametric implementations based on Gaussian parameters and quantile regression to forecast 40h-ahead of residual loads of future congestion for Southern Sweden

# State of the Art

- **Billault-Chaumartin, Eising, and Motte-Cortés, 2020**
  - Literature overview of papers regarding redispatch modeling in Germany
  - use hourly wind and PV feed-in, load and redispatch measures data between 2015 and 2019 to model redispatch direction (Up and Down) with Fast Fourier transformation
- **Titz, Puetz and Witthaut, 2024**
  - model for the hourly volume of redispatch and countertrade (GBT and SHAP) in the German transmission grid
  - wind power generation in northern Germany emerged as the main driver



# Redispatch volume in Germany with Gradient Boosted Trees

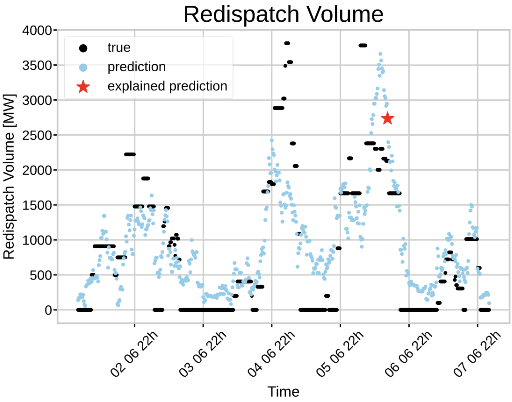



Figure 3: Redispatch volume in Germany from power grid features, Titz et al. 2024

# Challenges

- Unbalanced supply and demand in Germany
- Impacts distribution grid
- Higher concentration on renewable energies in northern Germany than the South
- Southern electricity demand is higher than every other region

$\Rightarrow$ leads to congestions

# Objectives

- Using different explanatory variables like meteorological data and energy asset prices to
  - Model day-ahead redispatch occurrence probability (up and down) on an hourly basis for each TSO in Germany
  - Model day-ahead redispatch loads (up and down) on an hourly basis for each TSO in Germany



# Outline

# Model selection

- Targets for each TSO:
  - Probability of congestions - for both directions together as well as separately
  - Total load of redispatch - up and down separately
- ML Algorithms
  - Classifier - XGBoost (Extreme Gradient Boosting)
  - Regression for day-ahead (24-hour) forecasting
    1. N-BEATSx (Neural Basis Expansion Analysis Time Series with exogenous variables, Olivares et al., 2023)
    2. N-HiTS (Neural Hierarchical Interpolation for Time Series Forecasting, Chalu et al., 2022)
    3. Benchmarks: ARIMA, XG Boost, Bidirectional Temporal Convolutional Network (BiTCN)
- Classification and regression models are used independently

XGBoost Description    N-BEATS Description    N-HiTS Description

# Training & Inference

- Separate classification for up, down and both congestion types
- Separate regression for up and down load

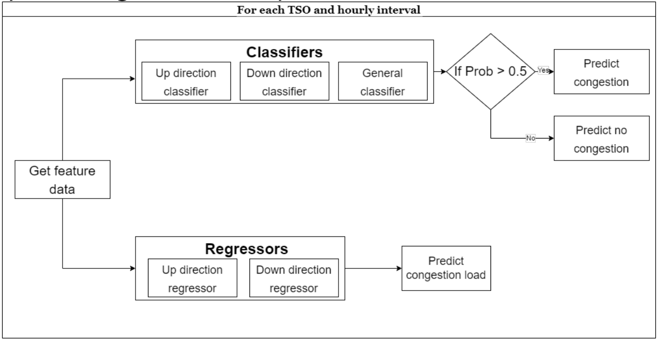



Figure 4: Main inference pipeline

N-BEATS Training

# Redispatch data - Target

- date and time
- affected regions and units
- measure reasons
- redispatch direction
- total load

Source: netztransparenz.de
Granularity: hourly data

# Features data

46 features

- Prices (USD)
  - Brent oil, natural gas, carbon emissions futures, CO2 certificates (daily)
  - day-ahead electricity (hourly)
- Weather
  - air temperature (hourly)
  - sunshine duration (hourly)
  - wind velocity (hourly)
- Date
  - weekday, weekend, holidays, hour/day/month
- Electricity consumption and production forecasts (MW/h)
  - renewable (hourly)
  - residual load (hourly)

# Data split

- Classifier Training

| Split | Time Period | $n$ |
|---|---|---|
| Train | 2020-01-01 to 2024-01-31 | 35,808 |
| Validation | 2024-02-01 to 2024-03-31 | 1,440 |
| Test | 2024-04-01 to 2025-01-31 | 7,344 |

Table 1: Data split for Classifier training, TSO 50 Herz

- Regression training
  - Moving window setup
  - 30 months training length, 2 months of validation and 1 one month of test, 11 total windows
  - Monthly recalibration

# Redispatch frequency

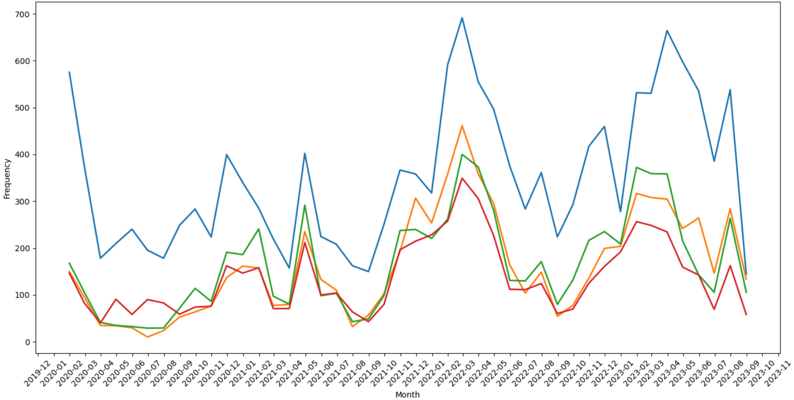



Figure 5: Number of redispatch from 50Hertz, Amprion, TransnetBW, TenneT

# Up and Down redispatch per TSO

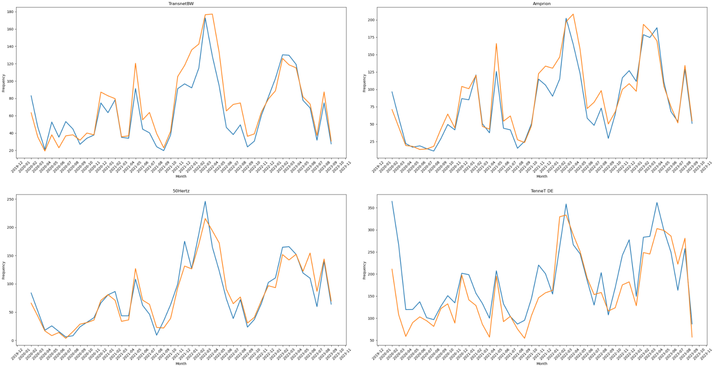



Figure 6: Up direction and down direction

# Redispatch Measure Reasons Over Time

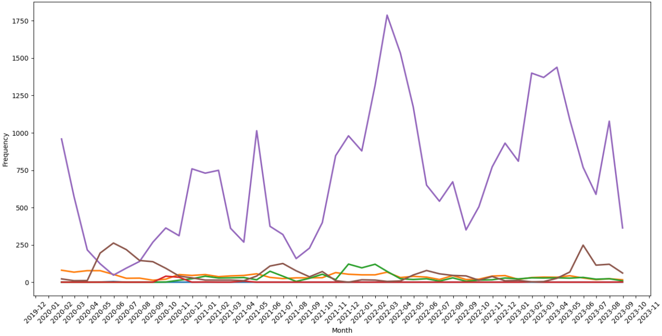



Figure 7: Electricity- and voltage-related redispatch, Electricity-related, Electricity-related countertrade DE-DK2, Voltage-related, Electricity-related countertrade DE-DK1, Electricity-related countertrade DE-NO2

# Monthly total load

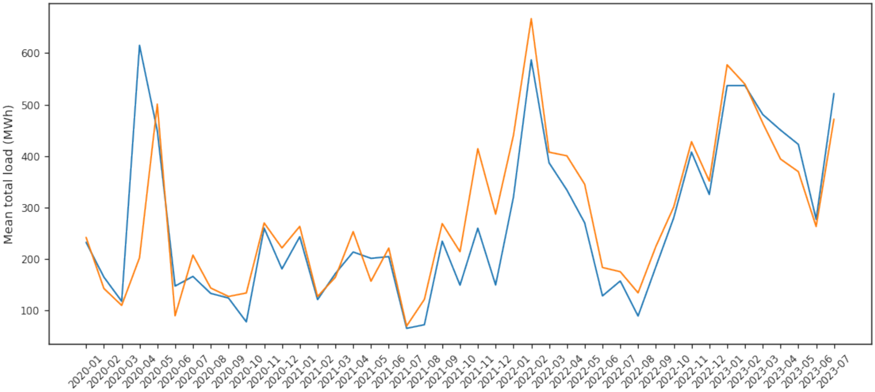



Figure 8: Up and down total load, 50 Hertz, monthly average

# Affected plants

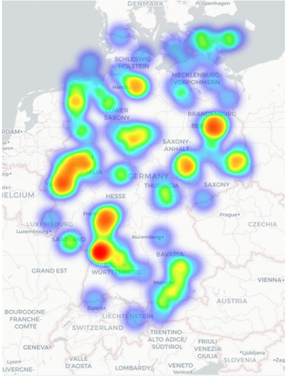



Figure 9: Affected units, Heat map based on total congestion load. Heat map video

# Redispatch occurrence probability

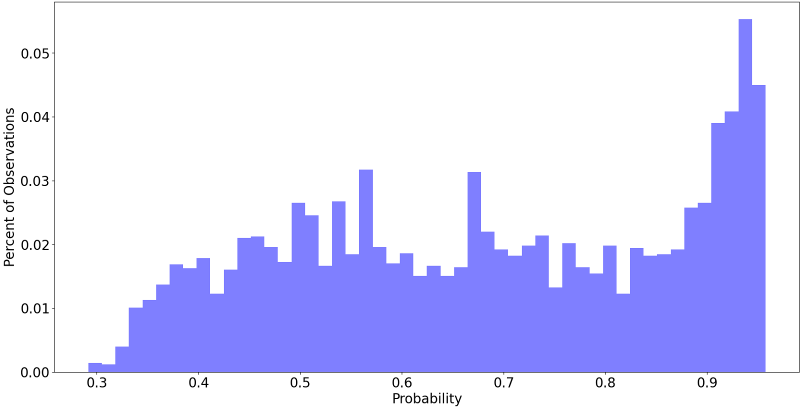



Figure 10: Probability distribution for test set: Up direction

# Feature importance

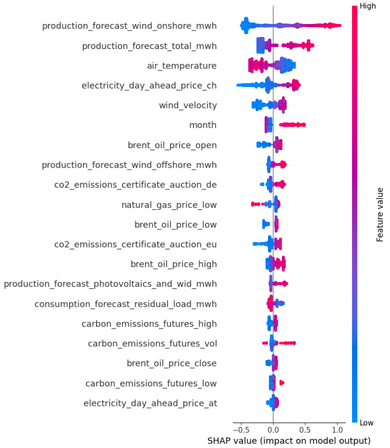



Figure 11: Shap values for training set: Up direction

# Precision and Recall: Test set

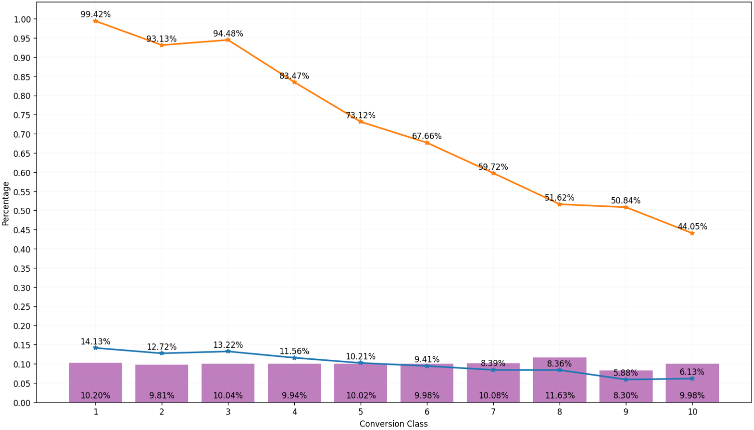



Figure 12: Up direction % of redispatch, redispatch rate, base in %

# Classification performance

| Direction | Dataset | F1 Score | Precision | Recall |
|---|---|---|---|---|
| up | Train | 0.82 | 0.82 | 0.81 |
| | Valid | 0.78 | 0.67 | 0.92 |
| | Test | 0.82 | 0.79 | 0.87 |

Table 2: 50 Hertz redispatch occurrence probability

# Regression predictions

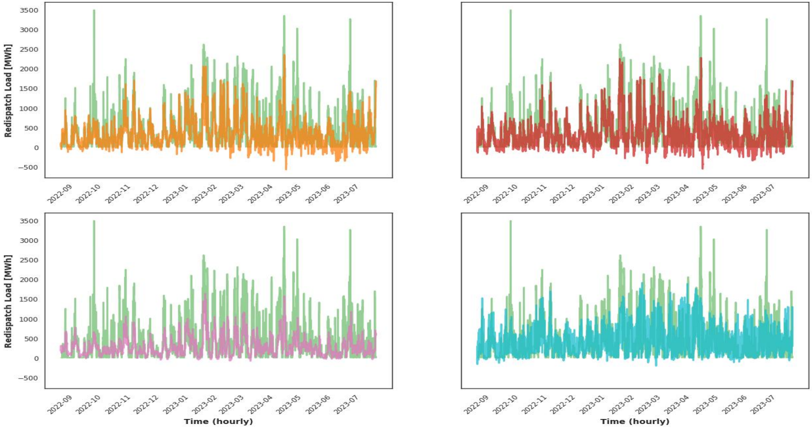



Figure 13: Actual Redispatch Load compared to N-HiTS, NBEATSx, BiTCN, XG Boosting TenneT DE, out-of-sample, up direction, 24-hour forecast horizon

# Regression predictions

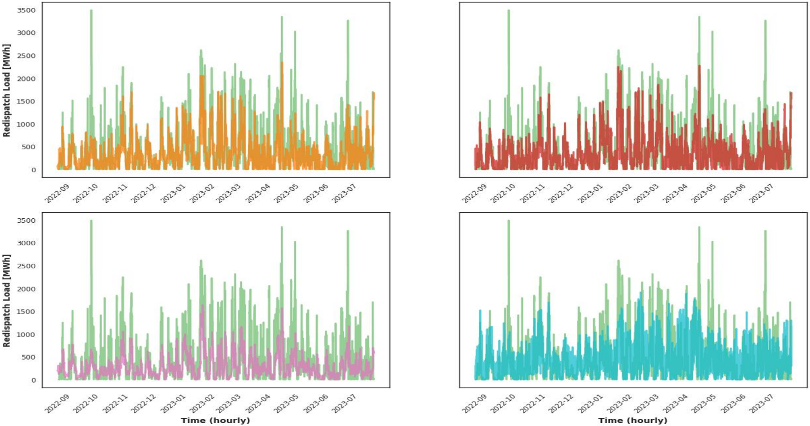



Figure 14: Actual Redispatch Load compared to N-HiTS, NBEATSx, BiTCN, XG Boost after applying absolute value, TenneT DE, out-of-sample, up direction, 24-hour forecast horizon

# Regression predictions - Zoom-in

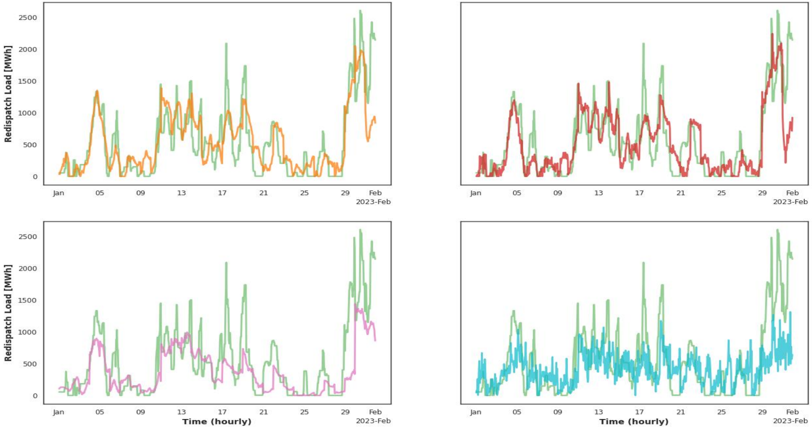



Figure 15: Actual Redispatch Load compared to N-HiTS, NBEATSx, BiTCN, XG Boost after applying absolute value, TenneT DE, zoom-in on the fifth window, Jan 2023, up direction, 24-hour forecast horizon

# Regression performance

| Model | RMSE | MAE | $R^2$ *score* |
|---|---|---|---|
| NHITS | **393** | **248** | **0.38** |
| NBEATSx | 399 | 256 | 0.36 |
| BiTCN | 414 | 261 | 0.31 |
| XGBoost | 562 | 379 | -0.25 |
| ARIMA | 612 | 403 | -0.48 |
| Naive Benchmark | 457 | 322 | 0.17 |

Table 3: TenneT DE prediction metrics, up direction, 24-hour forecast horizon

# How much can we save?

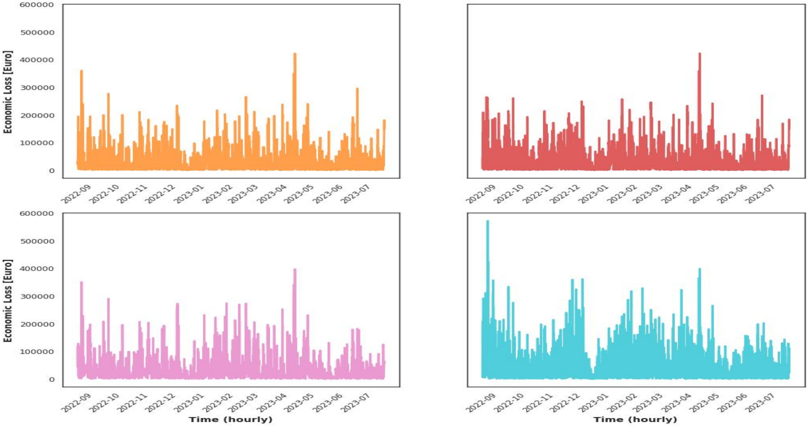



Figure 16: Loss in electricity price due to dispatching load for N-HiTS, NBEATSx, BiTCN, XG Boost, TenneT DE, up direction

# Conclusion

- Redispatch data presents some patterns that can be investigated by ML models
- The highest explanatory power to predict probability of redispatch: wind related variables as well as temperature and electricity price for Czech Republic
- NHITS and NBEATSx outperform other econometric and ML benchmarks to forecast day-ahead Redispatch load
- Considering possible economic implications leads to the same outcome

# Future research

- Integration of regression and classification models
- Interpretability: take advantage of N-BEATSx interpretable architecture, Accumulated Local Effects - ALE
- Other benchmarks: TSMixer (Chen et al. 2023) , UniTS (Gao et al. 2024), LLMtime (Gruver et al. 2023), zero-inflated models similar to (Yong et al., 2021)

# Pre-processing

- Local prices: converted to USD
- Missing data
  - Prices: forward-filling (taking the Friday value)
  - Weather: forward-filling
  - Other features: replaced with the median value
- Weather: hourly averaged to each TSO
- Naive split to border region TSO's
- Aggregation: hourly interval, TSO direction of redispatch
- Assumption: redispatches occuring at the same hours, TSO and direction are independent
- Dataset: four similar datasets for each TSO, with small differences (energy production sources, weather features)

# XGBoost Description

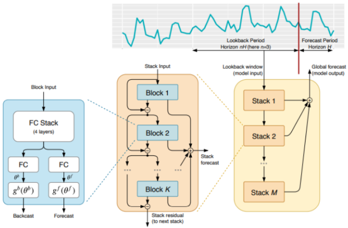
- Introduced in Chen and Guestrin, 2016
- Tree-based boosting algorithm
- Scales very well with large datasets

Back to "Pipeline" Boosting

# N-BEATS Description

- Introduced in Oreshkin et al., 2020
- Black-box or interpretable architecture
- Supports transfer learning
- Decomposes signal into *backcast* (history) and *forecast* (prediction)

- Two main building blocks:
  - *Blocks*: capture specific information using Fully-Connected (FC) layers and a learnable linear projection
  - *Stacks*: a collection of blocks

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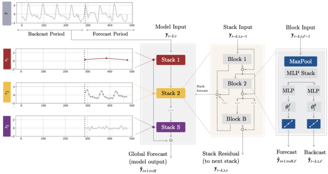
# N-HiTS Description

- Introduced in Challu et al., 2022
- An evolution of N-BEATS by:
  - Included kernel pooling at each block's entry point
  - Regularized basis function forms by hierarchical interpolation and multi-rate data sampling

- Unique parameters from N-BEATS:
  - *Pooling*: control how pooling is done (max, mean, etc.), and how much the inputs are shrinked
  - *Interpolation type*: three were proposed in the paper (linear, cubic, and nearest neighbor)

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