Econometric Game

Team 1

April 2025

1 Introduction

Recent focus on a transition towards renewable energy sources leads to the changing structure of the energy sector. Renewable sources are very geographically dependent, and high-energy potential areas might not coincide with high industry areas, which are those with the highest energy demand. The case of Germany is a textbook example of this issue: the industrial center of the country is the South, whilst, in the North, a big portion of the energy is produced, due to wind power. In addition, nuclear energy has been stopped, leading to an even greater dependence on sources that are not located in the South.
Furthermore, a particularly important, and potentially problematic, feature of renewable energy sources is their intermittence, and dependence on their sources, that are by definition of varying intensity. Indeed, this complicates the prevision of power supply on a day-ahead basis, and may lead to unanticipated changes in power supply. As a result of this expansion of renewable energy sources, congestion risk is expected to increase dramatically in the coming years, being potentially multiplied by six by 2040 (European Commission Joint Research Center, 2024).

Problem: The mismatch between the high energy supply and high energy demand areas, which leads to congestion, and often to redispatch measures, taken to relieve these congestion episodes. The main issue with redispatch is its high incurred costs, which are eventually reflected onto consumer prices.

Research question and objectives: The purpose of this study is to, first of all, determine the driving factors behind redispatching, in order to then determine a possible course of action which would deal with this issue more efficiently. Then this allows us to propose interpretation of these evidences and useful policy recommendations to mitigate this rising issue.

The rest of this paper proceeds as follows : Section 2 describes and dives into data from the German TenneT DE network, to identify main trends and key determinants of redispatch. Section 3 then introduces the methodology and models used in order to forecast redispatch probablility, which results are presented in Section 4. Eventually, Section 5 is dedicated to discussing the main results and its economic and policy implications.

2 Data Description

The used dataset contains redispatch data along with weather, electricity and market data, from the German TenneT DE network. It contains hourly data on upward and downward redispatch, from January 1, 2020 to July 31, 2023. This represents a total of 1,308 days and therefore 31,392 observations (15,696 for each direction of redispatch).

Summary statistics

First of all, we can display and study a set of summary statistics. We split them into three categories, to study them in the sample of observations without redispatch, with down redispatch and with upward redispatch. This allows us to see some first striking differences between those groups. In particular, wind power or day-ahead electricity price seem to be significantly different between these groups, and associated with more redispatch, be it downward or upward. This gives us a first light as to which elements to include in our forecasting model, and in our analysis of the determinants of congestion and redispatch.

Seasonality and Auto-correlation analysis

A quick look at redispatch data shows that it displays significant hourly variations as well as seasonality. This makes sense as redispatch are associated to demand/supply short-term and usually unexpected mismatch, which is likely to be associated with supply or demand shocks, that may be highly seasonal in the case of electricity consumption. This can be particularly seen in Figure 1.
There appears to be both hourly and monthly seasonality. Nevertheless, if informative, such figures cannot tell us everything of the seasonality and underlying trends in

Table 1: Summary Statistics by Redispatch type

Variable	**No redispatch**		**Redispatch down**		**Redispatch Up**	
	Mean	SD	Mean	SD	Mean	SD
Wind speed	3.09	1.12	3.79	1.55	3.80	1.55
Sun duration	13.14	17.74	12.98	17.80	12.43	17.41
Air temperature	10.41	7.12	9.56	7.19	9.44	7.11
Price CH	121.11	134.14	157.60	130.17	157.94	129.55
Price CZ	119.46	131.38	136.94	119.63	136.73	118.85
Price Be	117.35	124.81	139.99	120.64	140.04	119.80
Price NL	117.62	123.00	137.53	117.94	137.46	117.21
Price PL	100.90	71.00	114.34	72.38	114.59	72.55
Price AT	122.31	130.78	147.60	124.27	147.55	123.65
Price DE	119.47	126.81	130.71	119.45	130.32	118.63
Consumption forecast	11171.61	477.41	11177.32	552.55	11179.36	558.46

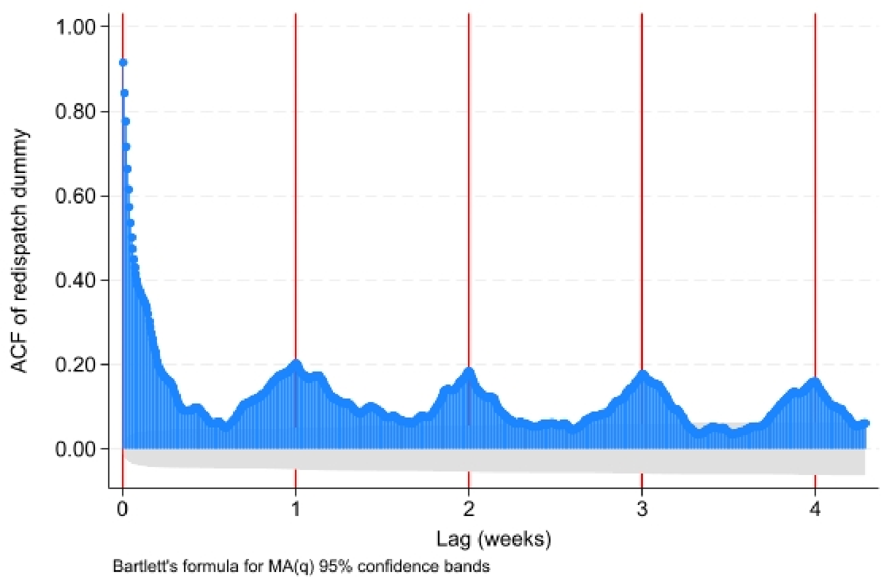


Figure 1: ACF of redispatch dummy, over a month

our observed data. To go further let us proceed to auto-correlation analysis. Figure 1 displays the auto-correlation function (ACF) of a dummy for redispatch. It features a clear auto-correlation on a weekly basis, indicating seasonality based on the day in the week. We also observe daily seasonality, repeated at a 24-hour horizon. This also indicates that forecasting model should take care of this important seasonality component.

SARIMA : Using SARIMA analysis, we perform a seasonal ARMA regression, allowing us to study both the persistence and auto-correlation of redispatch, as well as its seasonal component on a daily basis (ARMA24).

Table 2: ARMA Regression on Redispatch Dummy

	(1)
	Redispatch dummy
ARMA	
AR	0.903***
	(117.24)
MA	-0.0103*
	(-2.01)
ARMA24	
AR	0.0483***
	(12.70)
MA	-0.996***
	(-1417.28)
sigma	
_cons	0.182***
	(232.31)
N	31368

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The first coefficient on ARMA, studying the hourly persistence of redispatch, is very highly signficiant, around 0.9, implying a 90% persistence. This is a sign of high hourly persistence, that needs to be taken into account, through lag dispatch dummy variables.

3 Methodology

The modeling approach follows a supervised learning paradigm, where the objective is to predict the likelihood of congestion events occurring separately for UP and DOWN directions on an hourly basis. A key assumption underlying our modeling approach is that congestion events are not only influenced by historical congestion but also by external factors such as grid load, market prices, and weather conditions. Therefore, our model incorporates both time-based features (e.g., hour of the day) and lagged features to account for temporal dependencies.

We chose to use Random Forest Classifiers for modeling due to their ability to handle non-linear relationships and interactions between the features without requiring feature scaling. This decision is based on the assumption that the relationships between congestion and explanatory features are complex and non-linear, making tree-based models particularly suitable.

We train the model separately for the UP and DOWN directions. This separation allows the model to capture direction-specific behaviors and potentially improve the predictive performance, as factors influencing UP congestion may differ from those influencing DOWN congestion. This approach also helps mitigate the risk of averaging out important direction-specific information in a single model.

Additionnaly, we create four groups to take into account the different patterns that could arise through the day. This allows us to break down the results into sub-periods and analyse them at a different scale, for robustness.

As we will see, important factors seems to be the same across periods and across direction. In the following section, we will only display the resutls for "down". The results for "up", can be found in appendix.

Rolling Window Approach

A crucial aspect of our methodology is the use of a rolling window for training and testing the model. We divide the dataset into a training period from January 1, 2020, to June 30, 2022, and a testing period from July 1, 2022, to December 31, 2022. To ensure that the model can generalize to unseen data and adapt to changes over time, we implement a rolling window cross-validation strategy, where the training window slides forward by a fixed number of days (in this case, 180 days) for each iteration.

This approach allows the model to continuously update its knowledge based on the most recent data, making it more adaptable to changes in grid behavior over time. It also provides a realistic evaluation of the model's performance in predicting future congestion events, which is essential for operational deployment in a real-world setting.

The rolling window approach helps address the assumption that grid conditions evolve over time due to changing weather patterns, energy demand, and market dynamics. By updating the model regularly, we aim to mitigate the risk of overfitting to outdated patterns and ensure that the model can capture evolving congestion trends.

Prediction and Threshold Selection

Once the model is trained using the rolling window technique, we predict the probability of congestion occurring for each hour in the test set. The model outputs continuous predicted probabilities, which must be converted into binary classifications (congestion or no congestion). To make this conversion, we apply a threshold on the predicted probabilities. The threshold is optimized using the F1 score, which is the harmonic mean of precision and recall. This choice is motivated by the need to balance the false positive and false negative rates, especially given the potentially imbalanced nature of congestion events.

The optimal threshold is determined by maximizing the F1 score across different threshold values. This ensures that the threshold is selected to provide the best balance between precision and recall, which is critical in predicting congestion events accurately without underestimating or overestimating their occurrence.

	(1)
	Redispatch dummy
Day ahead price (DE & L)	-0.0170***
	(0.00109)
Wind speed	4.435***
	(0.867)
Sunshine duration	8.83e-05
	(0.000649)
Air temperature	-0.00557***
	(0.00164)
Wind velocity Bayern	-2.098***
	(0.375)
Constant	-0.808***
	(0.230)
Observations	62,784

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Logit regression of the redispatch dummy

4 Empirical Results

First of all, and in order to gain some additional insights into the drivers and determinants of redispatch, we use a logit regression of a redispatch dummy on a set of controls. Only the most important and significant of them are displayed in the following table.

One very striking result is that redispatch, which is largely associated with the use of renewable energy sources, is in a large part dependent on wind power, much more than Solar PVs. Especially, the wind velocity in Bayern, which is very industry-intensive, decreases a lot the redispatch likelihood, underlining the importance of geographical granularity and specific measures. This logit regression then also helps us understanding what are the main elements to include in our forecasting model.

RandomForest Results

Figure 2 displays the normalized feature importances for the model across different time periods of the day: Night, Morning, Afternoon, and Evening. The plot shows how important each feature is for the prediction of congestion events at different times of the day.
It is evident that some features, like `rolling_congestion_3h`, play a dominant role in all time periods, with significantly higher normalized importance values compared to other features. This indicates that recent congestion history is a strong predictor of future congestion events, regardless of the time of day. Other features, such as wind speed and market prices (e.g., `electricity_day_ahead_price_ch`), contribute less to the prediction and show consistent, but seems less important across all time periods.

The results also suggest that while the relative importance of features is somewhat consistent, there are subtle variations across the time periods. For example, during the Evening and Morning periods, the importance of the wind speed features appears to be higher than during other periods. This may reflect a time-dependent relationship between wind conditions and congestion events, likely due to varying grid behaviors during these periods.

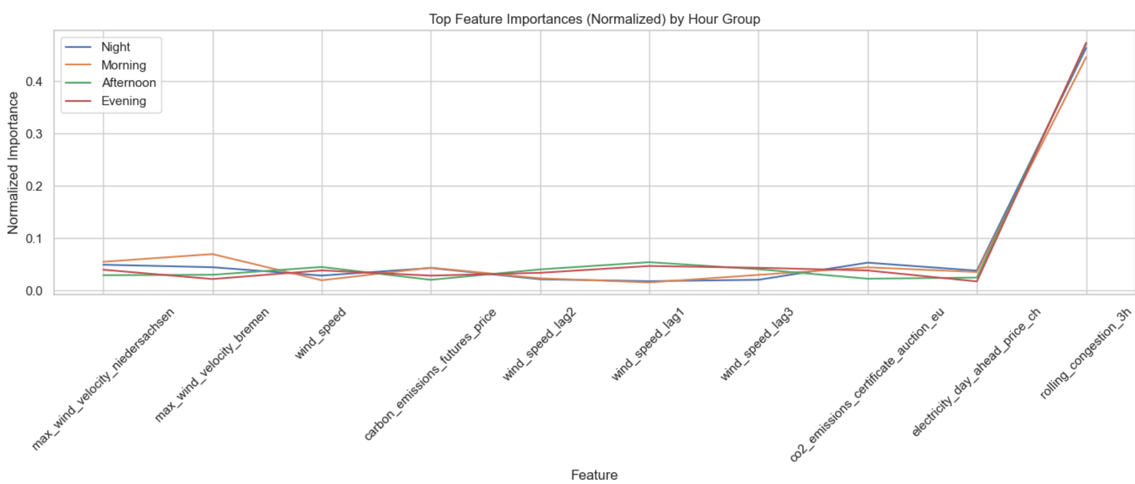


Figure 2: Top Feature Importances (Normalized) by Hour Group

Figure 3 compares the predicted probabilities of congestion (`predicted_prob`) with the actual observed congestion (`congestion_down`) for each hour of the day. The plot clearly shows that the predicted probabilities are consistently high, with the model predicting a congestion probability close to 0.8 for most hours. This suggests that the model has learned to predict congestion events with high confidence, but it also highlights the challenge of handling the imbalanced nature of the congestion events, where non-congestion events dominate.

The figure 3 indicates that the model generally performs well in terms of probability prediction, with the predicted probabilities closely aligning with the actual congestion occurrences. However, the predicted probabilities remain relatively constant throughout the day, which could suggest that the model is overly confident about congestion events happening at a constant rate across all hours. This uniformity in predictions may be indicative of an area for further model refinement, possibly through incorporating additional time-dependent features or considering the temporal clustering of congestion events.

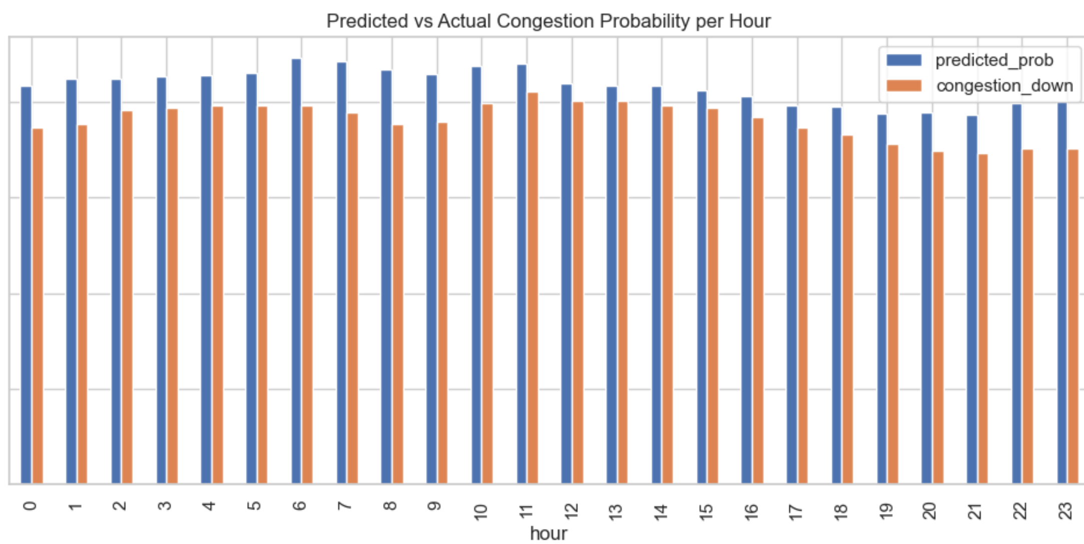


Figure 3: Predicted vs Actual Congestion Probability per Hour

Robustness chekcs

The model's performance is evaluated using a variety of standard classification metrics, including accuracy, precision, recall, and F1 score. These metrics provide a comprehensive assessment of the model's ability to correctly classify congestion events.

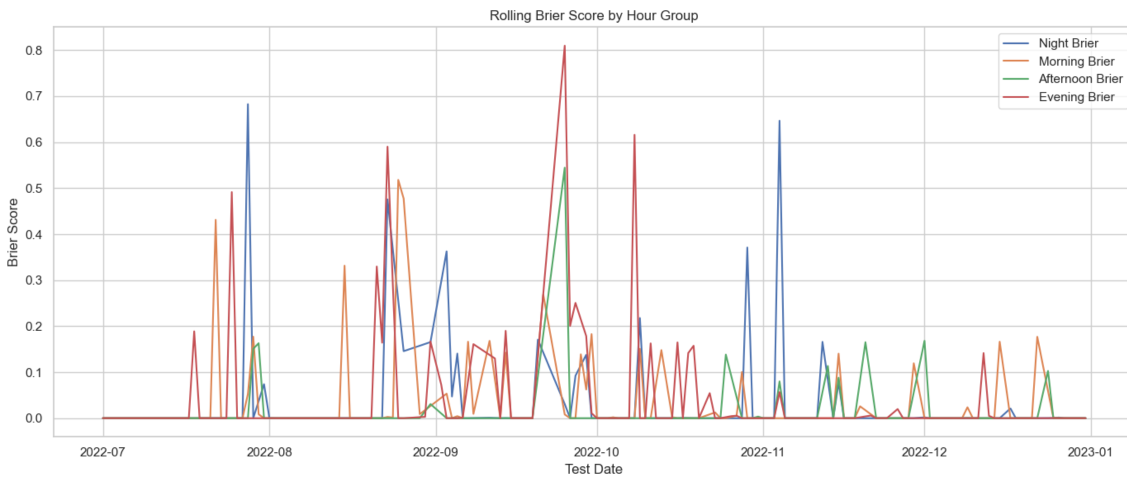


Figure 4: Brier Scores

In addition, we use the Brier score loss, which measures the mean squared difference between the predicted probabilities and the actual outcomes. A lower Brier score indicates better-calibrated predictions.

We also compute the confusion matrix, which gives us a detailed breakdown of the true positives, false positives, true negatives, and false negatives. This helps in assessing the model's ability to correctly predict both congestion and non-congestion events, providing further insight into its performance.

Rolling Window

The figure above presents the rolling Brier score for each hour group—Night, Morning, Afternoon, and Evening—over the test period from July 2022 to January 2023. The average Brier scores and log losses for each group provide insights into how well the model performed during different times of the day.

- The **Night** group, with an average Brier score of 0.0267 and an average log loss of 0.1177, shows relatively stable performance with low error rates.
- The **Morning** group has a slightly higher average Brier score of 0.0277 and log loss of 0.1121, indicating a marginal increase in prediction errors during the early part of the day.

- The **Afternoon** group has the lowest average Brier score of 0.0117 and log loss of 0.0426, suggesting that the model performs best in predicting congestion during this time.
- The **Evening** group, with the highest average Brier score of 0.0374 and log loss of 0.1562, exhibits the most significant prediction errors, possibly due to increased variability or a higher occurrence of congestion events during this period.

These results highlight that the model is most accurate during the afternoon and less effective during the evening, possibly reflecting changes in grid behavior and demand during these periods.

5 Discussion and Economic Interpretation

These findings are important in the sense that they allow one to get a better understanding of the drivers of grid congestion and costly redispatch. This has important real-world implications, that will lead to policy recommendations later on.
First, our findings go in line with earlier research, suggesting that wind power generation (particularly in the North of Germany) is a main driver of transmission grid congestion (Titz et al. 2024). Similar results exist for countries such as Denmark, Spain, or Sweden. More generally, it is now stringent that congestion depends on electricity supply uncertainty and variability, which is reinforced by the rapid and significant turn towards massive adoption of renewable power sources.
The positive link between day-ahead electricity price and redispatch can also be understood and explained through the lens of economic theory. Indeed, higher day-ahead prices may be a signal of supply and demand mismatch, and of resulting tensions on the electricity market. As a result, such tensions,and potential subsequent congestion of transmission lines, may lead to redispatch. Policymakers should take particularly care of that aspect, as day-ahead prices may then react to costly redispatch. In this case, a loop effect would arise, amplifying congestion and eventually redispatch expenses and losses for all actors, through the mutually reinforcing responses of redispatch and day-ahead electricity prices. This point naturally leads us to a set of important policy-recommendations implied by our findings.

Policy recommendations

As a result of the findings presented above, we finally propose a mix of policy recommendations that should help policy-makers reacting to and alleviating congestion

and redispatch. We have seen that both supply and demand sides may affect congestion and lead to redispatch. A set of measures can be taken, to adress both of these aspects, as well as their matching.
First, it is essential to better match supply and demand, meaning that precise information on available supply, at **hourly** basis needs to be made available and studied both by policymakers and electricity market regulators and suppliers. Using that, consumption should be then adapted, which could go through incentive programs. For instance, households electricity consumption should be directed, as much as possible, towards hours when there is excess supply, rather than hours of overconsumption. This can be done through incentives such as hour-specific electricity price (as is already done by some electricicity suppliers in countries like France). The same can be done for industries, together with measures accompanying the installation of new firms and plants in regions that are the better-equipped in terms of electricity production, to avoid worsening the imbalance that is currently observed in the central German network.
One part of the problem is renewable production intermittence, which calls for diversificiation of energy sources, as is often adovcated for. Importantly, another is transmission grid constraint. Indeed, one important reason for redispatch is avoiding overloading the transmissions grid system. The European Commission Joint Research Center mentions that "up to 310 TWh of renewable generation could be curtailed due to limitations in the grid in 2040 in a business-as-usual grid expansion scenario". As a result, two important policy implications appear stringently :

- Increasing transmission grid capacity appears to be urgent, especially in areas that are very renewable-energy-intensive.
- Then, the type of security constraint in usage appear to be a driver of congestion and increasing redispathcing expenses (Van den Bergh et al. 2015). For instance, using a curative N-1 rather than preventive N-1 secure system, may drastically reduce redispatch expenses[1]. This has to be regarded seriously by policymakers, and asses to find the best balance between grid security and economic viability.

Because of limited capacity and transmission grid constraints, it is important to internalize the location and geographical dimensions in the construction and installation of new renewable energy power plants. Indeed, it is crucial to account for the

[1]As but by Van den Bergh et al. : "In a curative N-1 secure system, the economic dispatch of conventional units and the curtailment of renewables can be changed after the line contingency occurred. In a preventive N-1 secure system, a line contingency has to be passed without changing the economic dispatch or curtailment."

geographical mismatch between electricity production and demand, which translates into a North-South imbalance in the case of the TenneT DE network. This calls for reducing the imbalance between production and consumption regions, and potentially bettering the integration to other electricity markets, potentially by enlarging the network, to include a wider area, eventually to neighboring countries such as Austria or Czech Republic.

6 Conclusion

In this study we have been able to forecast accurately the redispatch events in the German TenneT DE network. Using extended random forest techniques we managed to predict it in a very efficient way. Along with other econometric tools, such as logit regression, we managed to identify key determinants of such events, among which wind speed and day-ahead electricity prices. We also uncovered key features and patterns of redispatch, including its strong seasonality. This led us to propose key policy recommendations aimed at helping policy-makers adress this pressing issue.
Future research should try to gain advantage of more precise and granular databases, with geographical variables, allowing one to get a more precise understanding of the forces at play and the spatial imbalances of the electricity transmission grid.

7 References

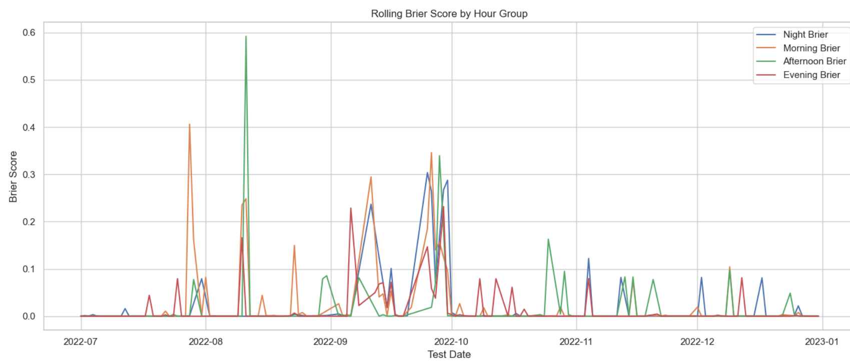
Council of European Energy Regulators, *Redispatching Arrangements in Europe against the Background of the Clean Energy Package Requirements*, 2021.

European Commission and Joint Research Centre (Thomassen, G. and Fuhrmanek, A. and Cadenovic, R. and Pozo Camara, D. and Vitiello, S.), "Redispatch and congestion management – Future-proofing the European power market". *Publications Office of the European Union*, 2024.

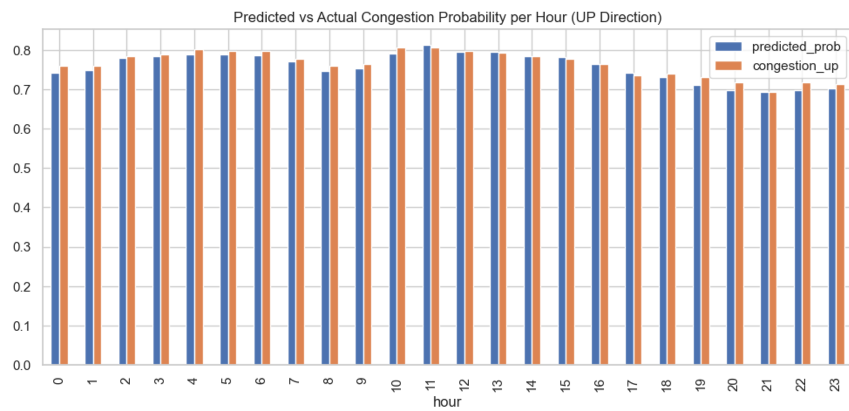
Maurizio Titz and Sebastian Pütz and Dirk Witthau. "Identifying drivers and mitigators for congestion and redispatch in the German electric power system with explainable AI", *Applied Energy*, 2024.

K. Van den Bergh and D. Couckuyt and E. Delarue and W. D'haeseleer. "Redispatching in an interconnected electricity system with high renewables penetration", *Electric Power Systems Research*, 2015.

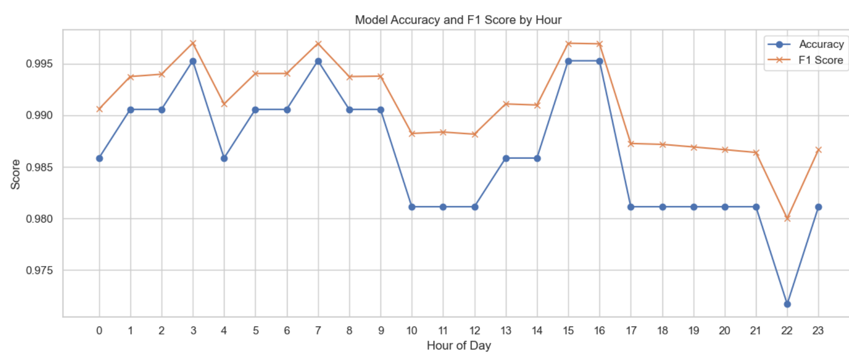
8 Appendix



Rolling Brier Score by Hour Group
Night Brier
Morning Brier
Afternoon Brier
Evening Brier
Brier Score
Test Date



Predicted vs Actual Congestion Probability per Hour (UP Direction)
predicted_prob
congestion_up
hour



Model Accuracy and F1 Score by Hour
Accuracy
F1 Score
Score
Hour of Day