Identifying Drivers and Mitigators for Congestion in the German Power System

Based on Titz et al., 2024

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1 Introduction and Background

1.1 Overview of Germany's Energy Transition

Germany has been a pioneer in the global shift toward renewable energy, spearheading an ambitious transformation known as the Energiewende. This initiative aims to phase out nuclear energy and fossil fuels while drastically reducing greenhouse gas emissions [1]. Over the past decades, significant investments in wind, solar, biomass, and other renewable sources have reshaped the nation's energy portfolio [2].

The transformation is driven not only by environmental concerns but also by the desire for energy independence and economic innovation [3]. Unlike traditional centralized power plants, renewable energy sources are inherently variable. This variability has spurred the integration of advanced technologies such as energy storage systems, smart grid solutions, and demand response mechanisms [4]. These innovations have enabled Germany to build a more decentralized and resilient power network.

1.2 Integration Challenges in the German Power System

While the Energiewende has accelerated renewable energy production, it has also introduced a host of integration challenges. The German power grid, originally designed for predictable and centralized generation, now must accommodate the fluctuating outputs of renewable sources [2]. The intermittent nature of wind and solar energy requires continuous adjustments to balance supply and demand.

Transmission networks are under significant strain as they transport power from regions with high renewable output to densely populated urban centers. The uneven geographical distribution of resources—with wind energy abundant in the north and high demand in the south—places considerable pressure on the existing infrastructure [4]. These challenges call for both technological upgrades and innovative operational strategies to maintain grid stability and reliability [1].

1.3 Grid Congestion Challenges in the German Power System

A critical issue emerging from Germany's energy transition is grid congestion. This occurs when transmission lines and network components are unable to handle the volume of electricity moving from generation-rich regions to high-demand areas. In Germany, the north-south divide is particularly pronounced: the north produces large quantities of wind energy, while the south hosts major industrial and urban centers requiring a consistent power supply[3].

This imbalance leads to bottlenecks within the transmission network, forcing grid operators to implement reactive measures such as redispatching conventional power plants—a costly and inefficient remedy. Additionally, traditional congestion management strategies, like curtailing renewable output, can undermine the overall objectives of the Energiewende.

Consequently, there is a growing emphasis on predictive analytics and advanced modeling techniques to forecast congestion events and manage power flows proactively. Investments in grid expansion, enhanced monitoring systems, and real-time control mechanisms are essential to ensure the infrastructure remains robust and adaptable. Addressing these challenges is crucial for realizing a sustainable and efficient future for Germany's power system.

This study is based on the work of Titz et al. (2024) [5], which investigated the key drivers and mitigators of congestion in the German power system using explainable AI techniques. Their findings provide a foundation for understanding redispatch mechanisms and congestion patterns, which are analyzed in this report using an XGBoost-based approach and SHAP values for model interpretability.

2 Key Terms and Definitions

Below are explanations of critical terms used throughout this report:

- **Grid:** The interconnected network of power generation facilities, transmission lines, substations, and distribution systems that deliver electricity from producers to consumers.
- **Congestion:** A condition where the transmission system reaches its capacity limits, causing bottlenecks that impede the smooth flow of electricity across the network.
- **Redispatch:** A process where grid operators adjust the output of power plants—by either increasing or decreasing generation—to relieve congestion and maintain grid stability.
- **Countertrading:** A market-based approach in which electricity is traded between regions or entities to balance supply and demand, thereby mitigating congestion without heavily relying on costly redispatch measures.

3 Problem Statement

3.1 Limitations of Current Reactive Methods

Current reactive methods for managing grid congestion, such as redispatch and countertrade of renewable output, are initiated only after congestion has already been detected in the power system. This approach is inherently backward-looking; it addresses issues only once they have manifested. As a consequence, the grid often operates under stressed conditions for longer periods before corrective actions are taken. Such delays can lead to increased operational costs, as power plants are required to adjust their outputs abruptly, often using fossil-fueled generators to compensate for the deficit.

Furthermore, reactive measures tend to disrupt the balance of the overall energy mix. When renewable generation is curtailed to ease congestion, it undermines the environmental goals set by the energy transition. The reliance on backup conventional generation not only increases emissions but also results in an inefficient utilization of available generation assets. This inefficiency can compromise the economic viability of renewable investments and limit the overall flexibility of the power system.

3.2 Need for Proactive Congestion Management

In contrast to reactive measures, proactive congestion management involves forecasting congestion events and implementing control strategies before critical thresholds are reached. By anticipating potential overloads, grid operators can optimize power flows in advance, reducing the need for expensive and disruptive redispatch measures. Proactive management techniques leverage advanced analytics, real-time monitoring, and predictive modeling to assess grid conditions continuously.

Proactive strategies not only improve grid reliability and stability but also support a higher penetration of renewable energy sources. By aligning power generation with anticipated demand and transmission capabilities, these methods minimize the curtailment of clean energy and contribute to a more sustainable energy mix. Moreover, early interventions enable a more balanced and efficient use of generation resources, thereby reducing operational costs and enhancing overall system performance. In a rapidly evolving energy landscape, the transition from reactive to proactive congestion management is essential for achieving both economic and environmental objectives.

4 Data and Dataset

4.1 Data Source: netztransparenz.de and Control Areas

The data used in this project primarily comes from the **netztransparenz.de** platform, where German transmission system operators (TSOs) publish extensive information on power generation, consumption, and grid operations. This data is generally available in 15-minute or hourly intervals, covering various *control areas*—geographically distinct regions, each managed by a different TSO.

These control areas form the foundation for regional analyses. Differences in generation

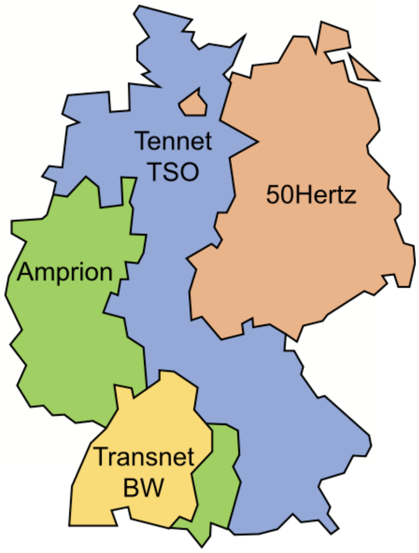

Figure 1: Control areas in Germany

and consumption structures between northern and southern Germany, as well as between rural and industrial regions, can only be properly identified when the responsibilities of different TSOs are taken into account. Recognizing these regional characteristics is crucial for pinpointing bottlenecks and overloads in the transmission network.

4.2 Description of Input Data

The model's primary input variables include both generation and consumption data, as well as price information and cross-border electricity flows. Specifically, these are:

- **Flow between neighboring countries:** Physical power flows between Germany and its neighboring countries (e.g., France, Austria, Switzerland). High cross-border flows often indicate potential network congestion, as they utilize a significant portion of the available transmission capacity.
- **Generation – Run-of-River Hydro:** Continuous electricity production from run-of-river power plants, which have limited flexibility. Although they usually provide a stable baseload, water flow variations can cause fluctuations in their output.
- **Dispatchable Generation in Binding Zones:** Controllable power plants (e.g., coal, gas, biomass) whose output can be ramped up or down in response to grid demands. These are essential for maintaining balance and mitigating congestion when renewable generation or load conditions change rapidly.
- **Generation of Solar Energy (Photovoltaics):** Solar power generation, heavily influenced by sunlight availability, which varies daily and seasonally. High solar

output can reduce reliance on conventional plants, but may also lead to overcapacity during peak sun hours.

- **Generation of Wind Energy – offshore and onshore:** Wind farms located on land (onshore) or at sea (offshore). Wind energy is highly volatile, often concentrated in coastal or high-wind areas, and its transport to demand centers (especially in southern Germany) can place significant stress on the grid.
- **Load:** Time-resolved data indicating electricity consumption in each control area. Accurate load forecasting is critical for anticipating peak demand periods and avoiding overloads on the network.
- **Price in Countries:** Spot or intraday electricity prices in different countries. Price differentials drive import and export decisions, which can increase cross-border flows and potentially contribute to network congestion.
- **Price Differences between Countries:** The extent to which electricity prices vary between Germany and its neighbors. Large discrepancies create strong economic incentives for imports or exports, leading to increased transmission utilization.
- **Residual Load:** The difference between total electricity demand and fluctuating renewable generation (primarily wind and solar). A high residual load indicates a greater need for conventional power plants, which can intensify congestion if transmission lines are already heavily used.

4.3 Target Data: Aggregated Redispatch

The central target variable in this study is the *aggregated redispatch* measure. Redispatch involves grid operators instructing certain power plants to increase or decrease their generation to maintain network stability. A **high redispatch requirement** points to frequent or severe grid bottlenecks and is often associated with significant operational costs.

By correlating the above input data (e.g., renewable generation, load patterns, price signals, and cross-border flows) with redispatch events, this analysis seeks to pinpoint the primary factors driving congestion. The ultimate goal is to help system operators and policymakers develop proactive measures that reduce the need for redispatch interventions and enhance overall grid efficiency.

5 Methodology

In this section, we describe the XGBoost model framework and the use of SHAP values for model interpretability.

5.1 XGBoost Model Framework

[6]

XGBoost is an optimized gradient boosting framework that has achieved state-of-the-art results in many machine learning tasks. In XGBoost, the prediction for an instance x_i is modeled as the sum of K regression trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F}.$$

Explanation:

– $\hat{y}_i$ is the predicted output for the ith instance.

– K is the total number of trees in the ensemble.

– $f_k(x_i)$ denotes the prediction of the kth regression tree for instance x_i.

– $\mathcal{F}$ represents the space of all possible regression trees.

Each function f_k is defined by a tree structure $q(x)$ that maps an input to a leaf index and a corresponding leaf weight w. The overall learning objective combines a differentiable loss function l with a regularization term Ω to penalize model complexity:

$$L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k).$$

Explanation:

– $L(\phi)$ denotes the overall loss function of the model (with ϕ representing the ensemble).

– n is the number of training examples.

– $l(y_i, \hat{y}_i)$ is a differentiable loss function measuring the error between the true label y_i and the predicted value $\hat{y}_i$.

– $\Omega(f_k)$ is the regularization term for the kth tree.

The regularization term is defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|w\|^2,$$

Explanation:

– γ is a regularization parameter that penalizes the number of leaves.

– T is the number of leaves in the tree.

– λ is a regularization parameter that penalizes large leaf weights.

– $\|w\|$ denotes the norm (typically Euclidean) of the vector of leaf weights w.

Training is performed in an additive manner. At iteration t, the model updates its prediction by adding a new function f_t that minimizes the following objective:

$$L^{(t)} = \sum_{i=1}^{n} l\Big(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\Big) + \Omega(f_t).$$

Using a second-order Taylor expansion, this objective is approximated as:

$$\tilde{L}^{(t)} = \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)^2 \right] + \Omega(f_t),$$

Explanation:

– $\hat{y}_i^{(t-1)}$ is the prediction for instance i at iteration $t-1$.

– $f_t(x_i)$ is the output of the new tree being added at iteration t.

– $g_i = \frac{\partial l(y_i, \hat{y}_i^{(t-1)})}{\partial \hat{y}_i^{(t-1)}}$ is the first-order gradient of the loss with respect to the current prediction.

– $h_i = \frac{\partial^2 l(y_i, \hat{y}_i^{(t-1)})}{\partial (\hat{y}_i^{(t-1)})^2}$ is the second-order derivative (Hessian) of the loss.

A crucial part of constructing f_t is determining the optimal splits in the tree. For a candidate split that partitions the data into left (I_L) and right (I_R) subsets, the gain from the split is calculated by:

$$\text{Gain} = \frac{1}{2} \left[\frac{\left(\sum_{i \in I_L} g_i\right)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{\left(\sum_{i \in I_R} g_i\right)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{\left(\sum_{i \in I} g_i\right)^2}{\sum_{i \in I} h_i + \lambda} \right] - \gamma,$$

Explanation:

– I_L and I_R are the sets of instances that fall into the left and right nodes after a split.

– I is the union $I_L \cup I_R$.

– The numerator $\left(\sum_{i \in I_*} g_i\right)^2$ represents the squared sum of gradients in a node.

– The denominator $\sum_{i \in I_*} h_i + \lambda$ adds the sum of Hessians and the regularization term.

– γ is subtracted as a penalty for adding an extra leaf.

XGBoost further includes advanced techniques such as handling sparse data, approximate split finding via weighted quantile sketch, and system optimizations (e.g., cache-aware access and out-of-core computation). These improvements enable the model to scale efficiently to billions of examples while maintaining high prediction accuracy.

5.2 SHAP Values for Model Interpretability

[7] Understanding how each feature influences the model's prediction is essential for transparency. SHAP (SHapley Additive exPlanations) values provide a principled approach for attributing the prediction difference (from a baseline) to individual features. Based on cooperative game theory, the SHAP value for a feature i is defined as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} \Big[f(S \cup \{i\}) - f(S) \Big],$$

Explanation:

– N is the set of all features used by the model.

– S is any subset of features from N that does not include feature i.

– $|S|$ is the number of features in subset S; similarly, $|N|$ is the total number of features.

– $|N|!$ denotes the factorial of the total number of features, and similarly for $|S|!$ and $(|N| - |S| - 1)!$; these factorial terms normalize the contribution.

– $f(S)$ represents the model's prediction when only the features in S are used.

– $f(S \cup \{i\})$ is the prediction when feature i is added to subset S.

– ϕ_i quantifies the contribution of feature i to the prediction.

The SHAP framework ensures that the sum of the SHAP values equals the difference between the model's prediction and the baseline expectation:

$$\sum_{i \in N} \phi_i = f(x) - \mathbb{E}[f(x)],$$

where:

– $f(x)$ is the prediction for the instance x.

– $\mathbb{E}[f(x)]$ is the expected (baseline) prediction.

SHAP values possess several desirable properties:

– **Local Accuracy:** The sum of SHAP values for all features equals the difference between the prediction and the baseline.

– **Consistency:** If a model change increases a feature's contribution for all inputs, the corresponding SHAP value does not decrease.

– **Additivity:** The model prediction can be expressed as the sum of individual feature contributions, making it straightforward to interpret.

By leveraging the tree structure in XGBoost, the Tree SHAP algorithm computes these values efficiently with polynomial time complexity. This integration allows detailed visualization (such as summary, dependence, and force plots) to explain how features drive the model's output.

6 Understanding XGBoost and SHAP with an Example

6.1 XGBoost Intuition: Predicting House Prices

To illustrate how XGBoost works, let's consider a simple example of predicting house prices based on three key features:

- **Size (m²)**: The total area of the house.
- **Rooms**: The number of rooms.
- **Location Score**: A numerical score (1–10) representing the desirability of the location.

We have the following dataset:

Size (m²)	**Rooms**	**Location Score**	**Price ($)**
100	3	8	250,000
150	4	7	300,000
200	5	9	500,000
120	3	6	200,000

Tabelle 1: Initial dataset with house prices

6.1.1 Step 1: Initial Prediction

XGBoost starts with an initial prediction, which is simply the mean of all target values:

$$\hat{y}_{\text{initial}} = \frac{250,000 + 300,000 + 500,000 + 200,000}{4} = 312,500$$

This value is assigned as the first prediction for all houses.

6.1.2 Step 2: Residual Calculation

The residual is the difference between the actual price and the predicted value:

Size (m^2)	**Rooms**	**Location Score**	**Price (\$)**	**Residual (\$)**
100	3	8	250,000	-62,500
150	4	7	300,000	-12,500
200	5	9	500,000	187,500
120	3	6	200,000	-112,500

Tabelle 2: Residuals after initial prediction

6.1.3 Step 3: Decision Tree on Residuals

A decision tree is trained to learn from the residuals. Suppose it makes the following split:

- If Location Score $<$ 8.5, predict -62,500.
- If Location Score 8.5, predict 187,500.

6.1.4 Step 4: Updating Predictions

The new prediction is calculated by adding a fraction of the tree's output to the previous prediction. Assuming a learning rate of 0.1:

$$\hat{y}_{\text{new}} = \hat{y}_{\text{old}} + 0.1 \times \text{Tree Output}$$

After one iteration, predictions update as follows:

Size (m^2)	**Rooms**	**Location Score**	**Price (\$)**	**New Prediction (\$)**
100	3	8	250,000	306,250
150	4	7	300,000	300,625
200	5	9	500,000	348,125
120	3	6	200,000	306,250

Tabelle 3: Updated predictions after first iteration

The process repeats for more trees until convergence, reducing errors with each step.

6.2 SHAP: Explaining Predictions

XGBoost is highly effective, but it behaves as a "black box." To explain its predictions, we use SHAP (SHapley Additive exPlanations).

6.2.1 SHAP Value Analogy: Sharing a Pizza

SHAP is based on cooperative game theory. Imagine splitting a pizza among friends:

- The pizza is the model's prediction (e.g., $300,000 for a house price).
- The friends are input features (Size, Location, Rooms).
- SHAP determines how much of the pizza each feature deserves.

6.2.2 How SHAP Works

SHAP starts with a baseline prediction, which is the average value of the target:

$$\text{Baseline} = \mathbb{E}[\hat{y}]$$

Then, it adds features one by one and checks how much each improves the prediction.

- If adding Size increases the prediction by $50,000, then SHAP(Size) = 50,000.
- If Location Score increases it by $30,000, then SHAP(Location) = 30,000.

6.2.3 Why SHAP is Important

- Trust the Model: SHAP provides transparency by showing feature contributions.
- Debugging: If a model makes incorrect predictions, SHAP helps identify problematic features.
- Explainability: Helps interpret model decisions for business or regulatory requirements.

7 Results and Discussion

This section presents the evaluation of the XGBoost predictive model, its performance metrics, feature importance using SHAP values, and implications for congestion management in the German power grid.

7.1 Model Performance Evaluation

The performance of the XGBoost model was evaluated using four key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). The results are as follows:

- **Mean Squared Error (MSE)**: 151043.48

- **Root Mean Squared Error (RMSE)**: 388.68
- **Mean Absolute Error (MAE)**: 259.27
- **Coefficient of Determination** (R^2): 0.64

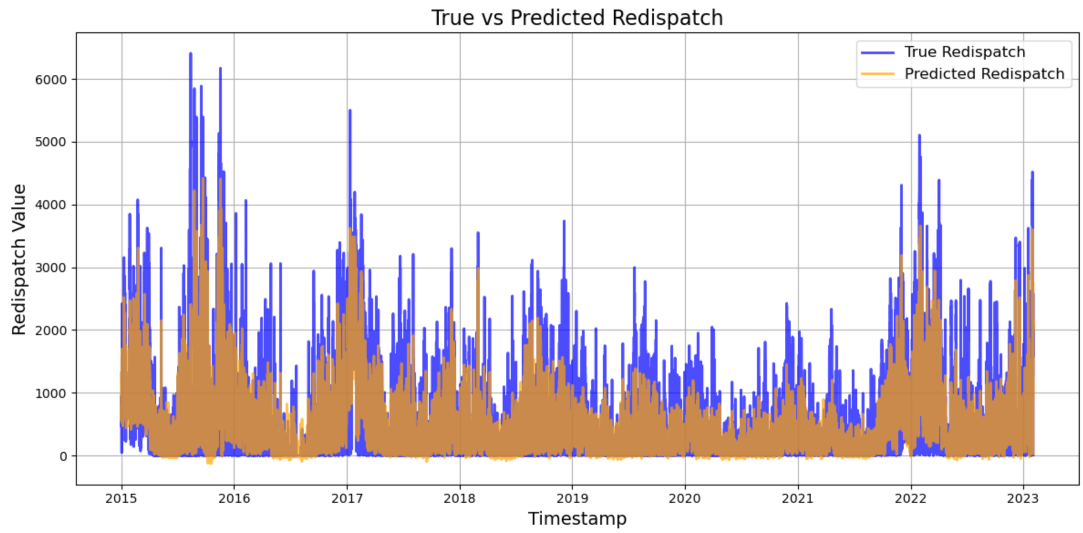

Figure 2: True and Predicted redispach

The MSE and RMSE values indicate the magnitude of errors in the model's predictions. The RMSE of 388.68 suggests that, on average, the predicted redispatch values deviate from the actual values by approximately 389 MW. Since RMSE is in the same unit as the target variable, it provides a clear measure of error magnitude.

The MAE value of 259.27 MW shows the average absolute difference between predicted and actual redispatch values. Compared to RMSE, the lower MAE suggests that large errors are relatively infrequent.

The R^2 score of 0.64 indicates that 64 % of the variance in redispatch values can be explained by the model. While this shows a moderate level of explanatory power, it also suggests that additional factors not included in the dataset might contribute to redispatch variations.

7.1.1 Analysis of Model Performance

The results demonstrate that the model is reasonably effective in predicting redispatch volumes but has some limitations:

- The MSE and RMSE values remain relatively high, indicating that while the model captures general redispatch trends, deviations from actual values can still be significant.

- The R^2 score of 0.64 suggests that while the model explains most redispatch fluctuations, there are external factors influencing redispatch that are not fully accounted for.

- The MAE is lower than RMSE, which suggests that most errors are moderate, but a few large prediction errors may increase RMSE.

7.1.2 Potential Improvements

To improve model accuracy and better explain redispatch variability, the following enhancements could be considered:

- **Incorporating additional features:** Including more variables such as real-time power grid congestion indicators, renewable generation curtailment measures, and weather conditions could improve predictive performance.

- **Refining feature engineering:** Applying advanced feature selection techniques or creating additional engineered features (e.g., lagged variables, interaction terms) may help capture more complex relationships.

- **Hyperparameter optimization:** Further fine-tuning of XGBoost hyperparameters such as the learning rate, max depth of trees, and boosting rounds could help enhance accuracy.

- **Ensemble modeling:** Combining XGBoost with other models (e.g., LSTM networks for time-series forecasting or ensemble approaches) may further improve performance.

7.2 Conclusion on Model Performance

Overall, the model provides valuable insights into redispatch patterns and achieves moderate predictive accuracy. While further refinements could improve its reliability, the results already highlight key congestion drivers and mitigation opportunities, reinforcing the importance of predictive analytics in power grid operations.

7.3 Feature Importance and SHAP Summary

To understand congestion drivers, SHAP values were used to measure feature contributions.

7.3.1 Key Feature Importance Rankings

The SHAP summary plot (Figure 5) reveals:

- **Run-of-river hydro generation** in Amprion and TransnetBW regions has the highest impact on redispatch volumes.
- **Wind power generation (50Hertz control area)** is a major congestion driver.
- **Day-ahead electricity prices in Austria and Switzerland** significantly influence redispatch.
- **Dispatchable generation in Amprion and TenneT** plays a role in congestion mitigation.
- **Load variations in Amprion and TenneT** are also key factors.

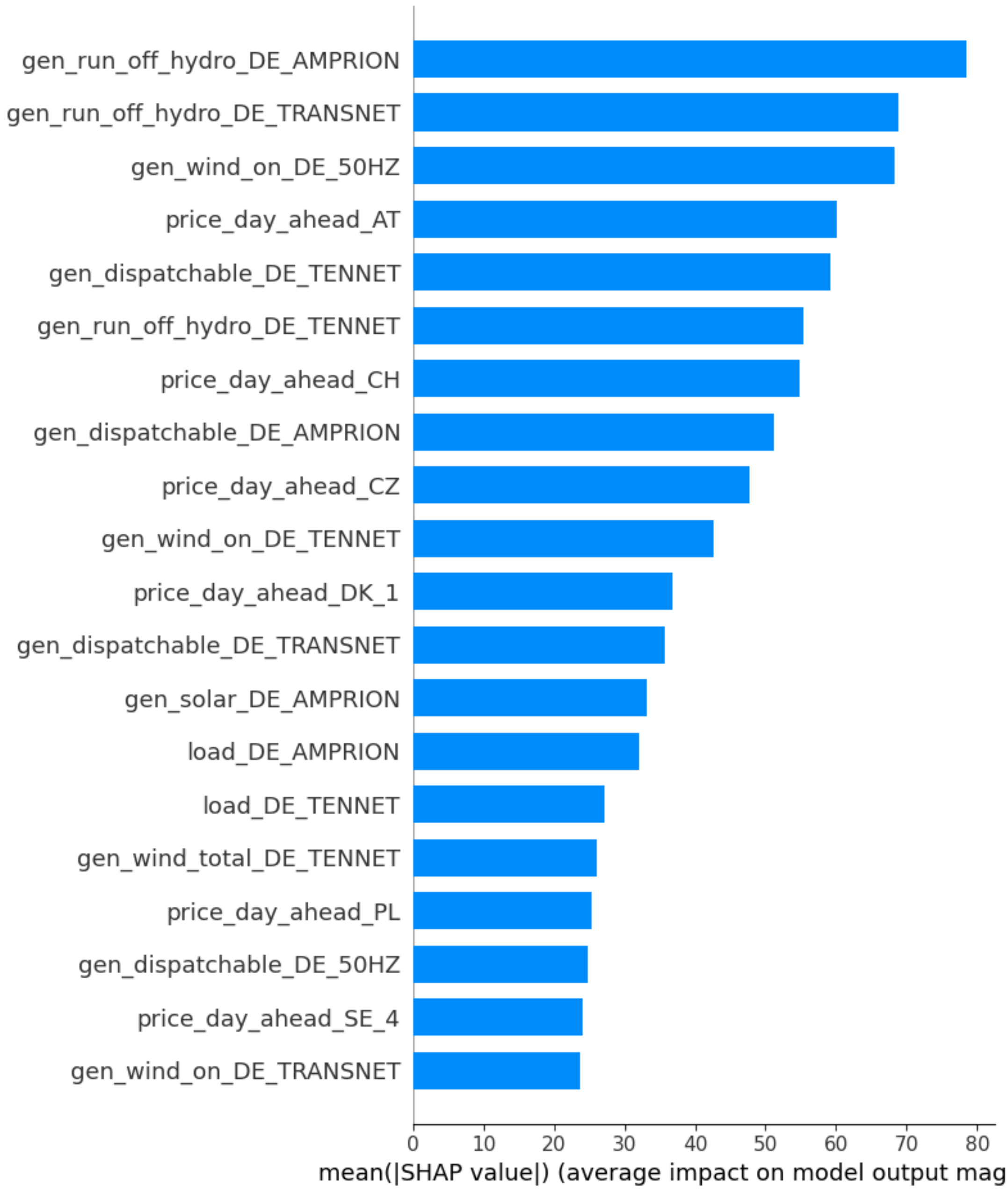

Figure 3: Feature Importance: Mean SHAP Values

7.3.2 SHAP Dependence Analysis

The SHAP dependence plot (Figure 4) shows:

- High wind power generation increases redispatch requirements.
- Run-of-river hydropower can mitigate or contribute to congestion, depending on the grid conditions.
- Electricity price differences across borders affect redispatch volumes.

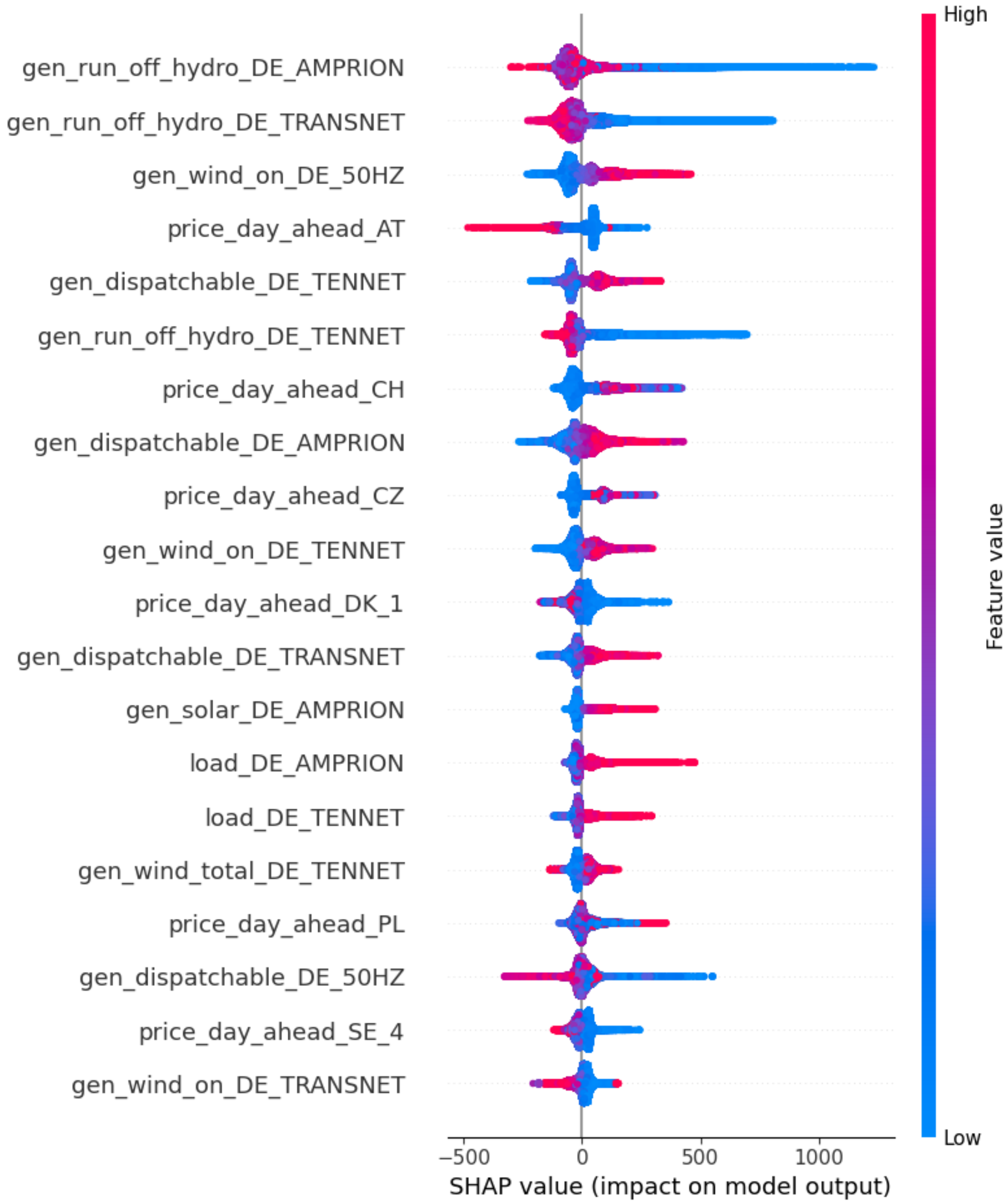

Figure 4: SHAP Dependence Plot: Feature-Wise Impact on Redispatch

7.4 Discussion of Findings and Implications for Grid Management

7.4.1 Proactive Congestion Management Strategies

The results indicate a need for proactive redispatch strategies due to intermittent renewable energy and cross-border influences. Some key strategies include:

- Hydropower coordination: Run-of-river hydro can help reduce redispatch costs if better integrated into grid operations.

- Wind curtailment strategies: Wind generation in 50Hertz and TenneT causes congestion, requiring localized curtailment measures.
- Cross-border congestion pricing: Dynamic pricing mechanisms could help redirect power flows to prevent overloads.

8 Comparison of Results with Existing Literature

8.1 Model Performance and Accuracy

In my study, I employed an XGBoost-based predictive model to estimate redispatch volume in the German transmission grid, using SHAP values for interpretability. The model achieved moderate predictive performance, with key metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 indicating a reasonable ability to predict redispatch values. The True vs. Predicted Redispatch plot (Fig. 4) demonstrates the model's capability to capture redispatch patterns over time, though with some variance.

The results differ from those in the study by Titz et al. (2024) [5], where a gradient-boosted trees model was used to predict redispatch volumes based on renewable generation, cross-border flows, and price differences. Their model achieved an R^2 score of 0.74 in cross-validation and up to 0.92 when retrained on the full dataset, whereas my model obtained an R^2 score of 0.64. This suggests that while both models capture key congestion drivers, my model explains a smaller portion of the variance in redispatch.

Several factors may explain the differences in model performance:

- **Hyperparameter tuning and model complexity:** The XGBoost model in this study may not be optimized to the same extent as in Titz et al., where more aggressive hyperparameter tuning could have led to better performance.
- **Differences in evaluation strategy:** While Titz et al. reported cross-validation scores and retraining results, my study focuses on general predictive accuracy. If their final R^2 score of 0.92 was obtained on the full dataset without strict train-test separation, this could explain the apparent performance advantage.

8.2 Feature Importance and SHAP Analysis

Feature importance analysis in my study identified run-of-river hydro generation in Amprion and TransnetBW as the most significant predictors of redispatch. Wind power generation in the 50Hertz control area and cross-border electricity prices also exhibited strong influences. This ranking is consistent with Titz et al. (2024), who found that wind power in Northern Germany was the most significant driver of congestion, while run-of-river hydro power in the Alpine region played a mitigating role.

My SHAP summary plots (Fig. 5) confirm that:

- High wind power generation in the north exacerbates congestion.
- Hydropower generation in southern Germany helps reduce congestion.
- Cross-border electricity trading, particularly with Denmark and Austria, plays a crucial role in congestion patterns.
- Solar power has a minimal effect on redispatch volumes, as also suggested in the seminar paper.

These findings confirm that renewable generation patterns and international electricity trading significantly impact congestion, reinforcing the conclusions drawn in prior research.

8.3 Differences in Findings and Implications

While my study and Titz et al. (2024) agree on the major congestion drivers, some differences exist:

1. Hydropower Influence: My analysis suggests that run-of-river hydro power has an even stronger congestion-mitigating effect than previously thought. This could indicate a need for better integration of hydropower into congestion management strategies.
2. Cross-Border Trading: The impact of cross-border trading with Austria and Switzerland appears less significant in my model compared to their findings, possibly due to differences in dataset preprocessing.
3. Redispatch Cost Trends: The seminar paper highlights the rising costs of congestion management, estimated at €2.3 billion in 2023. My study focuses more on redispatch volume rather than costs, suggesting that future work should incorporate economic analysis.

Overall, my findings reinforce the need for proactive congestion management and market design improvements to enhance grid stability.

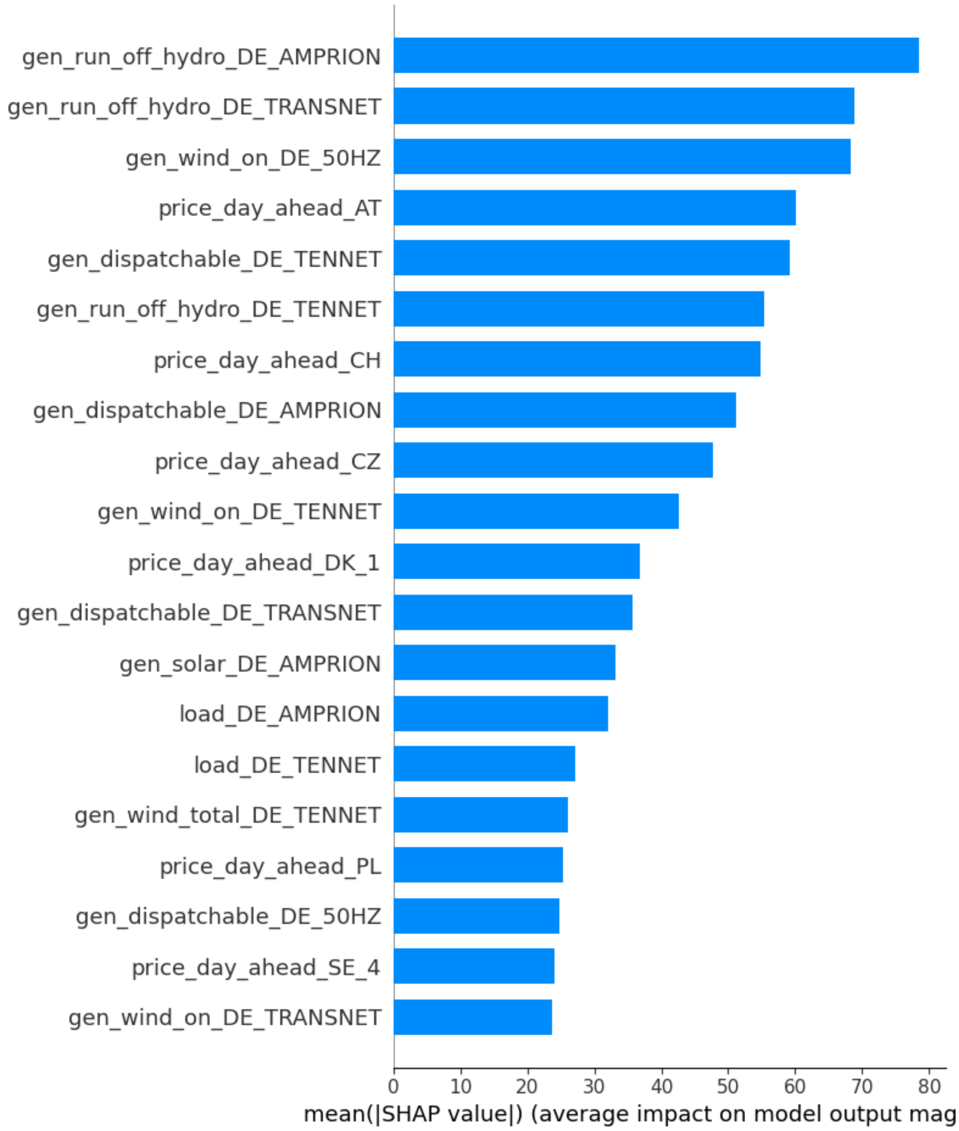

Figure 5: SHAP value summary plot: Feature impact on redispatch predictions

9 Conclusion and Recommendations

9.1 Summary of Key Findings

This study investigated the application of machine learning techniques, specifically XG-Boost, for predicting redispatch volumes in the German power grid. The key findings can be summarized as follows:

- The model achieved a coefficient of determination (R^2) of 0.64, indicating moderate predictive power, with an RMSE of 388.68 MW and an MAE of 259.27 MW.
- Feature importance analysis using SHAP values identified that run-of-river hydro generation, wind power generation (especially in the 50Hertz and TenneT control areas), and cross-border electricity prices significantly impact redispatch volumes.

- While the model successfully captured redispatch trends, residual errors suggest that additional factors such as grid congestion indicators, real-time weather patterns, and market behavior could improve predictive accuracy.
- The comparison with previous research (e.g., Titz et al., 2024) confirmed that wind power remains the primary congestion driver, while hydro generation has a mitigating effect, reinforcing the importance of regional flexibility in congestion management.

The results highlight the potential of machine learning models in congestion forecasting, but also underscore the need for further refinements to enhance model robustness and interpretability.

9.2 Future Work and Recommendations for Proactive Congestion Mitigation

Based on the findings, several directions for future research and grid management improvements can be proposed:

- **Enhancing Data Availability:** The predictive accuracy of congestion models could be improved by incorporating additional data sources, such as real-time transmission line capacities, power flow constraints, and dynamic congestion pricing signals.
- **Advanced Machine Learning Techniques:** Exploring deep learning models (e.g., LSTMs, transformer-based architectures) for time-series congestion prediction could improve the model's ability to capture long-term dependencies and sudden grid disturbances.
- **Integration of Market-Based Mechanisms:** Since electricity market behavior influences congestion, integrating bidding zone price differences, reserve market participation, and dynamic grid tariffs into the model could enhance its practical applicability.
- **Hybrid Approaches for Grid Management:** Combining predictive analytics with optimization-based congestion management strategies (e.g., reinforcement learning for redispatch scheduling) could create a more robust congestion relief framework.
- **Cross-Border Coordination:** Given the impact of international power exchanges, increased collaboration among European TSOs (Transmission System Operators) for data-sharing and real-time congestion forecasting is recommended to minimize redispatch costs.

- **Regulatory and Policy Considerations:** The study's findings highlight the need for regulatory adjustments to facilitate market-based congestion management solutions while ensuring grid stability. Future work could explore policy scenarios for incentivizing decentralized congestion relief strategies.

9.3 Final Remarks

Machine learning-based congestion forecasting presents a promising approach to enhancing grid stability and reducing redispatch costs. While the current model provides valuable insights, future research should focus on integrating additional data sources, improving model interpretability, and combining machine learning with market-driven congestion mitigation strategies. A proactive, data-driven congestion management approach will be essential to achieving a resilient and cost-efficient energy transition.

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