Assessing the Impact of Renewable Energy Growth on Electricity Prices

Project Report By Group 26

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Introduction and Business Problem

What is the impact of increased renewable energy adoption on electricity price in Finland?

Renewable energy adoptation in Finland has grown in recent years and set to cover 60 % of total production by 2030

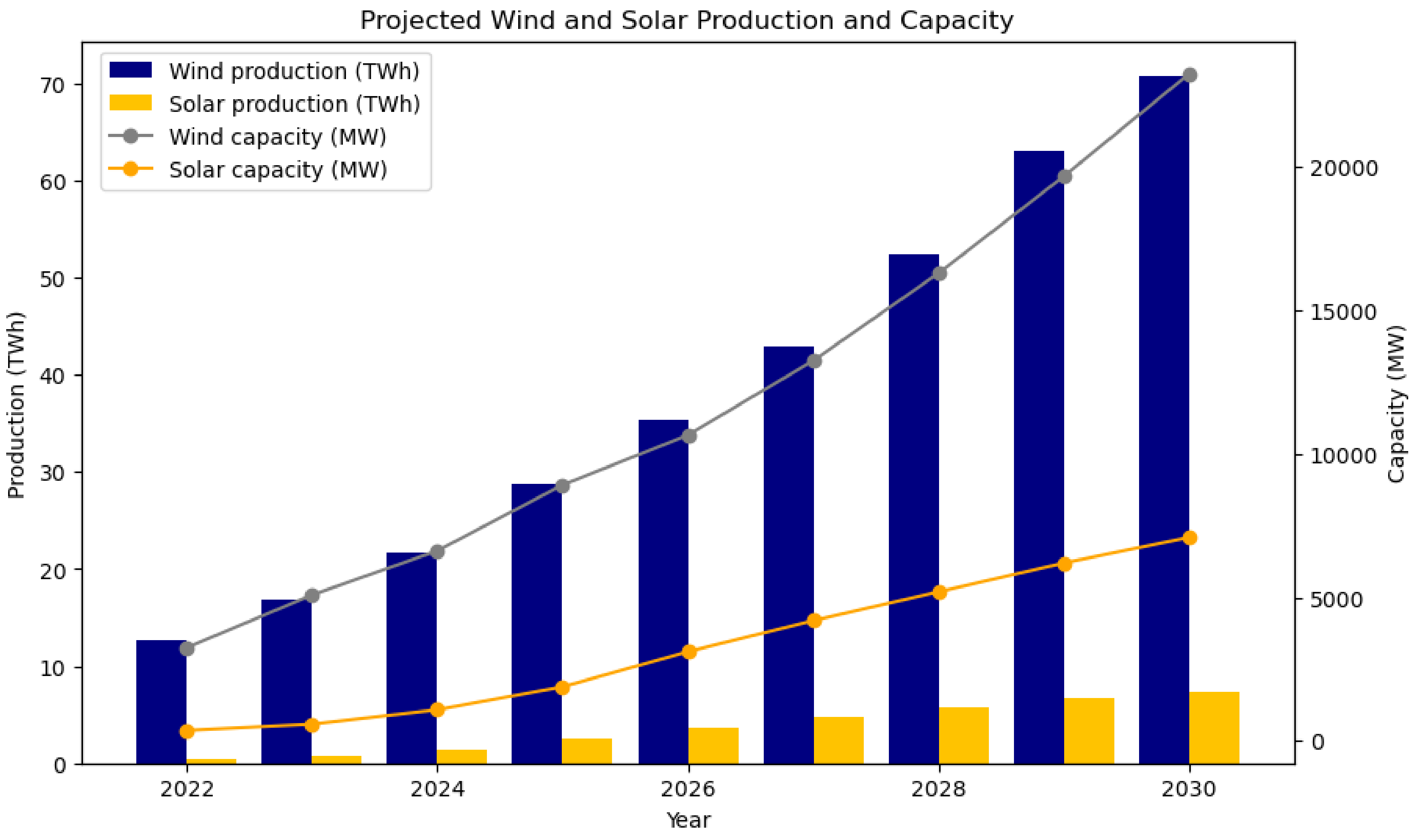
As Finland ramps up its renewable energy production, particularly from wind and solar power, the electricity market is undergoing a major transformation. Renewable energy sources are highly dependent on weather conditions and can introduce both price changes and volatility into the market.

Addressing the impact of renewable energy on electricity markets

Renewable energy generation, especially wind and solar, fluctuates based on weather conditions, making it harder to predict electricity prices accurately. Uncertainty in electricity prices can create risk for industries and businesses relying on stable energy costs.

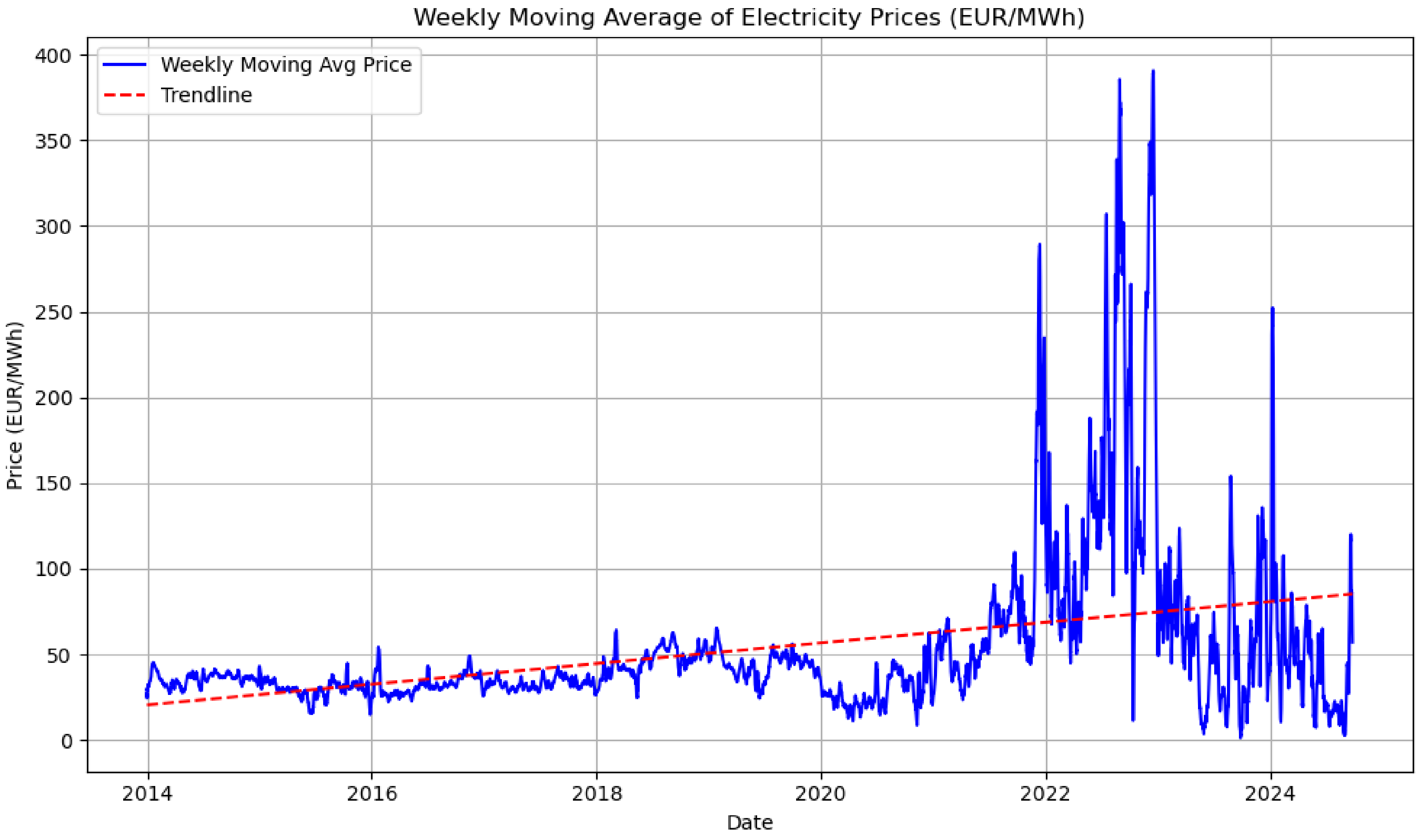
Purpose of the study

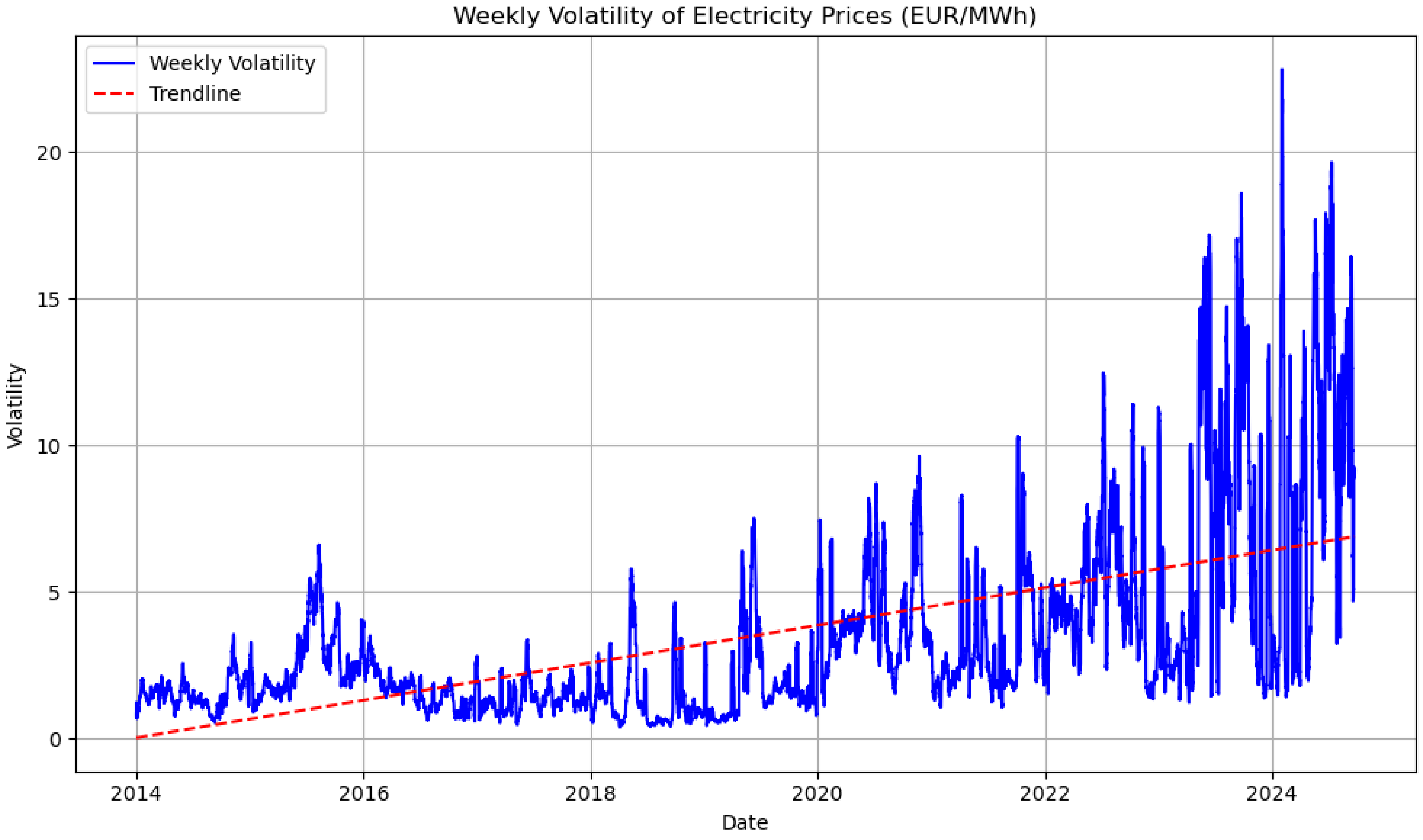
The purpose of this study is to model and predict electricity prices in Finland's evolving energy market, focusing on the impact of renewable energy growth, particularly from wind and solar, alongside other factors such as battery storage and import and export markets. Beneficiaries of the study are businesses and investors who can plan their energy procurement strategies and secure better contracts by reducing exposure to unpredictable price changes.



Business Problem

Trendlines point to a continuous rise in volatility and prices, especially since 2020

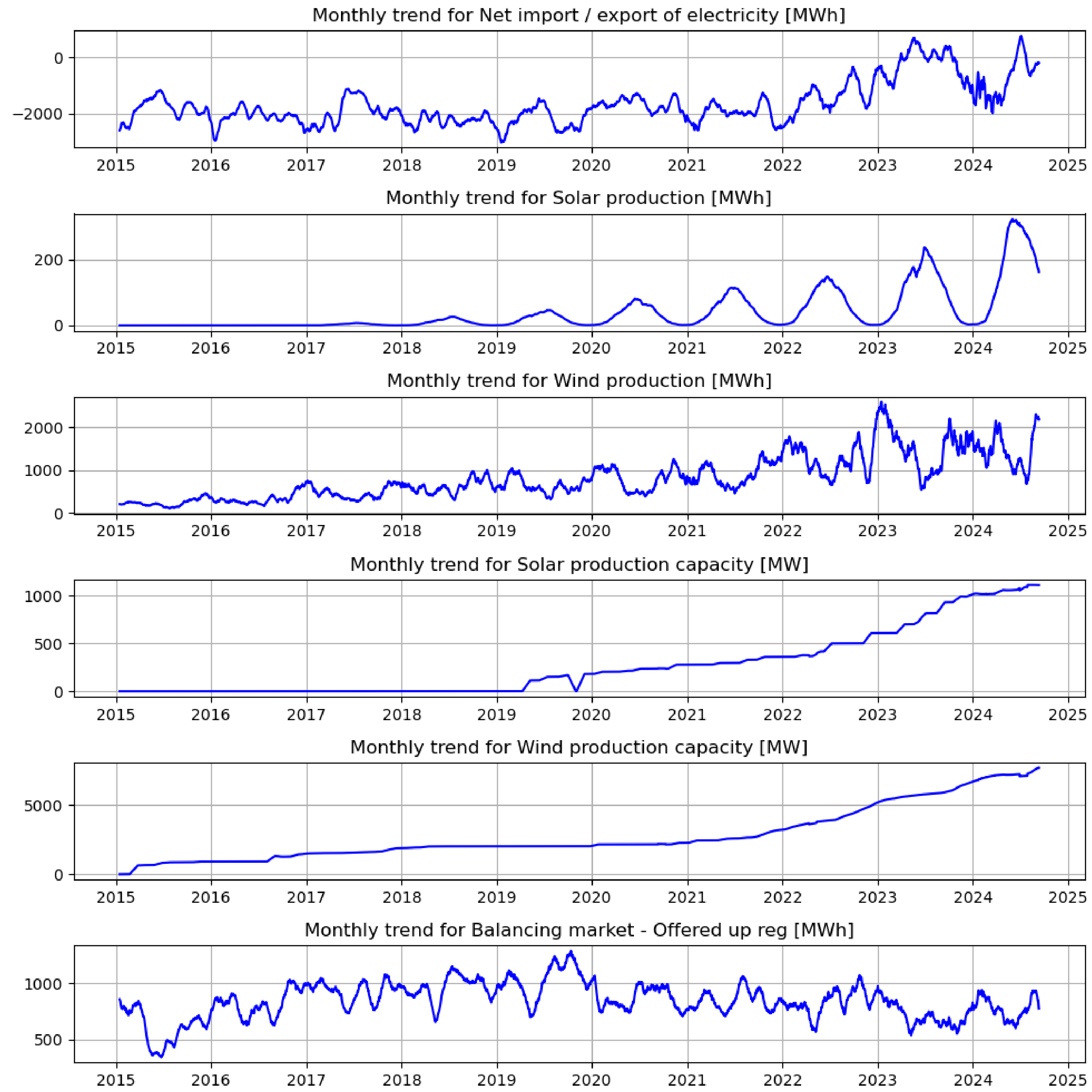




Features

Hourly time-series data was collected for 01/01/2015 - 24/09/2024 totaling 94.076 observations per feature

Variable	Description
Solar production [MWh]	Forecasted solar generation for the next day, updated daily. Based on weather and capacity data. Source: Fingrid database
Solar production capacity [MW]	Total estimated solar capacity, updated manually based on various sources. Source: Fingrid database
Wind production [MWh]	Wind generation data in 15-minute averages, combining measured and estimated values. Source: Fingrid database
Wind production capacity [MW]	Total estimated wind capacity, updated manually based on wind forecasts. Source: Fingrid database
Net import / export of electricity [MWh]	Real-time data of Finland's net electricity import/export, updated every 3 minutes. Source: Fingrid database
Day-ahead price [EUR / MWh]	Hourly electricity price collected from NordPool for Finnish market.
Balancing market - Offered up reg [MWh]	Sum of hourly up-regulation offers in the balancing market. Source: Fingrid database
Natural gas price for transmission network customers (27,778 - 277,777 MWh/year)	Monthly natural gas prices for transmission network customers in Finland up to 277, 777 MWh/year. Source: StatFin
Natural gas price for transmission network customers (277 778 - 1 111 111 MWh/year)	Monthly natural gas prices for transmission network customers in Finland up to 1 111 111 MWh/year. Source: StatFin



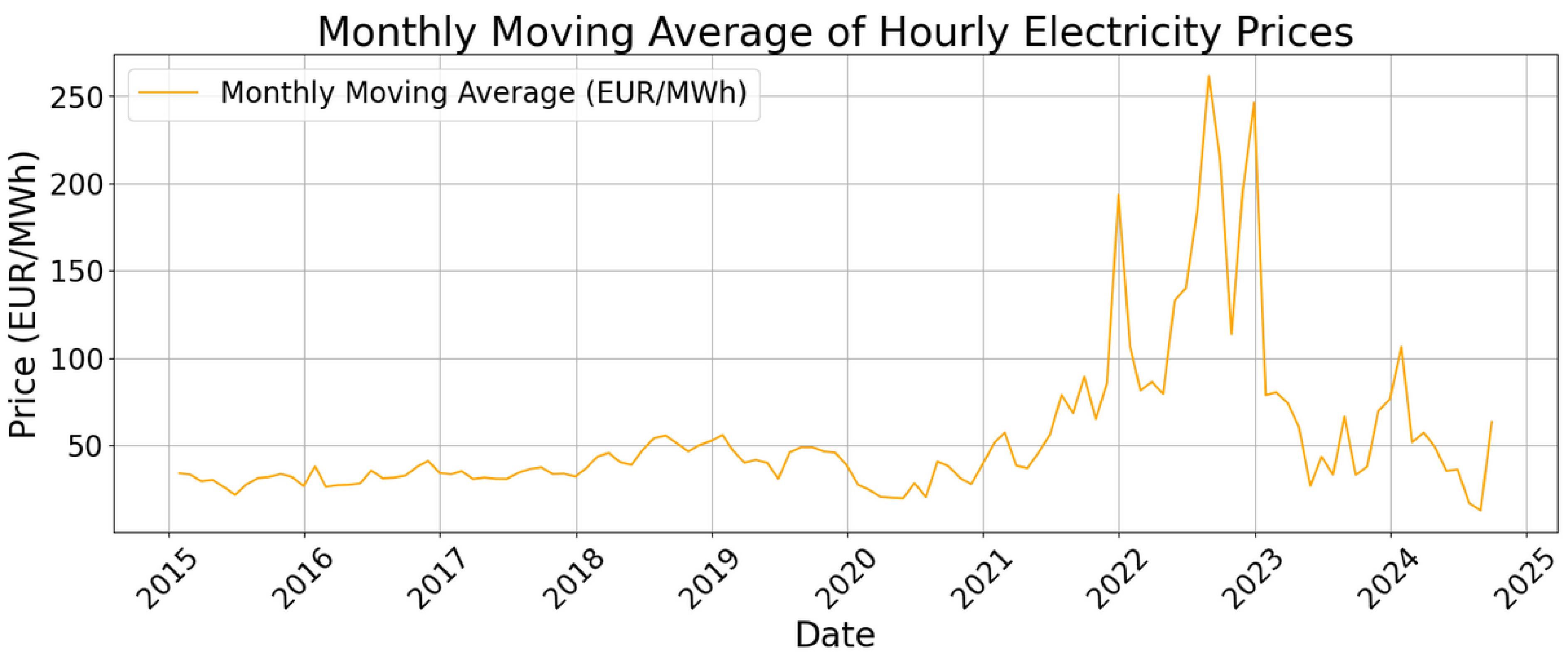
Analysis of Target

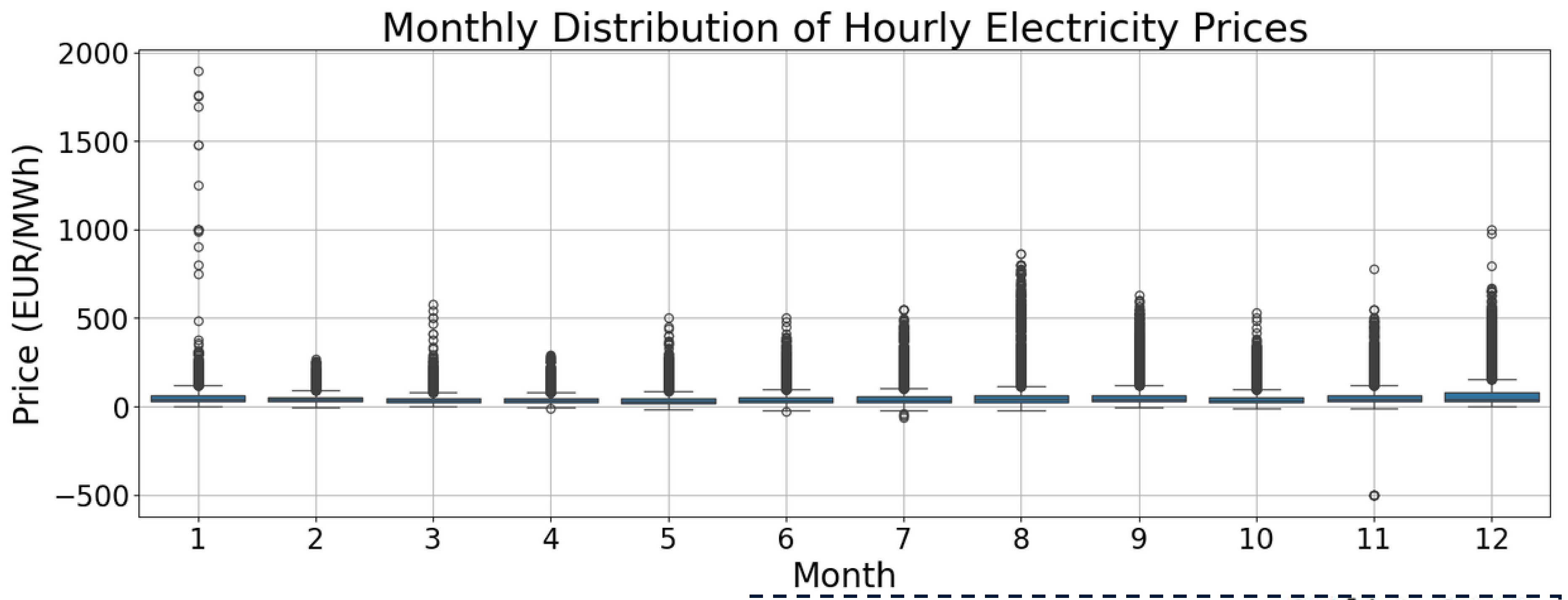
Day-ahead price [EUR/MWh] as target variable

- Hourly day-ahead electricity price for the Finnish market
- Data from NordPool
- Day-ahead market enables customers to sell or buy energy for the next 24 hours in a closed auction
- Whole of Finland comprises of a single pricing zone compared to some other markets

Data manipulation

- Outliers for target variable identified using a z-score of 3
- Outliers treated by capping them to 3 standard deviations from the mean
- **Problem:** Some outliers result from market failures, while others are caused by fluctuations in supply and demand balance (=*natural)*

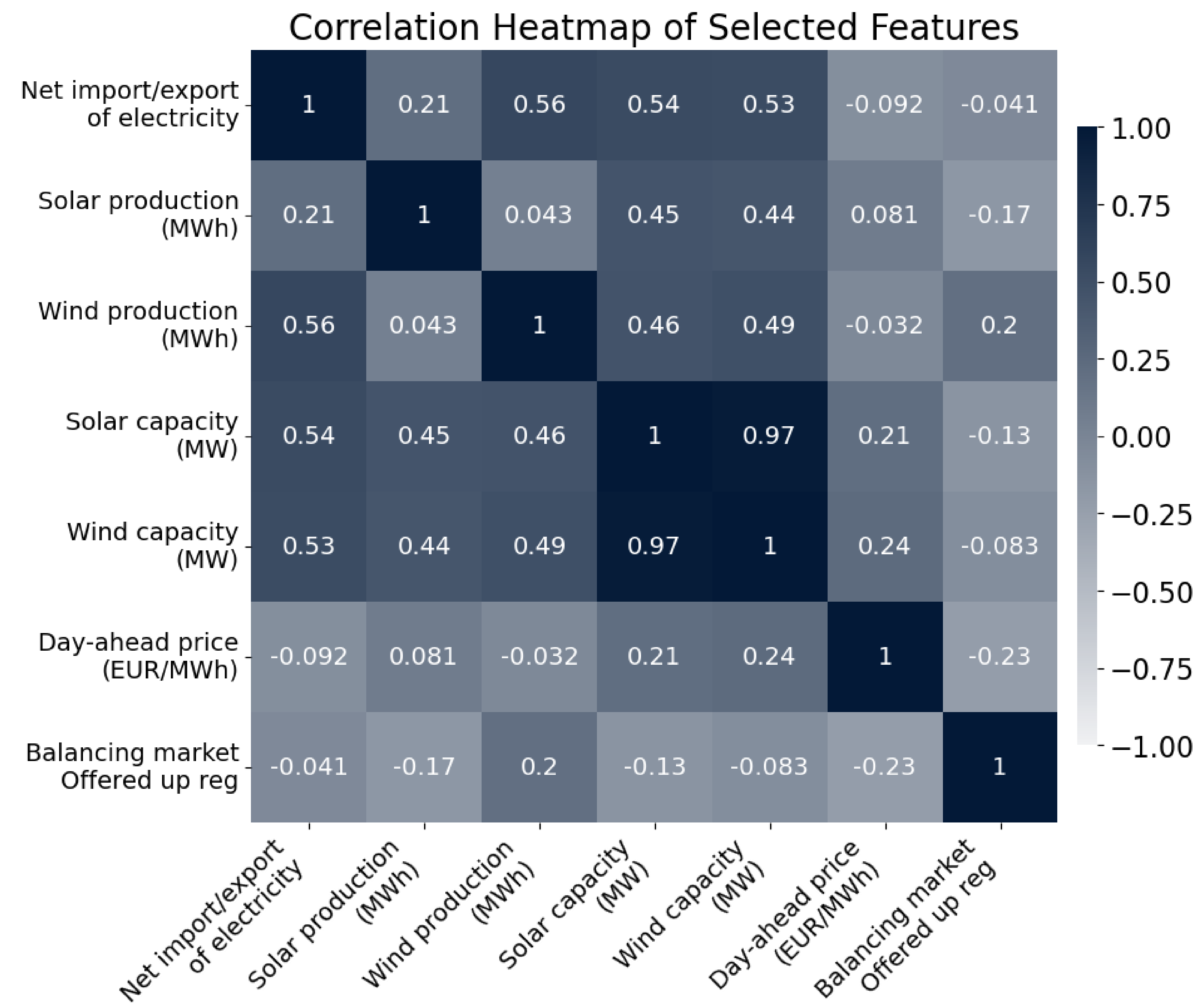




	Outlier Count
Day-ahead price [EUR / MWh]	2514
Gas futures [EUR / MWh]	0

We lagged the data to account for day-ahead prices, as these prices are determined one day in advance

Correlation of variables



Balancing markets, solar and wind capacity show moderate correlation with day-ahead prices

Methodology – Feature selection

Feature selection method

Features selected based on a wrapper-based selection, where features were added step-by-step, and our selected learning algorithms (Random Forest, XGBoost and Gradient Boost) evaluated their contribution to the model's predictive performance (measured by RMSE).

Adjusted forward selection

Our approach followed a process similar to forward selection, where features were ranked by their correlation with the target variable. Models were then incrementally trained, starting with the most correlated features and gradually adding less correlated ones. This allowed for an assessment of how each additional feature impacted the model's performance, helping to determine the optimal number of features to use (6-8 in our case).

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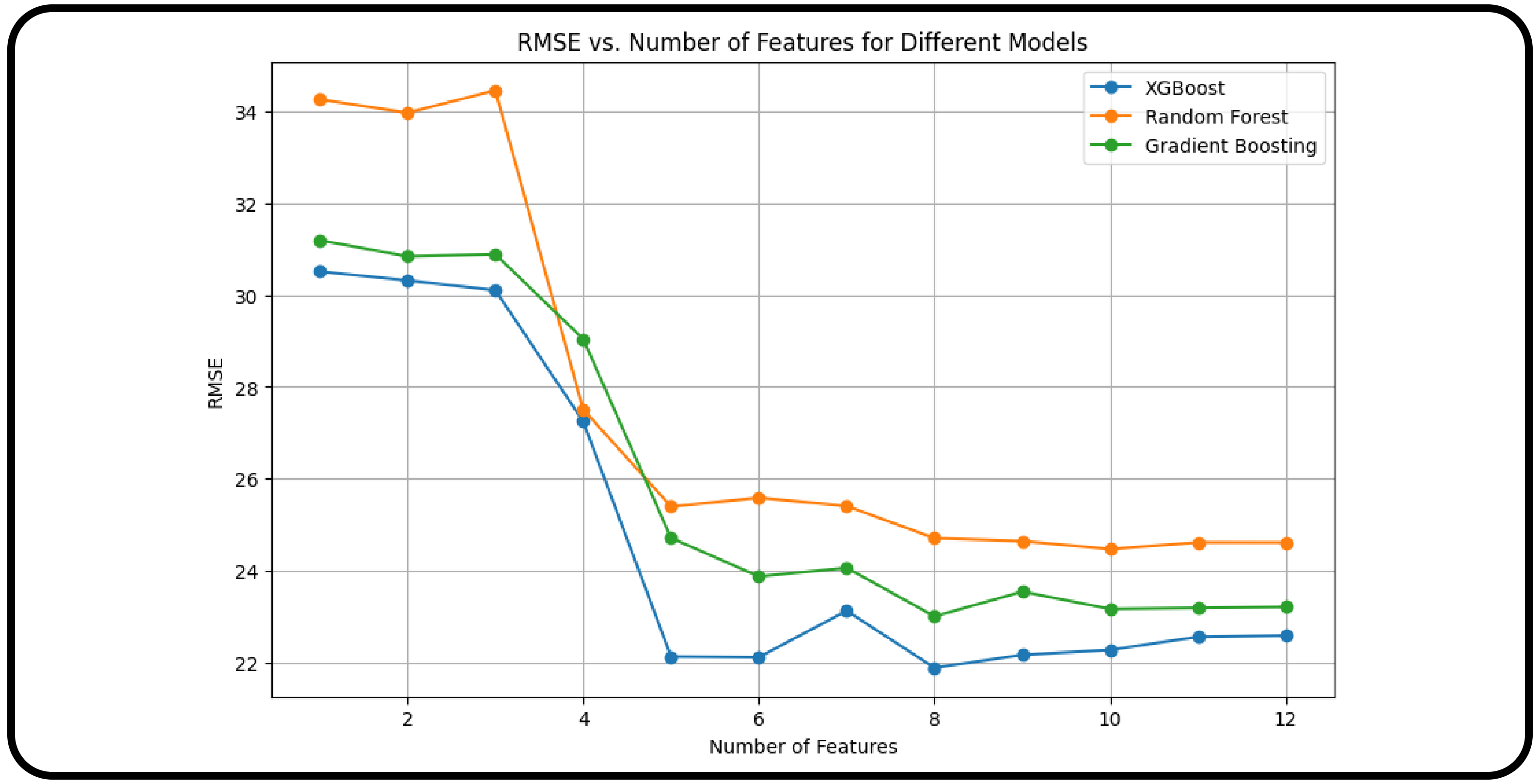
Net import / export of electricity [MWh]
Solar production capacity [MW]
Wind production capacity [MW]
Total production [MWh]
Wind production [MWh]
Total consumption [MWh]
Solar production [MWh]
Balancing market - Ordered down reg [MWh]
Balancing market - Ordered up reg [MWh]
Balancing market - Offered down reg [MWh]
Balancing market - Offered up reg [MWh]
Day-ahead price [EUR / MWh]
Power system state
Gas storage level [%]
Gas futures [EUR / MWh]
```

=14 features

```
Net import / export of electricity [MWh]
Solar production [MWh]
Wind production [MWh]
Solar production capacity [MW]
Wind production capacity [MW]
Day-ahead price [EUR / MWh]
Balancing market - Offered up reg [MWh]
```

= 6 features



No significant improvements in model performance after including more than 6 features

Methodology – Ensemble learning

Three different ensemble learning models applied for optimal performance

The models employed were XGBoost, Random Forest, and Gradient Boosting. XGBoost and Gradient Boosting are boosting techniques, where models are trained sequentially, with each model correcting the errors of the previous one to reduce bias. In contrast, Random Forest uses bagging, where multiple decision trees are trained on different random subsets of the data, primarily to reduce variance.

Reasoning behind the choice of models

For our study on predicting electricity prices, we believe XGBoost is the best choice because it captures complex feature interactions, handles lagged time series data effectively, and delivers high accuracy. Its efficiency, through techniques like tree pruning, also makes it well-suited for large datasets.

Random Forest, which builds independent decision trees, was tested to compare its strength in reducing variance even if it was anticipated that model bias would be higher compared to sequential algorithms.

Hyperparameter tuning

In the model, hyperparameter tuning is performed using GridSearchCV, a technique that systematically searches through a predefined set of hyperparameters to find the optimal combination for model performance. The predefined sets are presented in the table below.

Model	Hyperparameters
XGBoost	n_estimators: 100, 200, 300 max_depth: 3, 5, 7 learning_rate: 0.01, 0.1, 0.2
Random Forest	n_estimators: 100, 200, 300 min_samples_split: 2, 5, 10 max_depth: None, 10, 20
Gradient Boosting	n_estimators: 100, 200, 300 max_depth: 3, 5, 7 learning_rate: 0.01, 0.1, 0.2

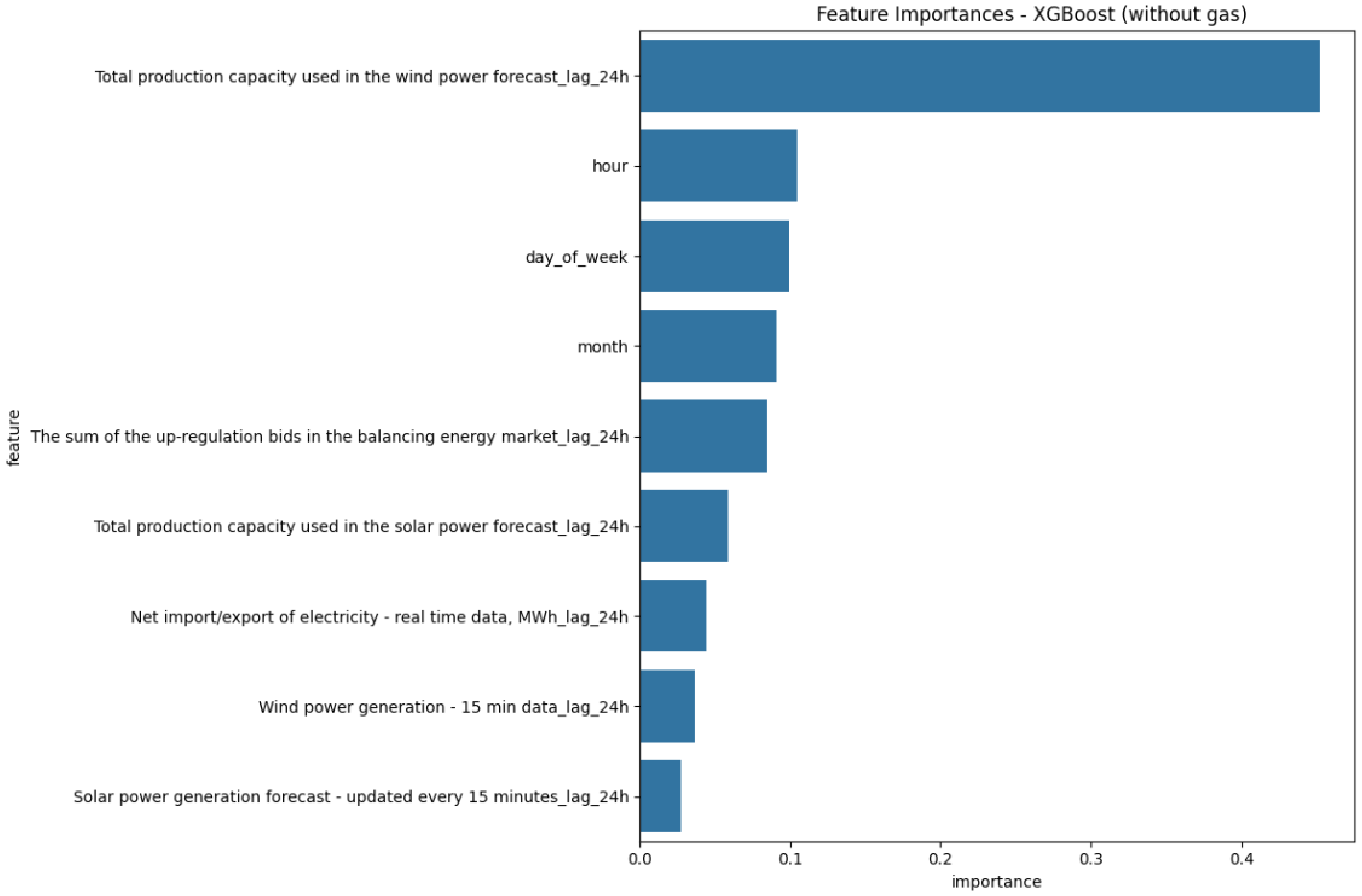
Model evaluation

The models were evaluated using metrics Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2. RMSE captures the model's overall predictive accuracy, and R^2 measures the proportion of variance explained by the model.

Model XGBoost: Feature Importance

Comments on most important features

- **Wind production** emerges as the most important feature. The variability in wind power, driven by weather conditions, leads to significant fluctuations in supply, directly impacting market prices.
- **Up-regulation bids'** prominence in the model indicates that electricity prices are influenced by real-time balancing efforts, especially when the grid requires intervention to maintain frequency stability. These bids signal tight market conditions, typically driving prices higher during supply shortfalls.
- **Net import/export** of electricity remains moderately important. This reflects Finland's participation in the broader Nordic electricity market, where cross-border electricity flows can affect domestic prices.
- Surprisingly, **solar power production capacity** and **wind power generation** (with 15-min lag) are less influential than expected. This suggests that capacity forecasts have a stronger influence on price than real-time generation. Solar production, which is less consistent in Finland due to seasonal sunlight variation, also has a smaller impact.



Model training results:

Model performance with gas features

Random Forest had the best performance with gas features*, showing the lowest RMSE (26.47) and the highest R^2 (0.849). This indicates that it was able to reduce variance and overfitting more effectively, likely due to the bagging approach that mitigates overfitting and enhances prediction stability. Variance reduction appeared to be more critical with the full dataset of variables.

Model performance without gas features

XGBoost outperformed the other models when gas features were excluded, with the lowest RMSE (26.51) and the highest R^2 (0.849). This suggests that XGBoost's ability to handle complex interactions and sequential learning was effective when the most correlated feature (gas prices) with the target variable was absent.

Gradient Boosting performed worst in both scenarios, which may depend on the fact that it can overfit more easily than XGBoost due to less advanced regularization techniques.

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Model Performance Comparison (with gas features):
                        RMSE        MAE         R2
Model
XGBoost            27.097195  12.451166  0.842188
Random Forest      26.471431  11.258638  0.849393
Gradient Boosting  28.181547  13.175094  0.829305

Best model with gas features: Random Forest

Model Performance Comparison (without gas features):
                        RMSE        MAE         R2
Model
XGBoost            26.519137  12.594360  0.848850
Random Forest      26.591428  11.340855  0.848024
Gradient Boosting  29.125064  13.570503  0.817684

Best model without gas features: XGBoost
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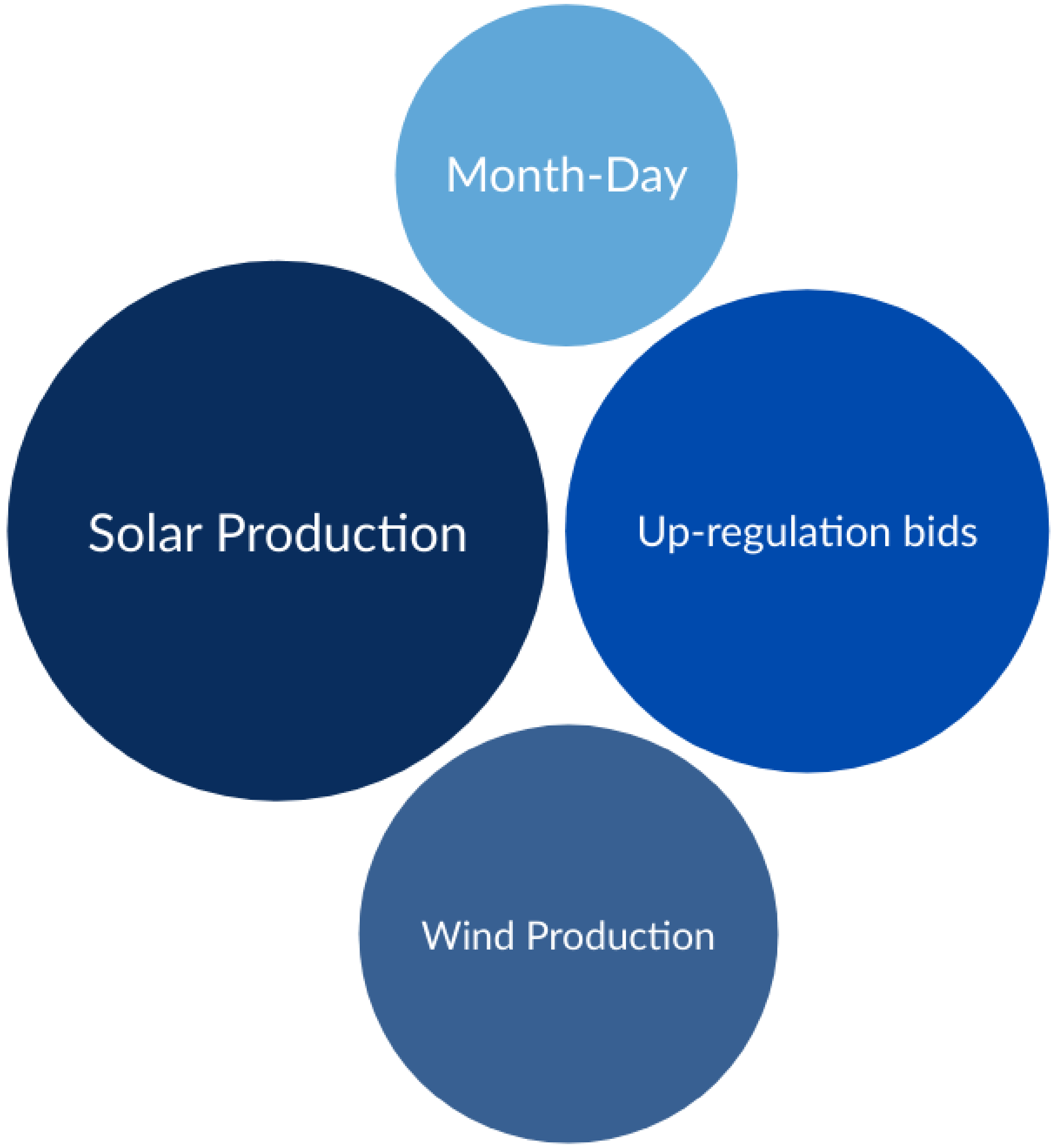
* Natural gas price for transmission network customers up to 277,777 MWh/year) and between 277 778 - 1 111 111 MWh/year

Random Forest performed best with full dataset and XGBoost with dataset missing gas prices

Predictive Model Analysis



Model	RMSE	MAE	R2
XGBoost	26.52 (27.10)	12.59 (12.45)	0.849 (0.842)
Random Forest	26.59 (26.47)	11.34 (11.26)	0.848 (0.849)
Gradient Boosting	29.13 (28.18)	13.57 (13.18)	0.818 (0.829)

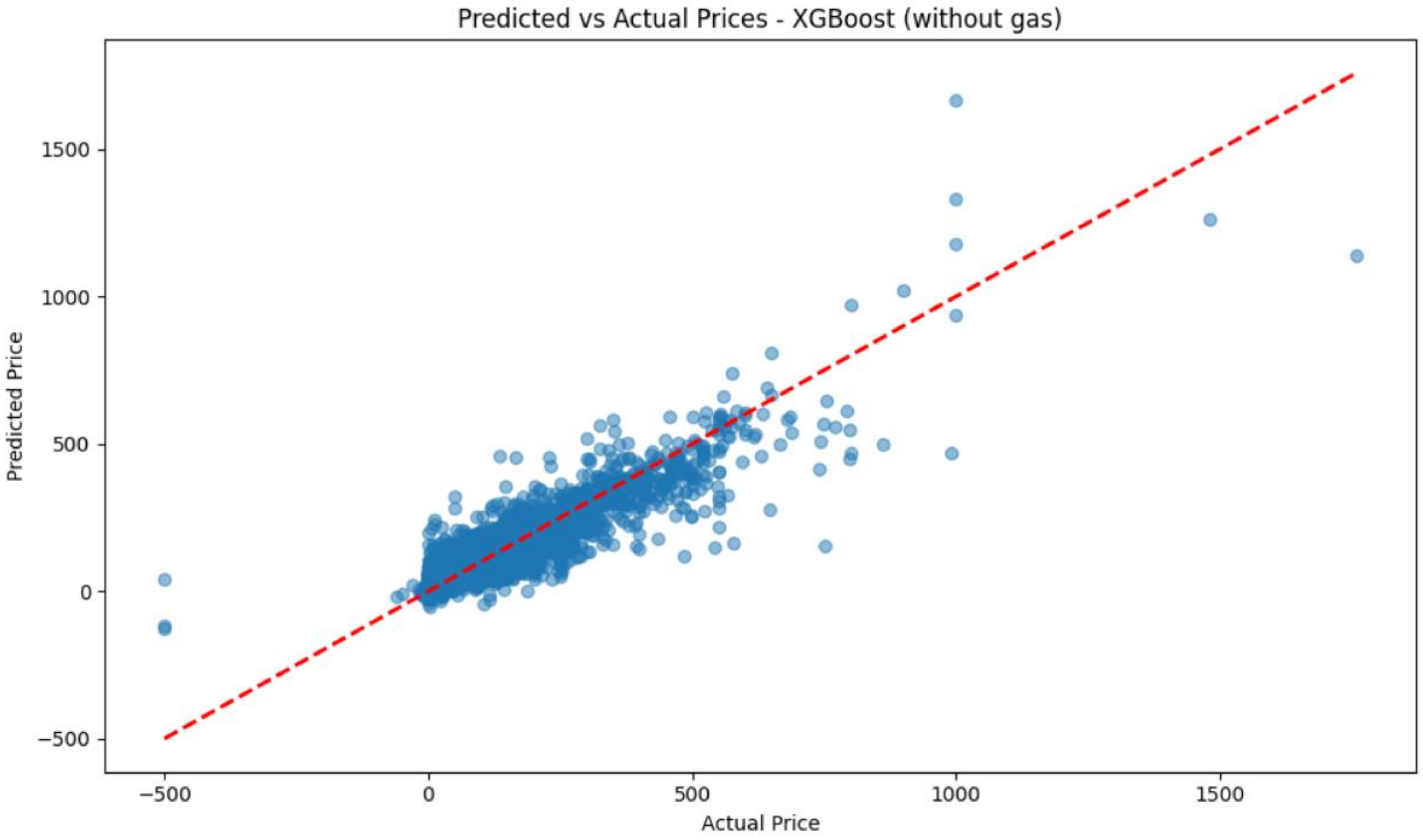
Values in parentheses indicate model performance with gas features included.

Production of renewables and sum of up regulation bids have the most impact on Electricity Prices

Model XGBoost:Predicted vs Actual Prices

Model performance

- The XGBoost model predicts day-ahead electricity prices with good accuracy for most actual prices, particularly between 0 € and 500 €.
- However, the model struggles to predict higher price spikes (above 500 €) by underestimating them. Price spikes are likely caused by extreme fluctuations in supply and demand, making them harder to predict accurately using the available features.
- Some bias is seen in the extreme low or negative prices, as well as high price spikes. The underperformance on both high and very low extremes suggests that while the model is robust for predicting typical price ranges, additional adjustments or the inclusion of other significant variables might be needed to better handle outlier events in the market.



Business Implications Based on Findings

1. Solar and wind production have significant effect on prices

- When wind production is high prices tend to fall and the opposite applies for solar production to lesser extent
- Businesses should take into account different variations in their energy strategies.

2. Sum up regulation bids have one of the most impact on electricity prices.

- Businesses could strategically adjust their electricity use during peak periods to manage price fluctuations.
- This would stabilize costs of high demand or volatile electricity.

3. Seasonality and time trends drive prices in the long-term

- Current renewables production (mainly wind) is skewed towards winter months
- Incorporation of solar to energy mix would smooth out seasonality effect

4. The current model struggles to predict price spikes

- While the models perform well in general, the outliers in the predicted vs. actual price plot indicate that significant price spikes remain difficult to predict accurately.
- This is particularly crucial when demand exceeds supply
- Short-term solution: businesses should lock into long-term energy contracts, to stabilize fluctuations.
- Long- term solution: especially large energy-consuming businesses should invest in energy storage systems and grid infrastructure to smooth out fluctuations.

5. Investment in Storage and Grid Infrastructure

- Companies, particularly those with energy-intensive operations, should consider investing in energy storage systems (like batteries) to better manage fluctuations in electricity prices driven by intermittent renewable generation. This can help mitigate the impact of price spikes and periods of high demand.

Emphasis on stability mechanisms to ensure stable electricity prices amid increasing renewable energy production

References

Fingrid, 2024. Sähkön tuotannon ja kulutuksen kehitysnäkymät. Available at: https://www.fingrid.fi/globalassets/dokumentit/fi/tiedotteet/ajankohtaista/sahkon-tuotannon-ja-kulutuksen-kehitysnakymat-q3-2024-fingrid.pdf. [Accessed 7 October 2024].