ELECTRICITY PRICE FORECASTING REPORT *Key Insights and Business Implications*

FORTES

Contents

1. Executive Summary

1.1 Objective

The main goal of this report is to provide accurate Electricity Price forecasts, quantify uncertainty, and provide actionable insights for decision-makers (energy traders, industrial consumers and grid operators).

Key model performances obtained:

Random Forest: High precision in detecting price spikes (Precision: 0.76), Directional Accuracy: 79.73%, RMSE: 27.49

Linear Regression: Highest directional accuracy (79.7%) with moderate volatility capture, RMSE: 19.58

Persistence: Best volatility capture (100%), RMSE: 14.02

2. Introduction & Context

2.1 Purpose

The purpose of this challenge and report is to forecast day-ahead electricity prices and understand the key factors driving these prices.

2.2 Background

Complex Market Structure:

The electricity market is divided into several submarkets, each with it's unique price signals. These include long-term futures, day-ahead and intraday spot markets, as well as over-the-counter (OTC) trading. This segmentation helps market participants plan and hedge against price fluctuations.

Real-Time Production and Consumption:

Unlike other commodities, electricity cannot be stored easily and must be produced at the moment of consumption. This creates a dynamic environment where supply and demand are balanced.

Price as the Central Control Element:

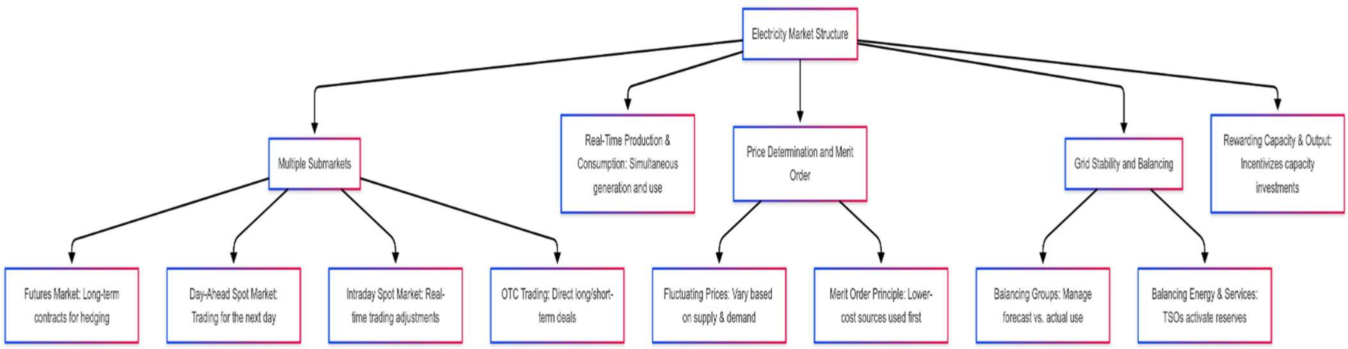
Market prices fluctuate based on supply and demand conditions. Producers and consumers monitor these signals up to the point of delivery to make efficient trading decisions. The price, determined by the marginal cost of the last unit needed, ensures that lower-priced generation has priority and that more expensive plants only operate when necessary.

Balancing and Grid Stability:

To maintain grid stability, Transmission System Operators (TSOs) procure balancing services that correct deviations from planned schedules. These services include reserves (e.g. frequency containment reserves and automatic restoration reserves) and ensure that any imbalances are quickly rectified, thus incentivizing accurate forecasting and scheduling.

Capacity and Flexibility:

The market rewards not only the actual output of electricity but also the capacity available to meet demand, this dual focus encourages investment in both generation and flexible consumption, to support a sustainable energy supply.



3. Exploratory Data Analysis (EDA)

3.1 Market Trends & Price Fluctuations

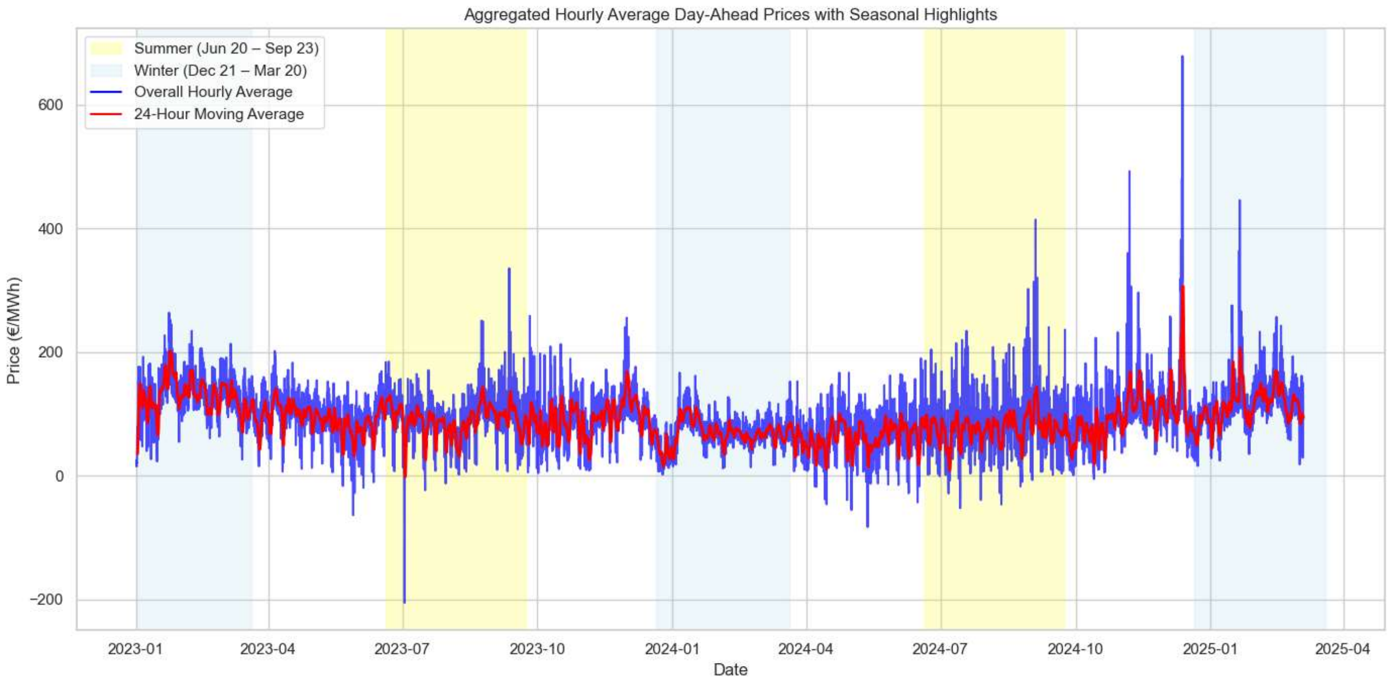
3.1.1 How do electricity prices fluctuate hourly, daily, and weekly across different countries?

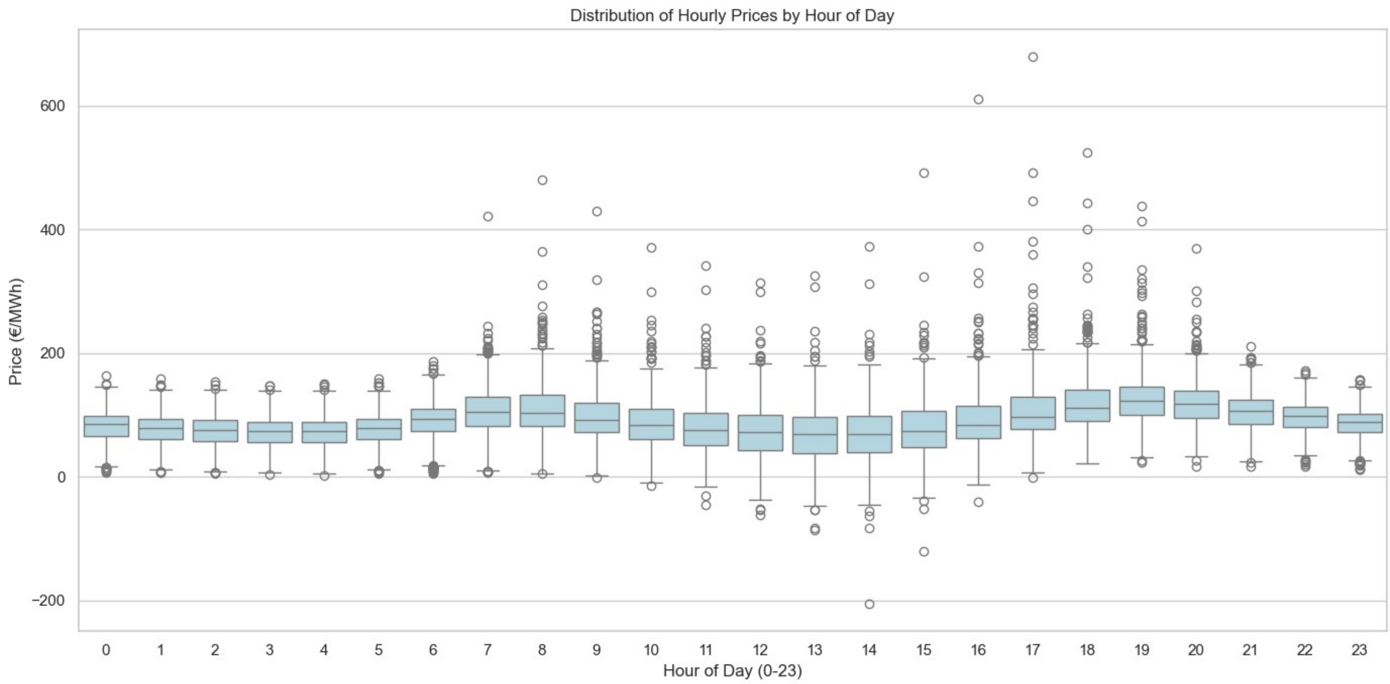
- **Hourly**

Since we had data from many countries, plotting everything at once would make the visualizations too cluttered and difficult to interpret across different timeframes. To address this, I opted for Hourly, Daily, and Weekly averages, along with moving averages, allowing us to analyze price movements over time without losing valuable information. For hourly trends, I also chose a boxplot since it offers a clear and visually appealing way to observe intraday patterns.

The analysis reveals a pattern, with prices typically peaking in the early morning and late afternoon when demand surges, while at night we see lower prices. Additionally, during peak demand hours, we observe a higher price standard deviation, indicating greater price variability, probably due to increased market volatility and supply-demand imbalances.

This variation in price fluctuations differs between countries, influenced by factors such as market structure, energy generation mix, and operational practices.

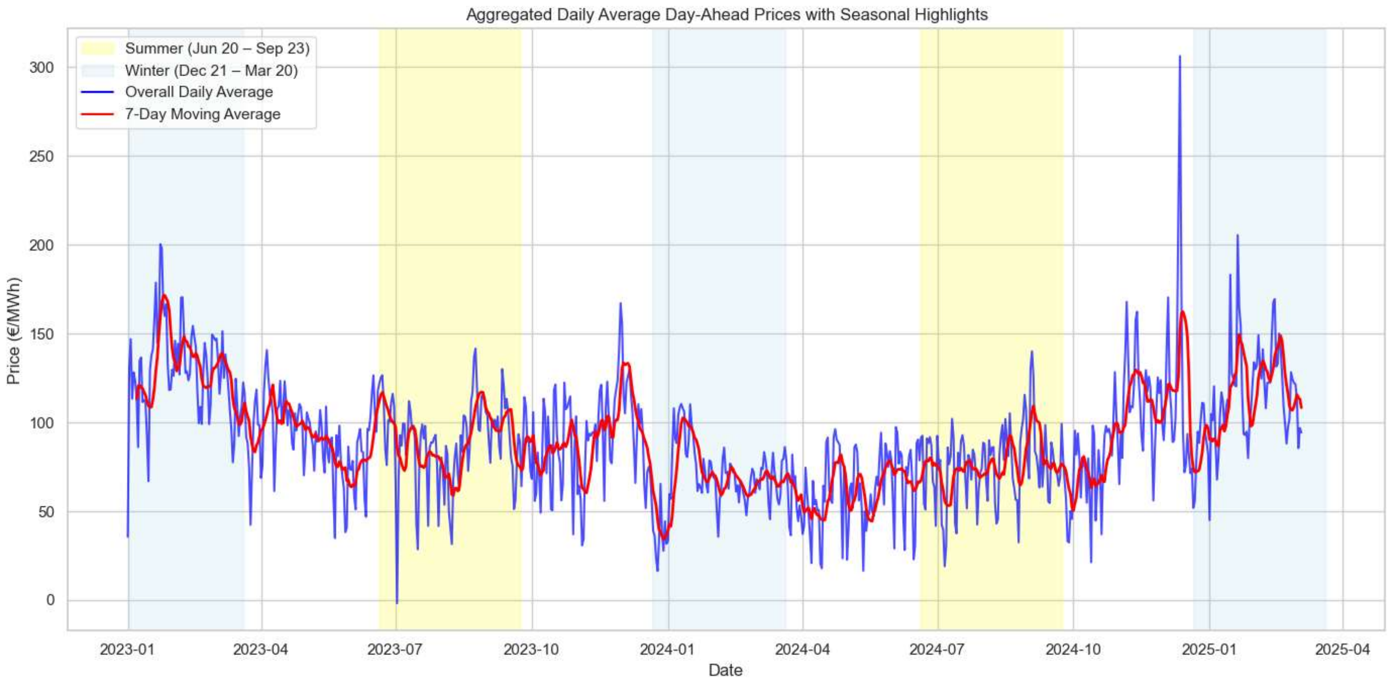


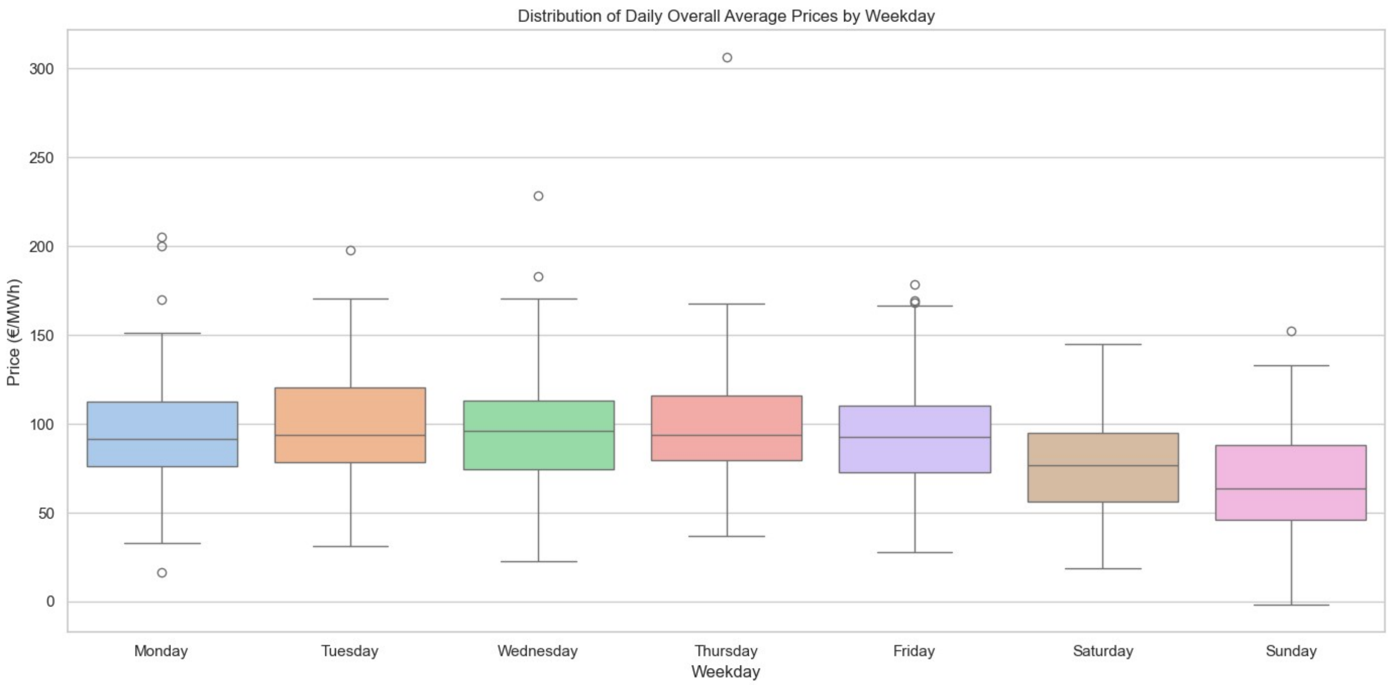


- **Daily**

Day-to-day variations show that weekdays generally show higher prices compared to weekends, likely due to increased industrial and commercial demand.

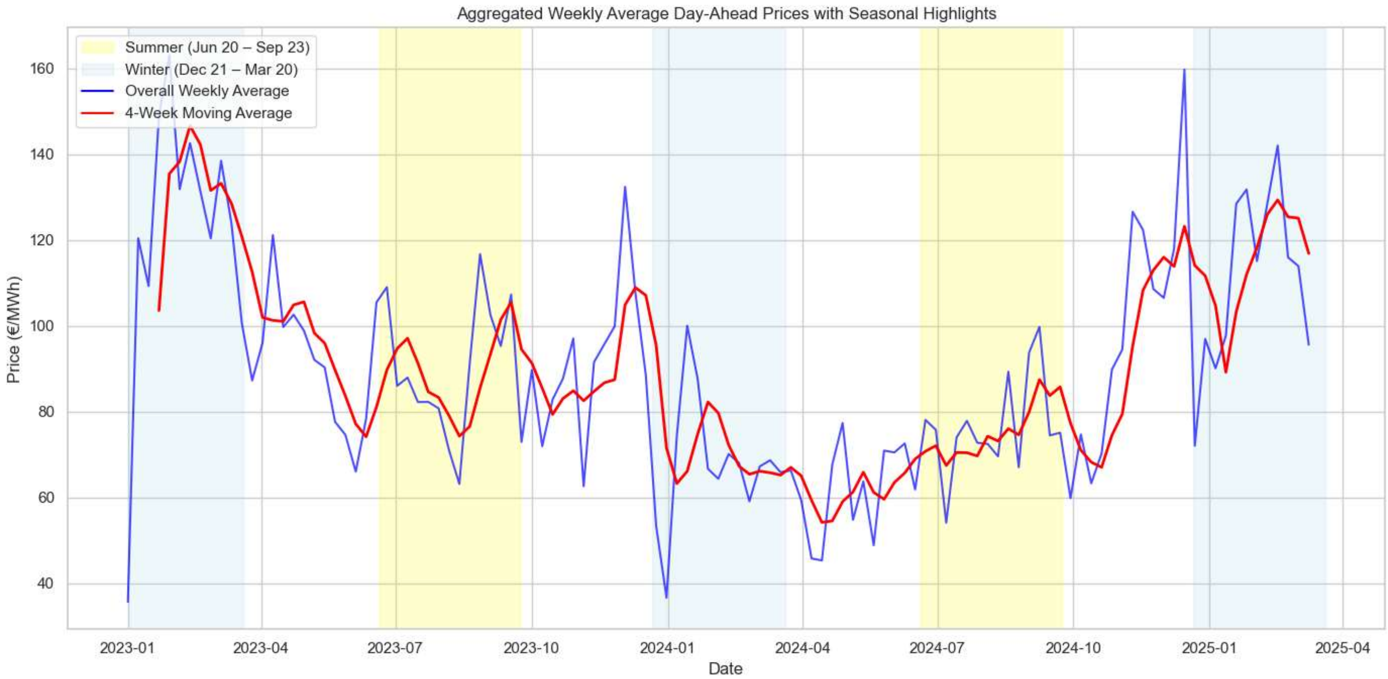
Weekends tend to have a lower consumption profile, leading to low and stable prices.





- **Weekly**

On a weekly scale, price trends reflect broader market dynamics. Despite not being identified, certain weeks, especially those influenced by weather patterns, may demonstrate shifts in prices. Also, countries with higher renewables may show higher weekly volatility, caused by intermittent generation.



3.1.2 How do electricity consumption patterns change in the same timeframes, and how does this impact pricing?

Consumption data show distinct patterns. Peak consumption hours are closely tied with price peaks. This is more evident during the first morning hours and evening peaks when residential and commercial activities are at their highest. On a daily scale, the drop in consumption during off-peak hours aligns with lower prices. Over a week, higher overall consumption on weekdays translates into higher prices, while weekends tend to exhibit both lower consumption and prices. We can also see that a higher residual load (the difference between actual consumption and renewable generation) indicates a higher net demand, which typically pushes prices up.

The daily electricity consumption follows a clear pattern, with peak demand observed during morning and evening hours. This corresponds to the typical human activity, with higher demand in the morning when people start their day and, in the evening, when they return home.

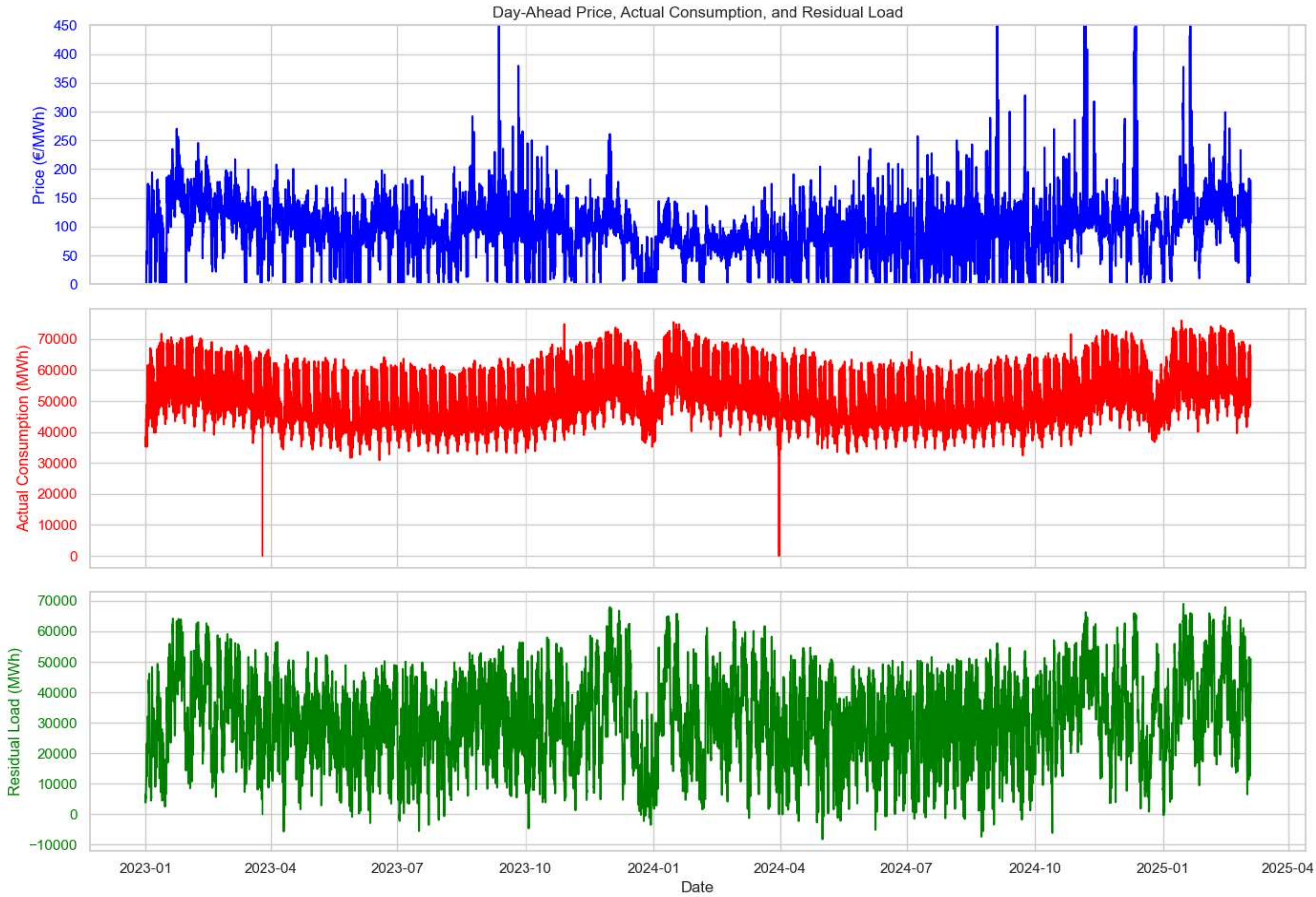
Impact on Pricing:

- Prices tend to increase during peak demand hours due to higher consumption and constraints on generation capacity,

- During lower demand periods (e.g. at night), prices tend to drop as there is excess supply and less load on the grid,

- Fluctuations in renewable energy generation also influence pricing. When renewables generate more electricity, prices drop due to lower marginal costs,

- So, when demand surges, whether predicted or unanticipated, the pressure on supply pushes prices up, especially if generation or import capacities are constrained.



3.1.3 How does electricity generation (actual vs. forecast) align with price trends?

Electricity prices depend on how much electricity is being produced compared to how much is being used. When analyzing actual vs forecasted generation, we gain insight into how the market anticipates supply and how unexpected shortfalls or surpluses can move prices.

Alignment of Generation with Price Trends

When Actual Generation Matches or Exceeds the Forecast

- The market is less likely to experience a supply deficit,
- Prices tend to remain stable or lower, reflecting higher supply vs demand.

When Actual Generation Falls Short of the Forecast

- A supply gap emerges, often leading to price spikes if demand remains unchanged or if demand rises,

- This scenario can be observed in the line plot when the green (actual) line dips significantly below the orange (forecast) line, coinciding with '*jumps'* in the blue (price) line.

Renewables vs Conventional Generation

Renewables (wind, solar, hydro, etc,) can be dependent of weather factors, introducing variability and forecast uncertainty.

Conventional sources (coal, gas, nuclear, etc) offer more predictable baseload generation but are still susceptible to outages that may occur.

In periods where renewables outperform their forecast, prices often stay lower. Alternatively, if conventional sources unexpectedly reduce output, prices may spike if demand cannot be met.

Insights from the Scatter Plot (Generation Error vs, Price)

Negative Error (Actual < Forecast) → Higher Prices

- Points clustering at the left side (negative x-values) often show elevated y-values (prices),

- This confirms that shortfalls in generation relative to forecasts typically lead to increased price volatility and possible spikes.

Positive Error (Actual > Forecast) → Stable or Lower Prices

- Points on the right (positive x-values) are generally associated with moderate or lower prices, because having extra supply helps to ease the pressure on the market,

- Extreme oversupply, however, won't always lead to significantly lower prices, especially if factors like demand or market regulations get in the way.

Data Near Zero Error

- The cluster around zero indicates forecasts are typically accurate within a moderate range, corresponding to stable prices. Large deviations on either side are the main drivers of price extremes.

Detailed Interpretations

Accuracy of Generation Forecasts

- The market heavily relies on day-ahead and intraday forecasts to schedule power generation,

- Higher accuracy (Actual ≈ Forecast) generally yields price stability; large errors (especially under-forecasting) correlate with price spikes.

Impact of Renewables

- Wind & Solar generation can change rapidly with the weather. If they produce more electricity than expected, it usually helps keep prices from rising too much,

- Sudden drops in renewables, if unexpected, the grid has to switch to costlier power sources (conventional) that can quickly cause the prices to rise

Seasonal and Daily Variations

- Seasonal factors and daily cycles can cause repeated patterns of forecast error,

- Price spikes are more likely when these patterns deviate from predictions (e.g. a cloudy day unexpectedly cutting solar output).

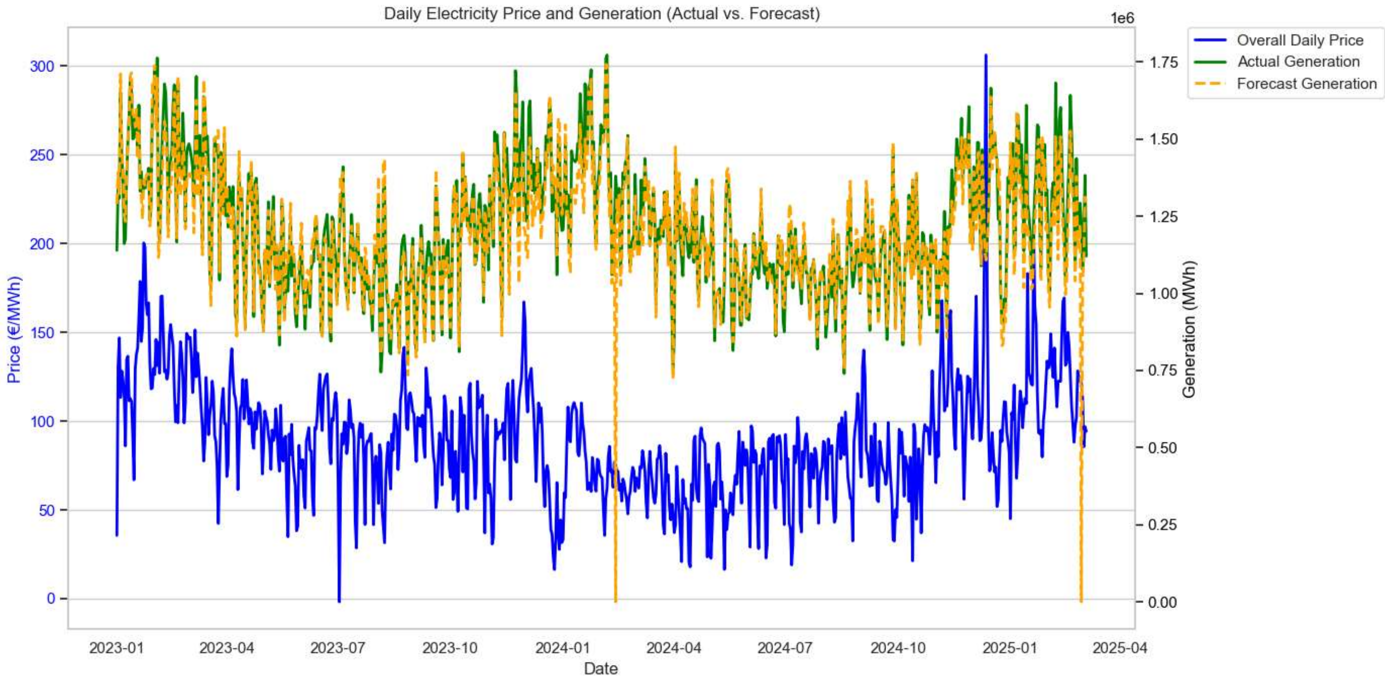
Conventional Generation Gaps

- Conventional power plants sometimes shut down unexpectedly due to outages or maintenance. If a large plant suddenly goes offline, it can quickly cause a supply shortage, showing up clearly as a negative error combined with high prices.

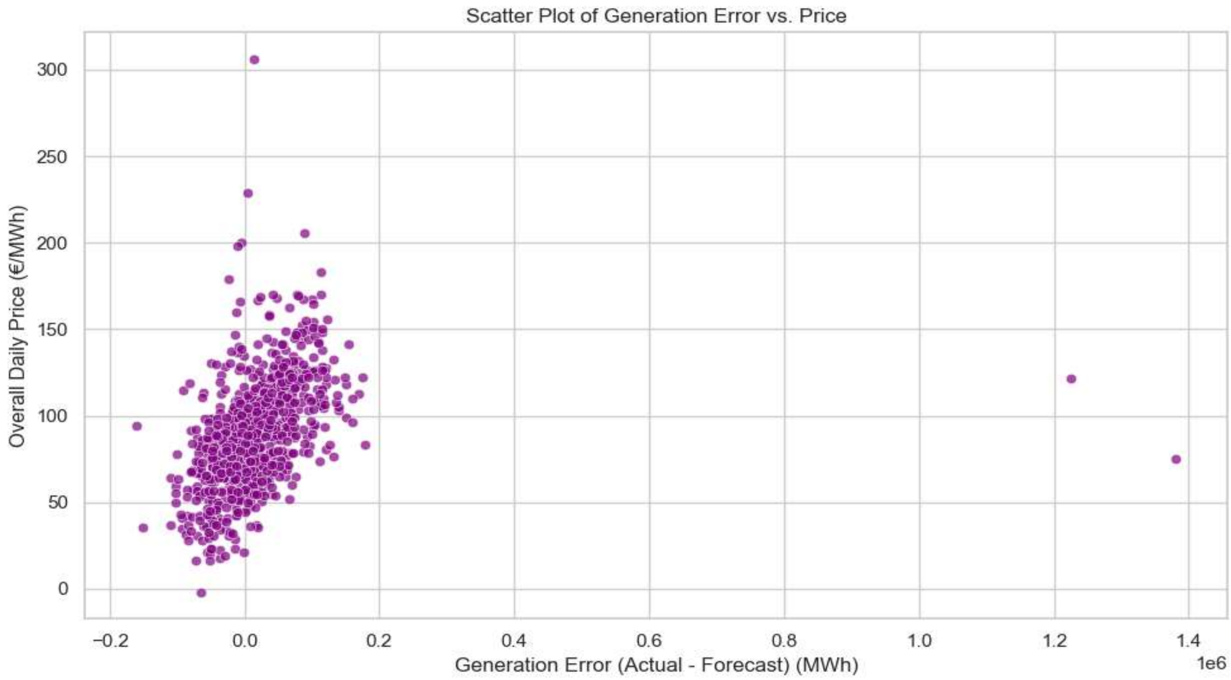
Overall Conclusion

Actual vs Forecasted Generation alignment is crucial for stable electricity prices. When forecasts are accurate, the market can balance supply and demand with minimal volatility. On the other hand, significant shortfalls in actual generation (compared to forecasts) lead to supply pressure and price spikes, as illustrated by both the line plots (where the actual generation dips below forecast) and the scatter plot (where negative errors align with higher prices).

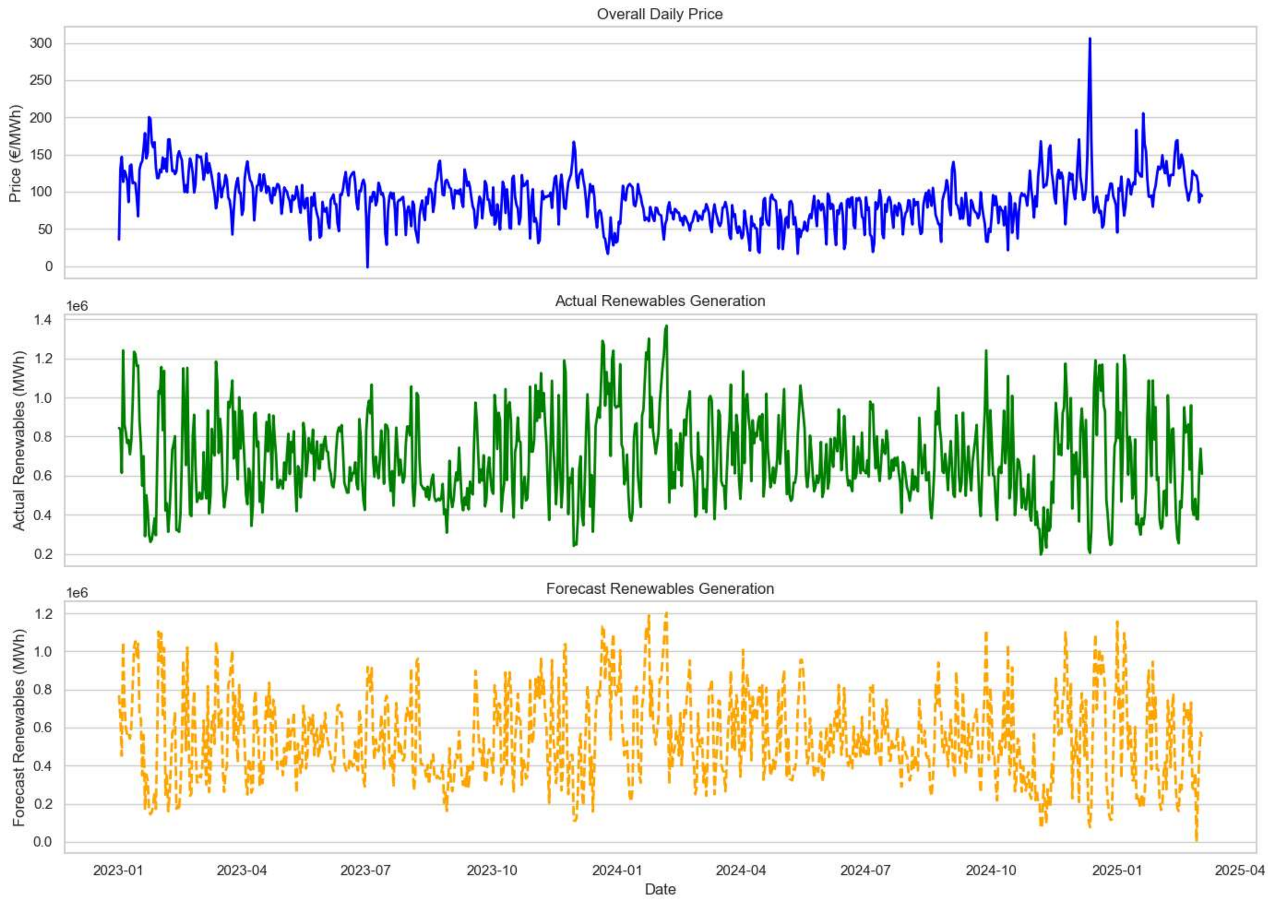
In short, the data show that accurate, reliable forecasts of generation (both renewables and conventional) are instrumental in maintaining stable and predictable electricity prices. Where mismatches occur, especially under-generation, prices tend to become unstable and often spike significantly.

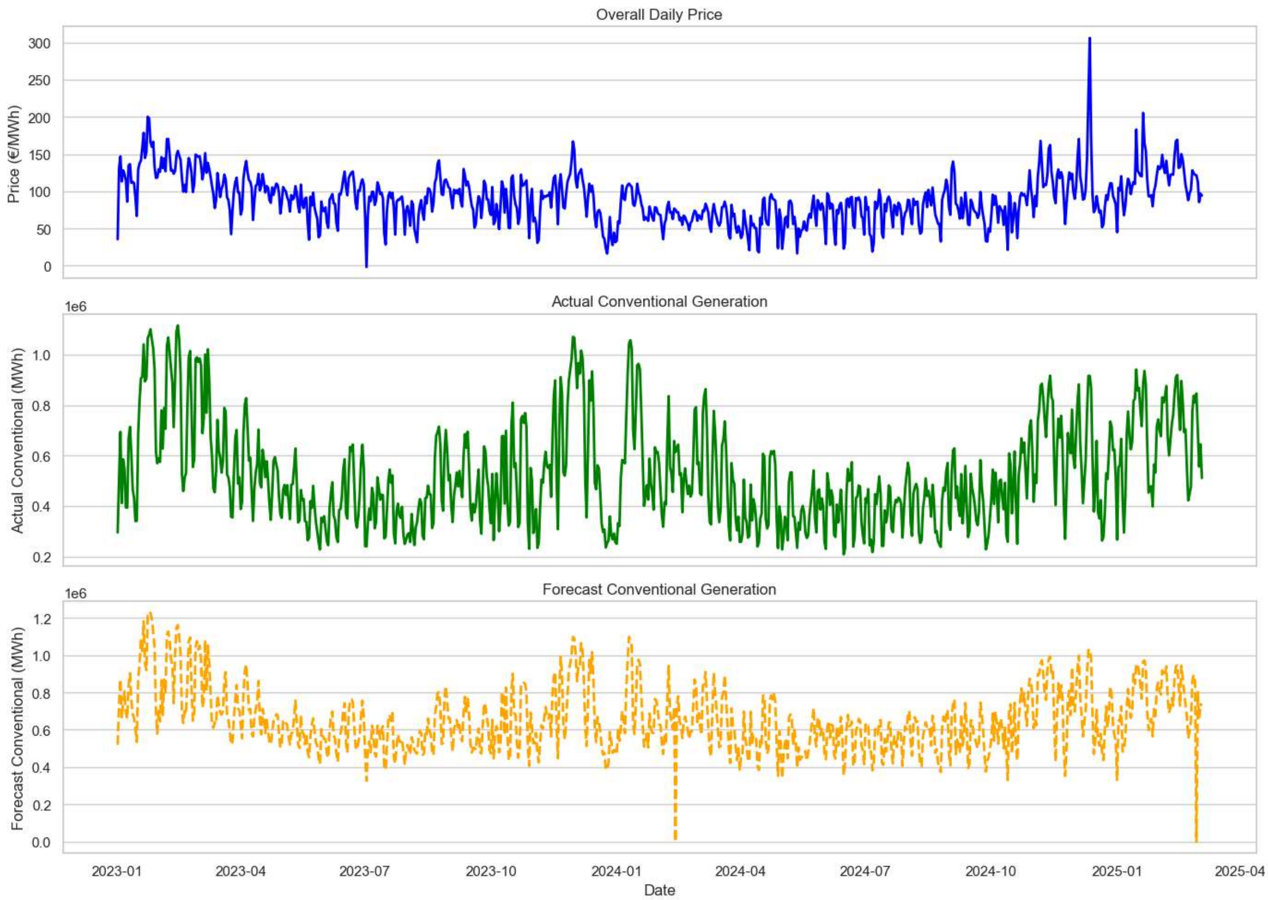


Daily Electricity Price and Generation (Actual vs. Forecast)
1e6
Overall Daily Price
Actual Generation
Forecast Generation
Price (€/MWh)
Generation (MWh)
Date



Scatter Plot of Generation Error vs. Price
Overall Daily Price (€/MWh)
Generation Error (Actual - Forecast) (MWh)
1e6


Overall Daily Price
Price (€/MWh)
Actual Renewables Generation
Actual Renewables (MWh)
Forecast Renewables Generation
Forecast Renewables (MWh)
1e6
Date
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04


Overall Daily Price
Price (€/MWh)
Actual Conventional Generation
Actual Conventional (MWh)
Forecast Conventional Generation
Forecast Conventional (MWh)
1e6
Date
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04

Key Insights:

- **Hourly, Daily, and Weekly Trends**
  - **Hourly:** Electricity prices typically follow a daily cycle, peaking in the early morning and late afternoon due to demand surges, while dropping at night. Higher price variability is seen during peak hours, reflecting market volatility,
  - **Daily:** Weekdays have higher prices due to industrial and commercial demand, while weekends see lower and more stable prices,
  - **Weekly:** We can also see broader trends, with some weeks showing significant shifts in prices driven by factors like weather conditions, regulatory changes, and the amount of renewable energy entering the grid.
- **Consumption vs Pricing**
  - Peak consumption hours (morning/evening) align with price peaks, probably driven by residential and commercial activities,
  - Lower nighttime demand leads to lower prices due to excess supply.
- **Impact of Renewables on Price Volatility**
  - Higher renewable generation lowers prices,
  - Shortfalls in renewables lead to an increase in price, requiring expensive quick-ramping power sources,

- **Actual vs Forecasted Generation & Price Impact**
  - **When actual generation meets or exceeds forecasts:** Prices remain stable or lower,
  - **When actual generation falls short:** Price spikes occur due to supply shortages,
  - Renewables introduce more forecast uncertainty, impacting market stability,
  - Negative forecast errors (under-generation) correlate with higher prices, while positive errors (over-generation) lead to stable/lower prices.

3.1.3 What patterns emerge from scheduled commercial exchanges and cross-border physical flows?

Strong Correlation Between Scheduled and Actual Flows

The time series plots demonstrate a strong correlation between scheduled and cross-border physical flows. The scheduled values closely track the physical flows, indicating that the scheduling system does a good job predicting and managing interconnection usage under normal circumstances.

Deviations and Mismatches

Despite the overall alignment, the difference between Net Export and Cross Border Export plot reveals consistent short-term discrepancies between scheduled and actual flows. These deviations, while generally within ±2,000 MWh, occasionally reach higher magnitudes, suggesting operational adjustments in real-time. Potential causes include:

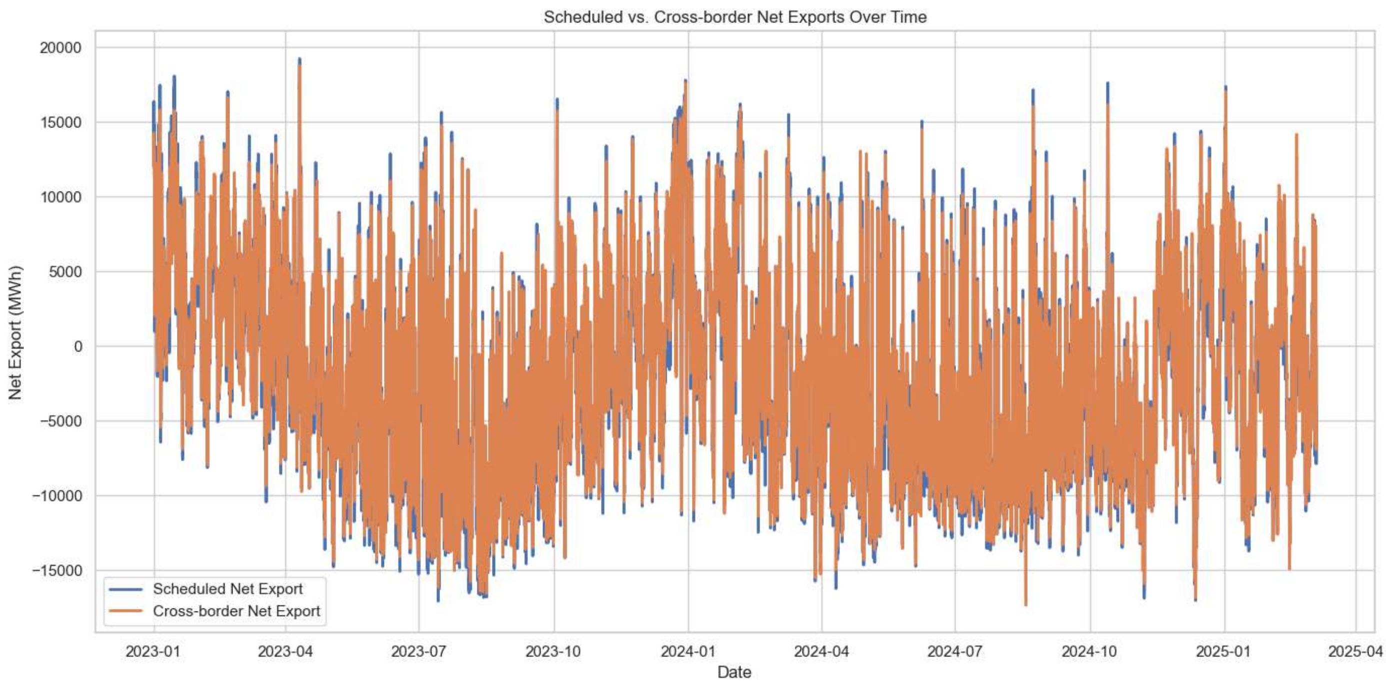
- Forecasting inaccuracies,
- Grid balancing measures,
- Transmission constraints,
- Unexpected changes in generation or demand.

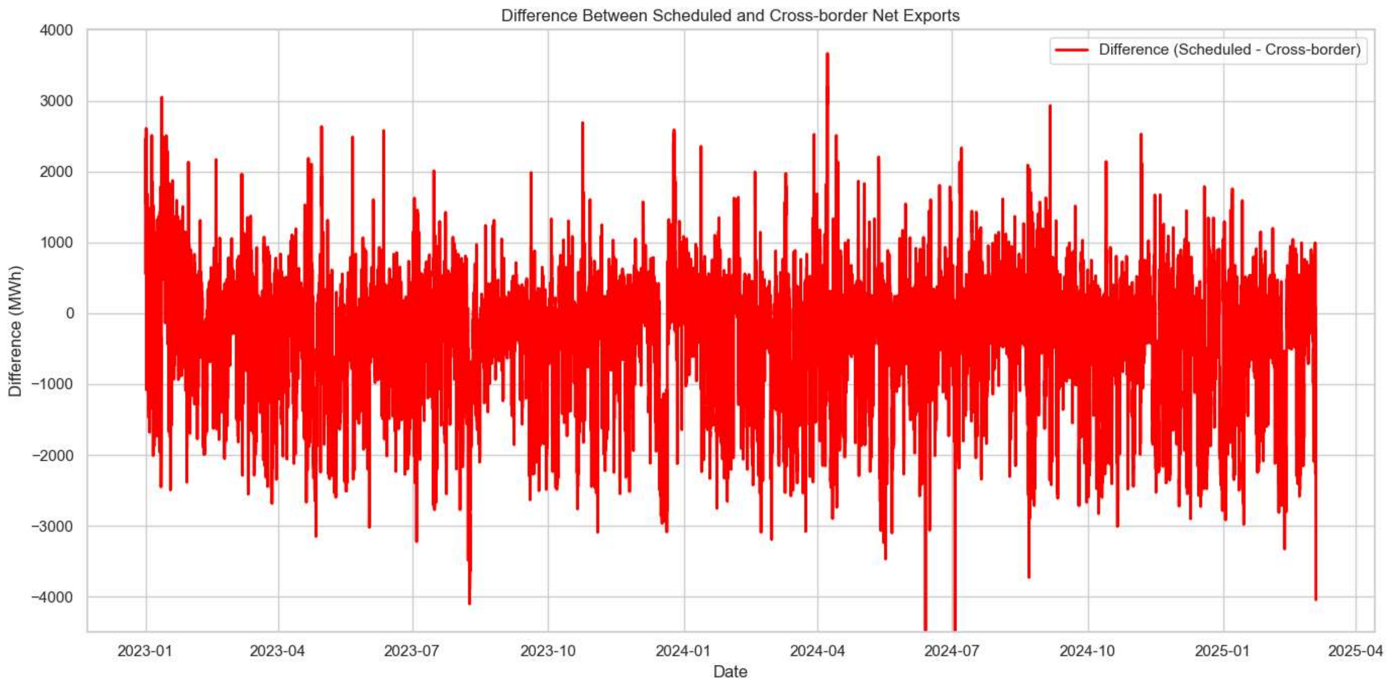
Seasonal and Volatility Patterns

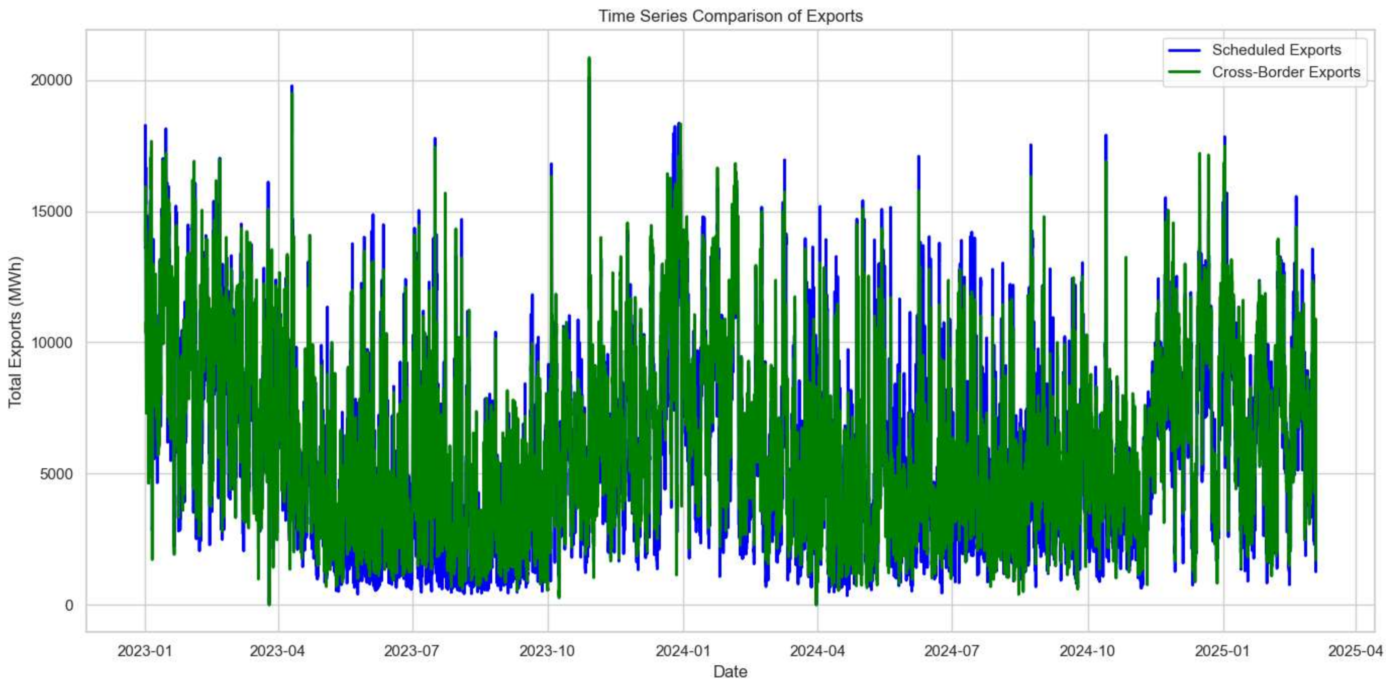
Volatility in export values tends to increase during colder periods, possibly reflecting greater fluctuations in electricity demand and generation. These seasonal patterns highlight why it's important for grid operations to remain flexible and maintain strong coordination across borders.

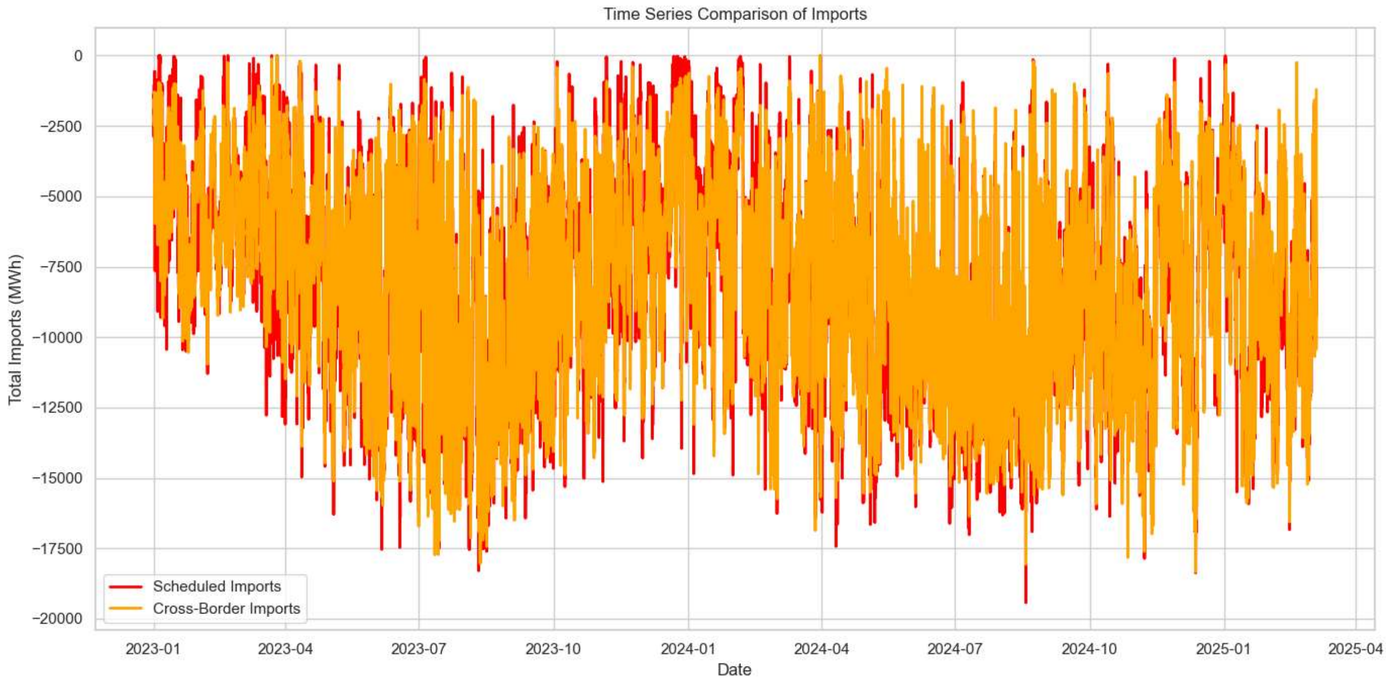
Consistency Across Imports and Exports

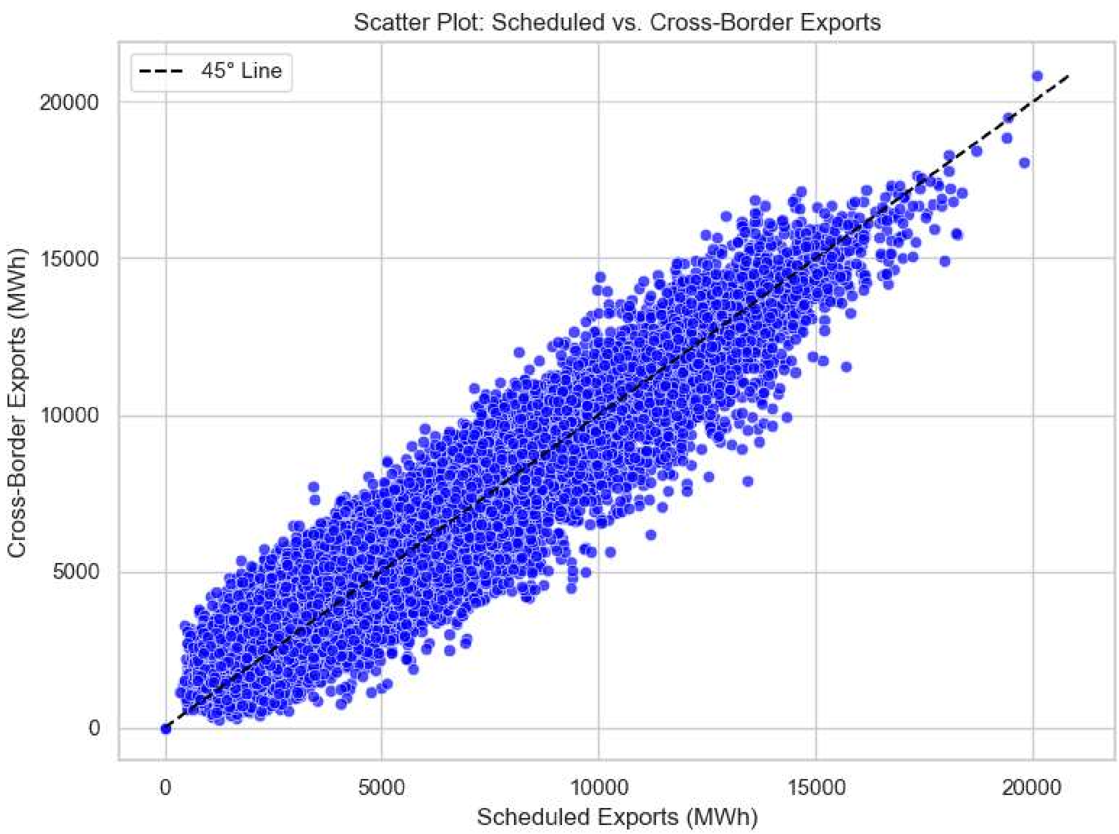
Analysis of both imports and exports shows that scheduled and actual values behave similarly in terms of pattern and magnitude. Scatter plots of scheduled versus cross-border values confirm this, with data points clustering along the 45° line. This indicates a high degree of accuracy in scheduling across both directions of flow.

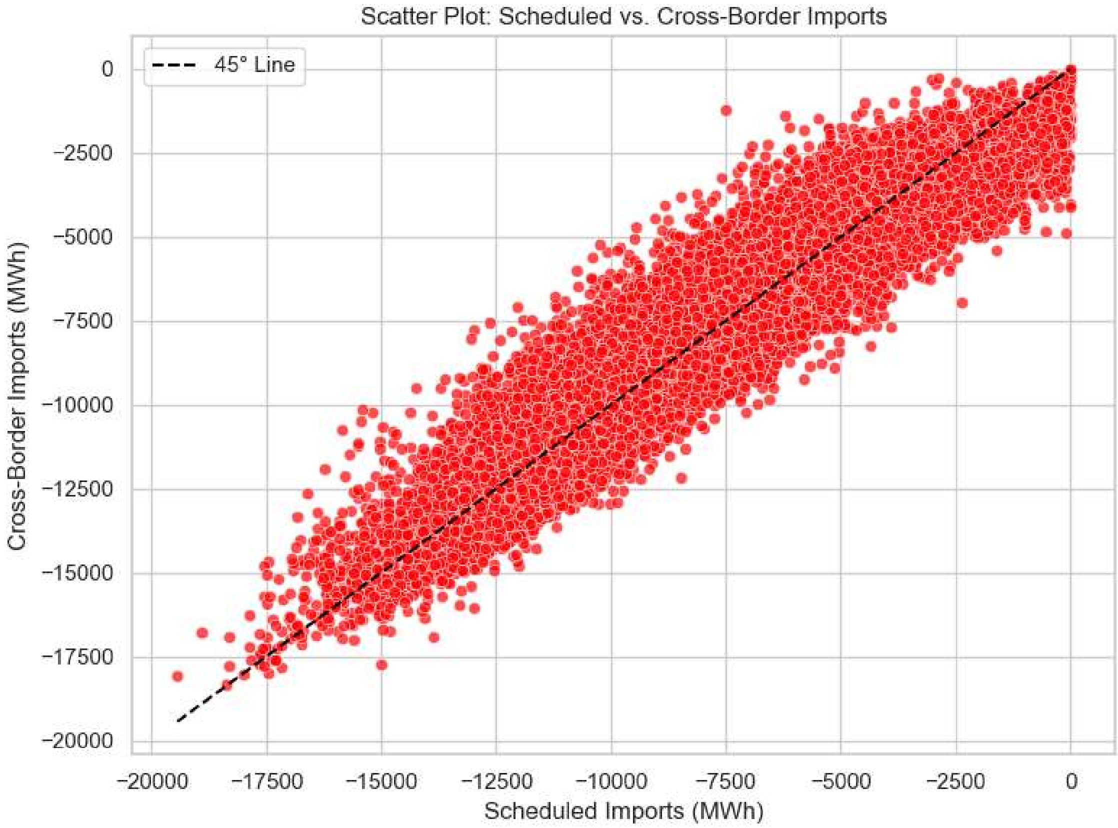



Difference Between Scheduled and Cross-border Net Exports
Difference (Scheduled - Cross-border)
Difference (MWh)
4000
3000
2000
1000
0
−1000
−2000
−3000
−4000
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date


Time Series Comparison of Exports
Scheduled Exports
Cross-Border Exports
Total Exports (MWh)
20000
15000
10000
5000
0
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date


Time Series Comparison of Imports
Total Imports (MWh)
0
−2500
−5000
−7500
−10000
−12500
−15000
−17500
−20000
Scheduled Imports
Cross-Border Imports
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date


Scatter Plot: Scheduled vs. Cross-Border Exports
45° Line
Cross-Border Exports (MWh)
20000
15000
10000
5000
0
0
5000
10000
15000
20000
Scheduled Exports (MWh)



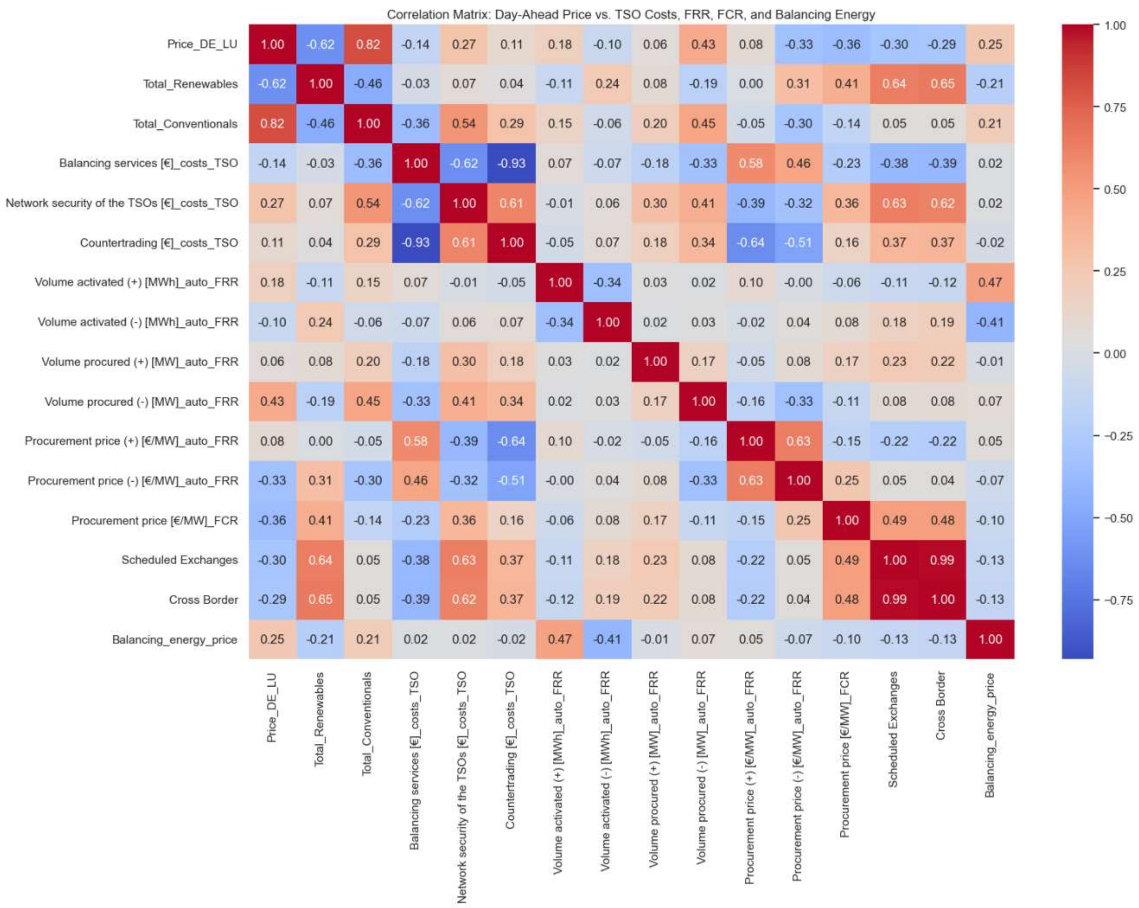
Key Insights:

Comparing scheduled commercial exchanges with actual cross-border flows shows the system is generally aligned, with reliable forecasting. Although there are occasional short-term differences, they're usually minor and reflect normal real-time adjustments in grid management. Seasonal changes also underscore why adaptive scheduling and strong interconnection frameworks are essential.

3.2 Correlation & Feature Relationships

3.2.1 Which features show the strongest correlation with electricity prices?

The correlation matrix below clearly shows that total renewable generation and total conventional generation have the highest impact on electricity prices.



3.2.2 How do prices correlate between countries?

The heatmap below shows the correlation coefficients between day-ahead electricity prices (€/MWh) across different European countries. Here is how prices correlate between countries:

High Correlations (≥ 0,9):

Countries with strong electricity interconnections and market integration tend to have very high correlations.

- Germany/Luxembourg and the Netherlands (0,95)
- Germany/Luxembourg and Austria (0,91)
- Belgium and France (0,93)
- Czech Republic and Slovakia (0,9+ with Austria, Germany)

Moderate Correlations (0,7 - 0,89):

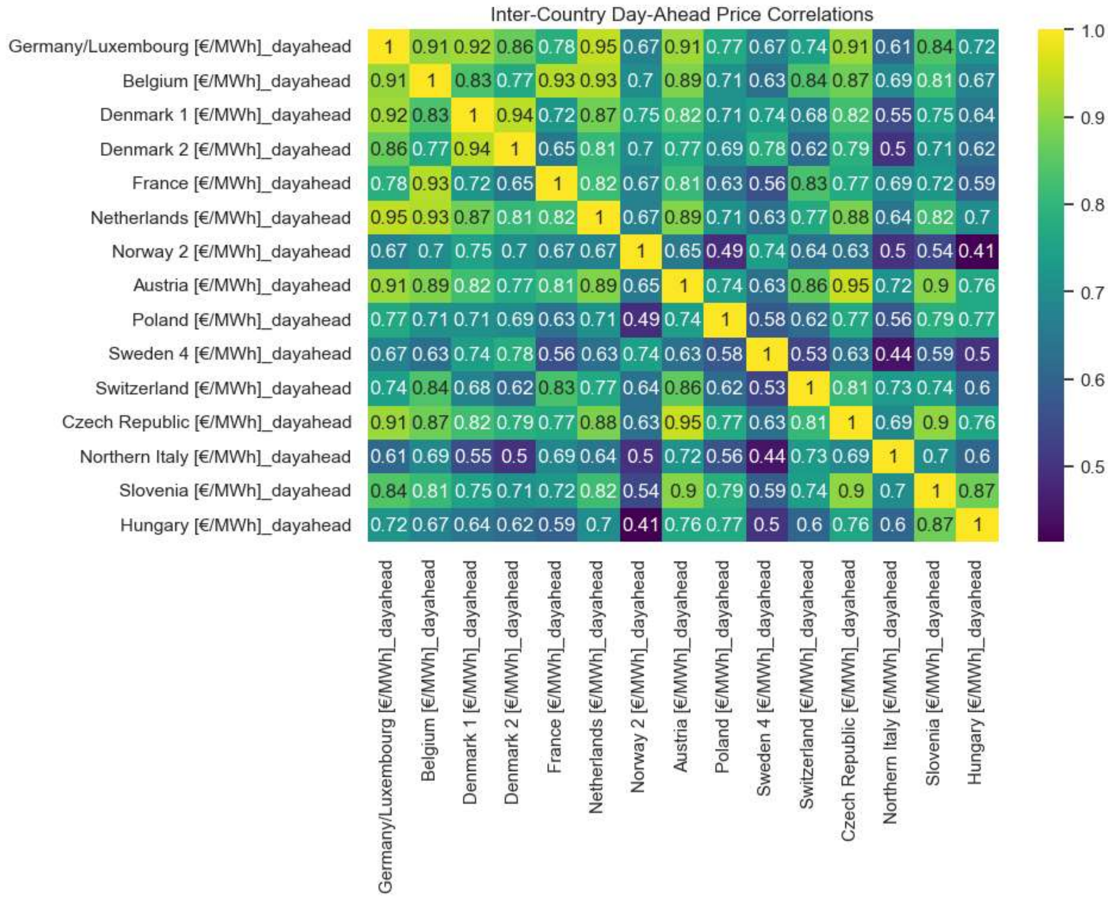
This range includes many countries that are geographically close or regionally linked but have slight market or infrastructure differences.

- France and Belgium (0,93)
- Germany and Poland (0,77)
- Austria and Slovenia (0,9)

Lower Correlations (< 0,7):

These suggest less integration, either due to geographic distance, less developed interconnectors, or differing market structures.

- Northern Italy and most other countries show lower correlations (0,5 to 0,7)
- Norway 2 has notably lower correlations with Hungary (0,41) and Northern Italy (0,5)



Key insights:

High Market Integration in Central Europe:

- Countries like Germany/Luxembourg, Austria, Netherlands, Belgium, and the Czech Republic show strong price correlations (≥ 0,9), indicating high market coupling and efficient cross-border electricity trading.

France as a Regional Hub:

- France shows high correlation with Belgium (0,93) and Germany (0,78), supporting its role as a key electricity transit and trading partner in Western Europe.

Nordic-Baltic and Central Europe:

- Denmark 1 and Sweden 4 (0,78), as well as Denmark 1 and Germany (0,92), suggest strong price integration between Nordic and Central European markets via Denmark.

Lower Correlation for Peripheral Countries:

- Norway 2, Northern Italy, and Hungary show generally lower correlations (< 0,7) with most other countries. Could be because of:
    - Limited interconnection capacity,
    - Distinct market conditions or regulatory environments.

Southern Europe Shows Mixed Integration:

- Northern Italy correlations range widely, from 0,44 to 0,69, showing some integration with countries like Austria and Slovenia, but weaker ties with Western/Nordic countries.

Hungary and Slovenia Are Strongly Correlated (0,87):

- Shows tight market connections and probably common supply-demand patterns across Eastern Europe.

3.2.3 What is the relationship between forecasted vs. actual electricity generation and consumption?

Actual Consumption:

Actual generation often mirrors real-time changes that affect prices. For instance, when there is an unexpected drop in generation, like an unplanned plant outage or reduced renewable output, it usually leads to higher spikes in prices.

Forecasted Consumption:

Forecasted values give market players an idea of what to expect, but differences between forecasts and actual generation often cause price fluctuations. If forecasts overestimate or underestimate available generation, it can throw the market out of balance, resulting in noticeable price spikes or drops.

In summary, when forecasts closely match actual generation, prices tend to be more stable. Alternatively, significant forecast errors are associated with increased price uncertainty and volatility.

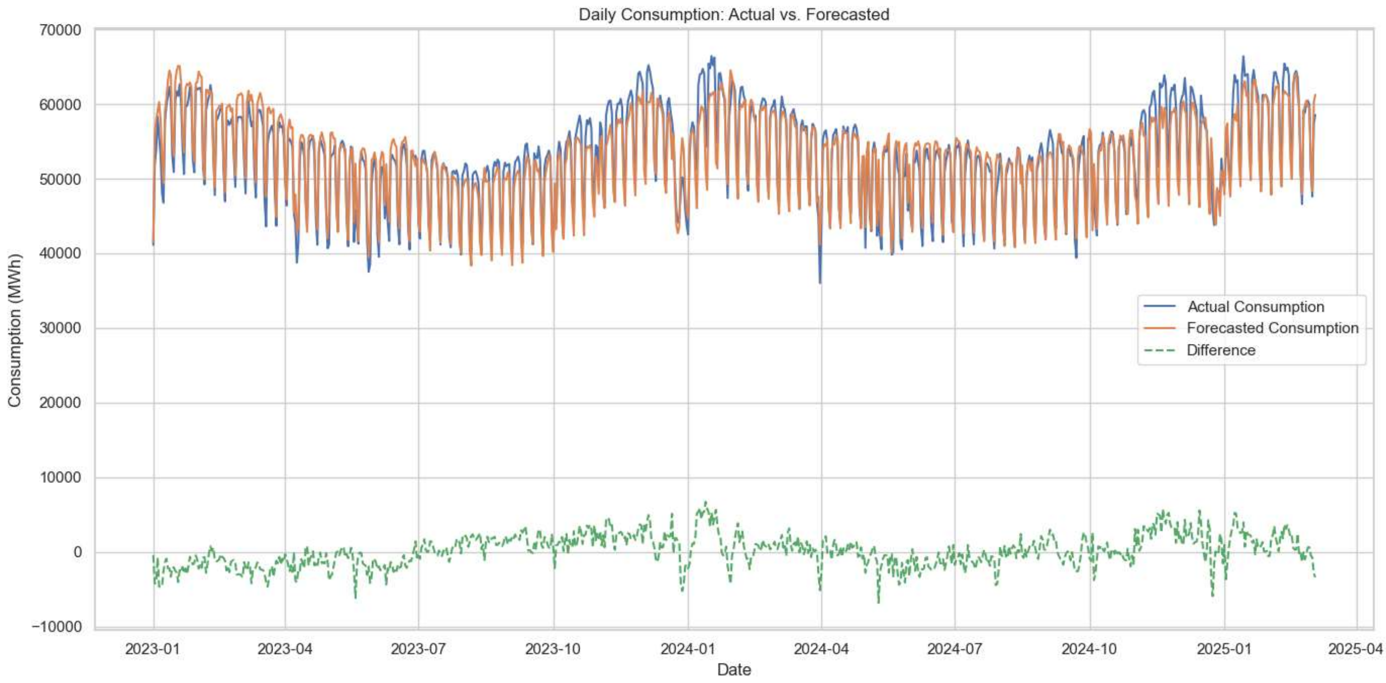
Renewables vs Conventional Forecasting

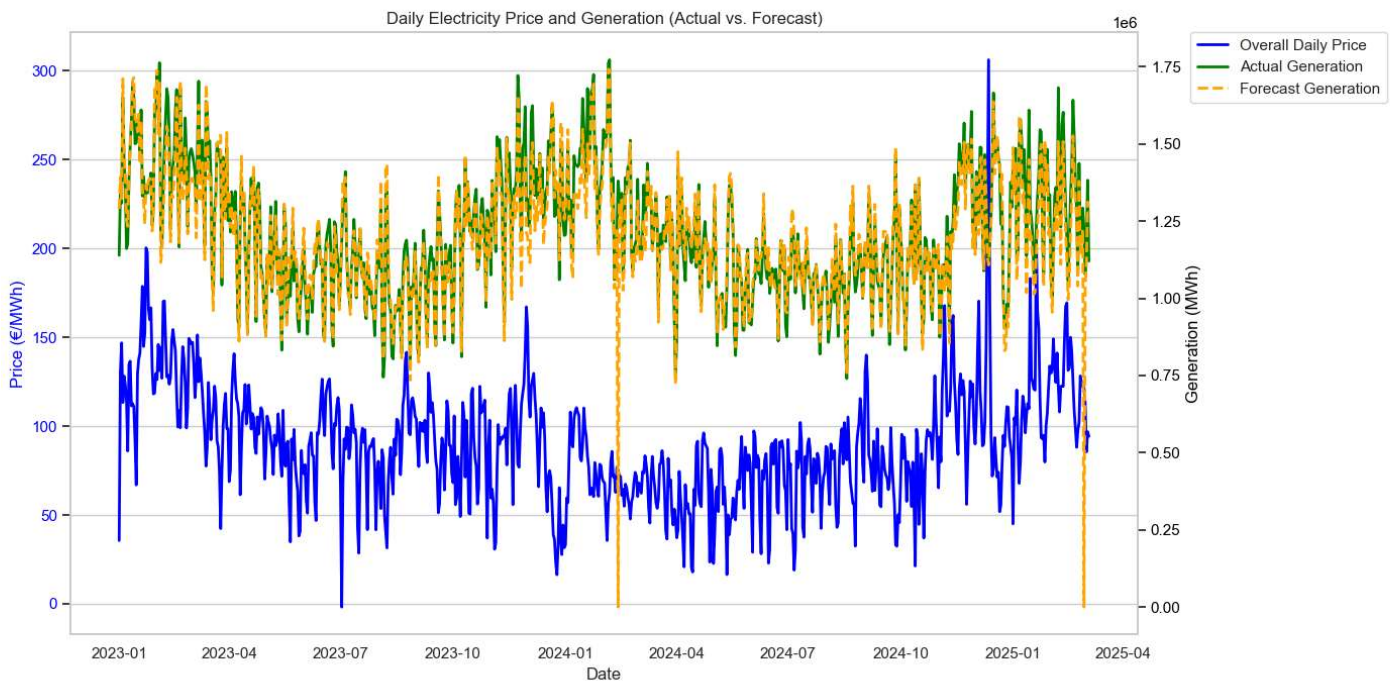
- **Renewable Generation:**
    - Forecasts are less accurate, showing larger and more frequent deviations.
    - Due to the variable nature of renewables (for e.g wind and solar), the forecast tends to overestimate the output often.
    - This leads to a generation shortfall that must be balanced by other means (e.g. reserves or imports), especially during high-demand periods.

- **Conventional Generation:**
    - More reliable and predictable. The actual output closely follows forecasts.
    - When renewable generation underperforms, conventional sources are often used to compensate, resulting in actual conventional generation exceeding its forecast.

- There is a relationship between generation forecast errors and electricity prices:
    - Under-forecasting generation (actual < forecast) leads to supply shortages, driving price spikes.
    - Over-forecasting (actual > forecast) can cause surplus supply, which tends to reduce prices.
- The scatter plot shows a negative correlation: as the generation error becomes more negative, prices tend to increase,
    - Price responses are asymmetric, the market punishes supply shortages more strongly than it rewards excess supply.

The relationship between forecasted and actual generation/consumption is generally aligned, with conventional generation and demand forecasts being more accurate, while renewable generation shows significant variability. Forecast errors, especially under-predictions of supply, correlate strongly with electricity price spikes, making forecast accuracy a key driver of market stability. Seasonal factors and energy source characteristics influence this relationship, with renewables and winter conditions contributing to most challenging for forecasting systems.


Daily Consumption: Actual vs. Forecasted
Consumption (MWh)
70000
60000
50000
40000
30000
20000
10000
0
−10000
Actual Consumption
Forecasted Consumption
Difference
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date


Daily Electricity Price and Generation (Actual vs. Forecast)
Price (€/MWh)
300
250
200
150
100
50
0
1e6
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Generation (MWh)
Overall Daily Price
Actual Generation
Forecast Generation
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date

Key Insights:

Forecast Accuracy & Market Stability

- Accurate forecasts of generation and consumption contribute to electricity price stability.
- Forecast errors, especially large discrepancies, are directly linked to price volatility and market imbalances.

Renewables vs Conventional Generation

Renewables:

- Show larger, more frequent forecast errors,
- Tend to be overestimated, especially under volatile weather conditions,
- Resulting shortfalls often require costly balancing through reserves or imports.

Conventional:

- Highly predictable, actual output aligns closely with forecasts,
- Often ramps up to compensate for underperforming renewables.

Impact on Electricity Prices

- There is a negative correlation between generation forecast errors and prices,
  - Under-forecasting (actual < forecast) → price spikes due to supply shortages,
  - Over-forecasting (actual > forecast) → price dips due to surplus,
- Price responses are asymmetric: the market reacts more sharply to shortages than to surpluses.

3.3 Price & Consumption Impact Analysis

3.3.1 How do scheduled commercial exchanges influence price fluctuations and what is the impact of cross-border physical flows on electricity prices?

Scheduled Commercial Exchanges: Strong Influence on Prices

Scheduled commercial exchanges, particularly exports from Luxembourg, exhibit the strongest positive correlation with day-ahead electricity prices. The feature with the highest correlation, *"Luxembourg (export) [MWh]_scheduled_exchanges,"* shows a correlation of nearly 0,6, indicating that:

- These exchanges reflect market expectations of supply and demand.
- They play a proactive role in price formation.
- Lagged versions (up to 12 hours) of this feature continue to show strong correlations, suggesting that scheduled exchanges have lasting predictive power on prices.

This pattern suggests that market participants use scheduled exchanges to signal and respond to anticipated conditions, which directly impacts pricing in the day-ahead market.

Cross-Border Physical Flows: Moderate to Low Influence

Cross-border flows, such as exports and imports, show weaker correlations with day-ahead prices compared to scheduled exchanges. For example:

- The feature *"Luxembourg (export) [MWh]_cross_border"* ranks high, but its correlation is notably lower than its scheduled exchange counterpart.
- Lagged cross-border flows exhibit moderate correlation values, particularly in the range of 0,2 to 0,3, indicating a delayed and reactive impact on prices.

These flows mainly represent real-time grid management and physical balancing, rather than predictive market behaviour. As a result, they tend to react to current price signals instead of driving them.

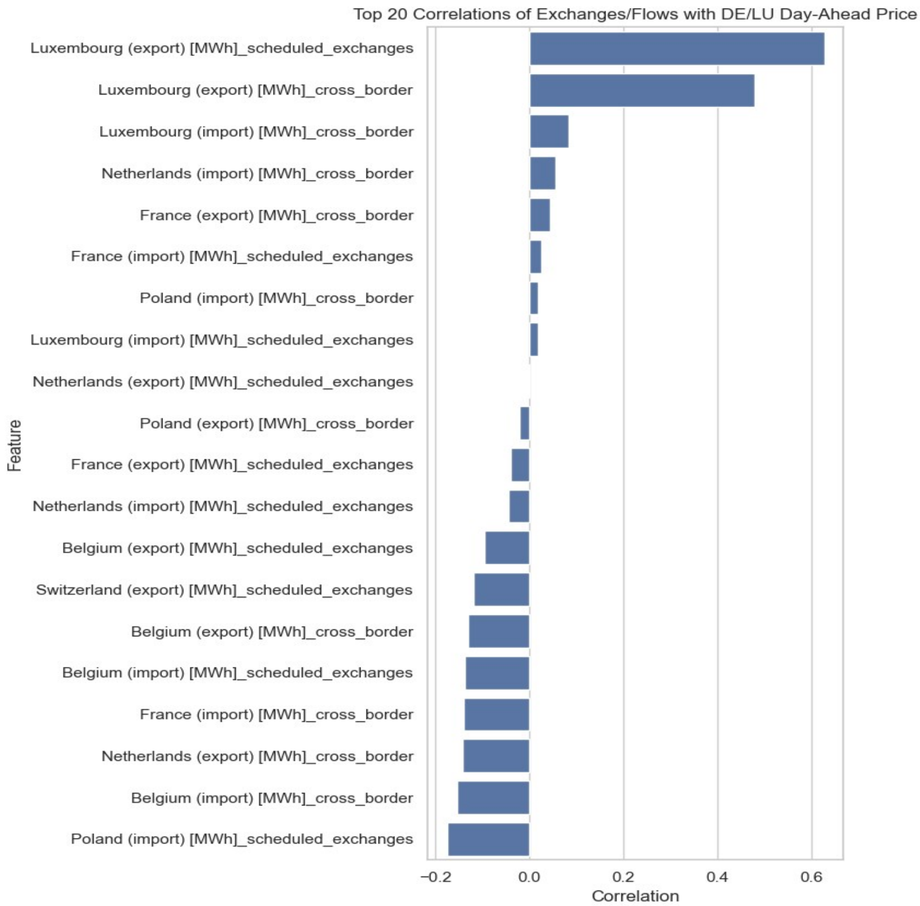
Time Series Insights: Behavioural Differences Between Scheduled and Actual Flows

A visual comparison of scheduled versus actual cross-border exchanges further reinforces the distinction between these two metrics. Scheduled imports and exports exhibit smoother, more predictable patterns aligned with market expectations and planning. In contrast, physical cross-border flows are significantly more volatile and often diverge from scheduled levels.

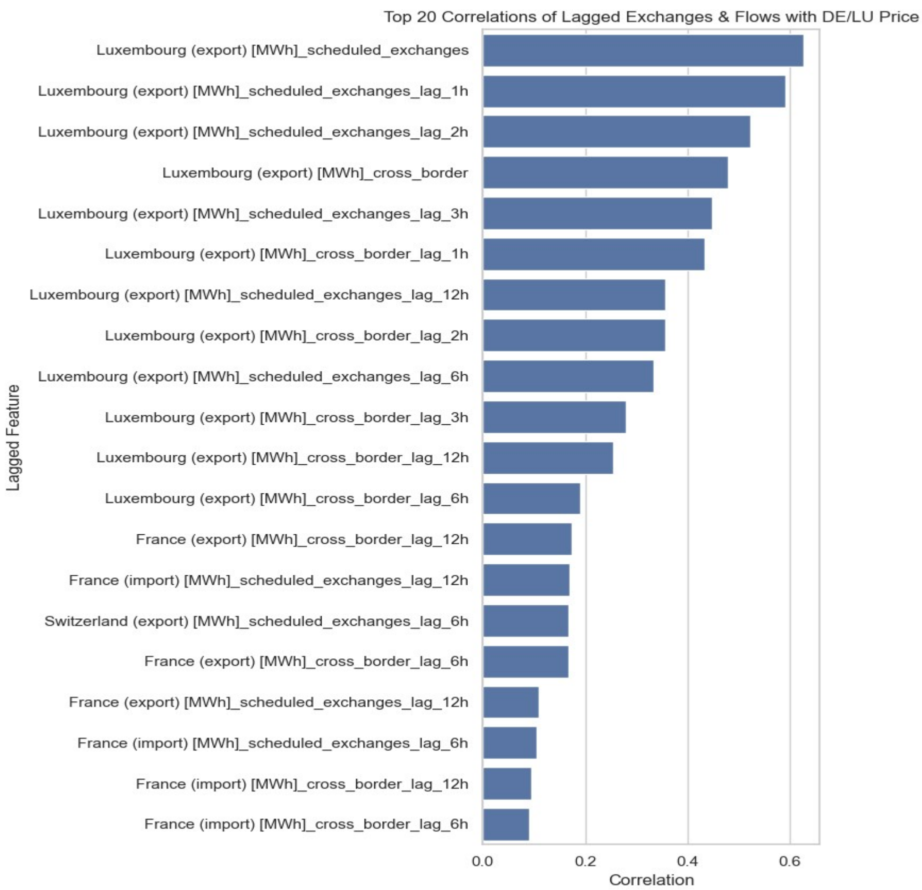
This behavioural difference suggests that:

- Scheduled exchanges act as a leading signal, capturing expectations and intentions of market participants, and are thus more influential in day-ahead price formation.
- Cross-border flows respond to real-time system conditions, such as imbalances or congestion, and therefore serve a reactive, balancing function.

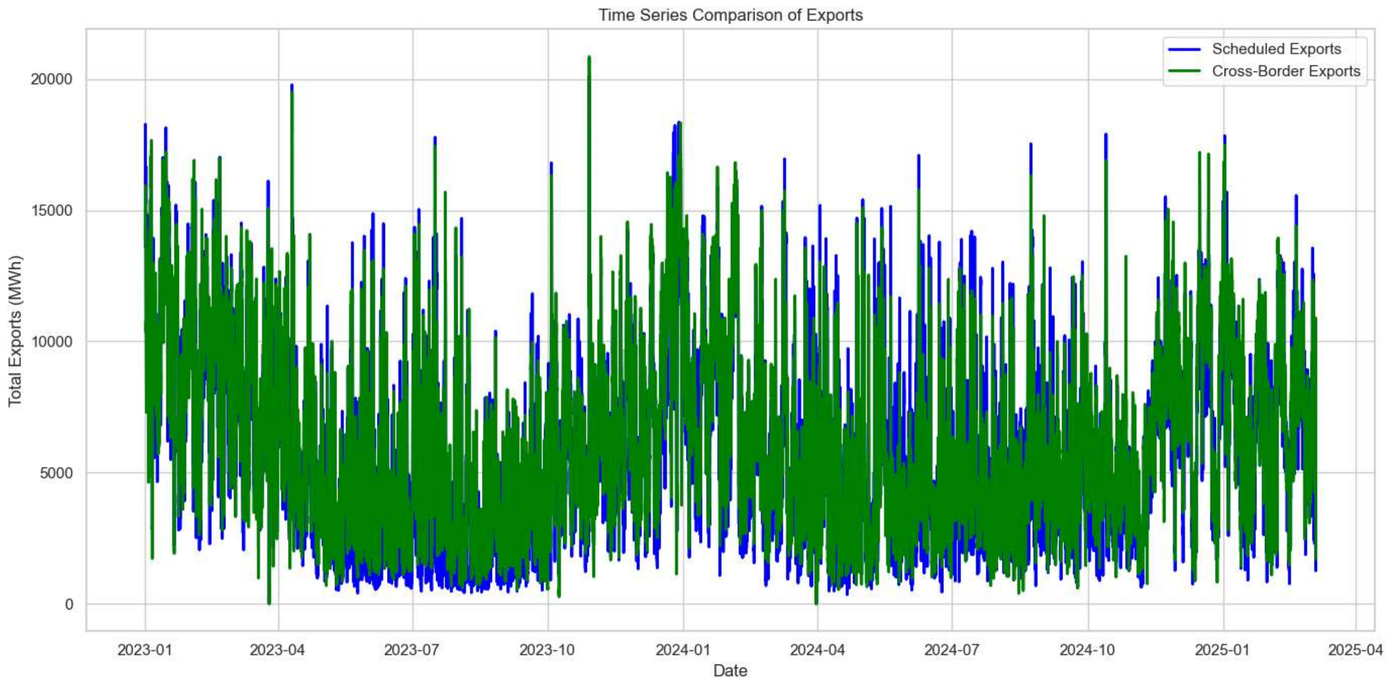
Consequently, while both indicators are relevant, **scheduled exchanges are a stronger predictor** of price movements, whereas physical flows provide important operational context.

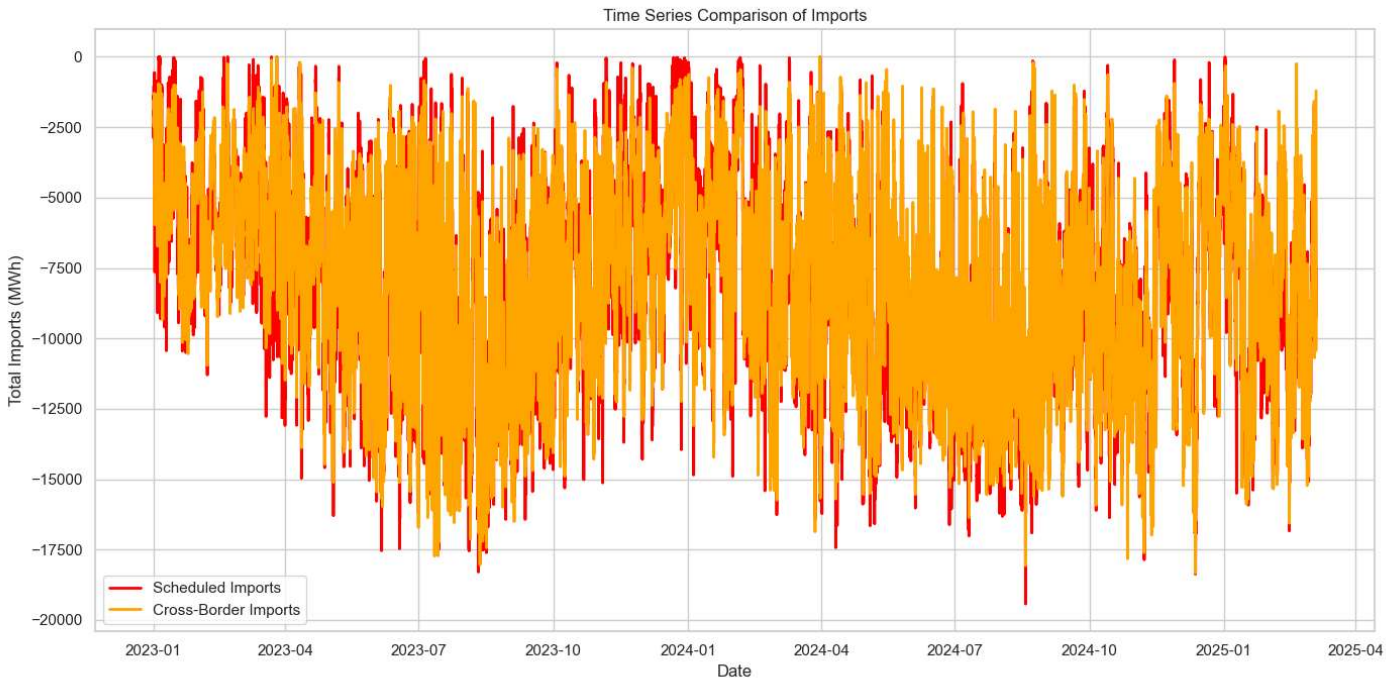


Top 20 Correlations of Exchanges/Flows with DE/LU Day-Ahead Price
Luxembourg (export) [MWh]_scheduled_exchanges
Luxembourg (export) [MWh]_cross_border
Luxembourg (import) [MWh]_cross_border
Netherlands (import) [MWh]_cross_border
France (export) [MWh]_cross_border
France (import) [MWh]_scheduled_exchanges
Poland (import) [MWh]_cross_border
Luxembourg (import) [MWh]_scheduled_exchanges
Netherlands (export) [MWh]_scheduled_exchanges
Poland (export) [MWh]_cross_border
France (export) [MWh]_scheduled_exchanges
Netherlands (import) [MWh]_scheduled_exchanges
Belgium (export) [MWh]_scheduled_exchanges
Switzerland (export) [MWh]_scheduled_exchanges
Belgium (export) [MWh]_cross_border
Belgium (import) [MWh]_scheduled_exchanges
France (import) [MWh]_cross_border
Netherlands (export) [MWh]_cross_border
Belgium (import) [MWh]_cross_border
Poland (import) [MWh]_scheduled_exchanges
Feature
−0.2
0.0
0.2
0.4
0.6
Correlation



Top 20 Correlations of Lagged Exchanges & Flows with DE/LU Price
Luxembourg (export) [MWh]_scheduled_exchanges
Luxembourg (export) [MWh]_scheduled_exchanges_lag_1h
Luxembourg (export) [MWh]_scheduled_exchanges_lag_2h
Luxembourg (export) [MWh]_cross_border
Luxembourg (export) [MWh]_scheduled_exchanges_lag_3h
Luxembourg (export) [MWh]_cross_border_lag_1h
Luxembourg (export) [MWh]_scheduled_exchanges_lag_12h
Luxembourg (export) [MWh]_cross_border_lag_2h
Luxembourg (export) [MWh]_scheduled_exchanges_lag_6h
Luxembourg (export) [MWh]_cross_border_lag_3h
Luxembourg (export) [MWh]_cross_border_lag_12h
Luxembourg (export) [MWh]_cross_border_lag_6h
France (export) [MWh]_cross_border_lag_12h
France (import) [MWh]_scheduled_exchanges_lag_12h
Switzerland (export) [MWh]_scheduled_exchanges_lag_6h
France (export) [MWh]_cross_border_lag_6h
France (export) [MWh]_scheduled_exchanges_lag_12h
France (import) [MWh]_scheduled_exchanges_lag_6h
France (import) [MWh]_cross_border_lag_12h
France (import) [MWh]_cross_border_lag_6h
Lagged Feature
0.0
0.2
0.4
0.6
Correlation


Time Series Comparison of Exports
Scheduled Exports
Cross-Border Exports
Total Exports (MWh)
20000
15000
10000
5000
0
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date


Time Series Comparison of Imports
Scheduled Imports
Cross-Border Imports
Total Imports (MWh)
0
−2500
−5000
−7500
−10000
−12500
−15000
−17500
−20000
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date

Key Insights:

- Scheduled exports from Luxembourg show the strongest positive correlation (~0,6) with *DE/LU day-ahead prices*, making them a leading indicator of price movement.

- Lagged scheduled exchange data (up to 12 hours) maintains strong correlations, suggesting lasting predictive power over short time horizons.

- Cross-border flows, show weaker and more variable relationships with prices, indicating a more reactive nature to market and grid conditions.

- Scheduled exchanges exhibit smoother, more stable trends, while cross border flows show high volatility and frequent deviations from schedules.

- Both exports and imports show seasonal patterns, with reduced activity in the summer months, likely due to changes in demand or renewable availability.

- Scheduled commercial exchanges are a strong driver of price fluctuations, as they reflect market expectations, economic signals, and bilateral trading decisions.

- Cross-border flows are more reflective of operational grid, offering less predictive power but valuable context for real-time system dynamics.

- For price modelling and forecasting, scheduled exchange data should be prioritized, while cross border flow data is better suited for real-time monitoring and post-event insights.

4. Modelling Approach

Models Used:

- Persistence Model,
- Linear Regression Model,
- Random Forest Model.
- Gradient Boosting Regressor for Quantile Regression

Why these models:

The Persistence model assumes that the next value in the time series is the same as the last observed value. This model serves as a benchmark to evaluate whether more complex models provide a meaningful improvement, If the models that are more complex, does not outperform the persistence model with significance, suggest that the data lacks predictive structure.

The Linear regression model is a fundamental statistical method that assumes a linear relationship between independent variables and the target variable.

The Random Forest Model is a more complex, no-linear model that can capture intricate relationships in the data and is robust to overfitting. Can model complex interactions between features without requiring explicit specification of the functional form.

Methodology:

The models used on this challenge were trained on a cleaned dataset provided by the Strommarktdaten" (SMARD), The main goal was to forecast electricity prices (€/MWh).

Data Preparation and Data Cleaning

- **Timestamp Standardization:**
    - Removed the column 'final date', retaining only the date information,
    - Renamed the 'start-date' column to "Date" to standardize the timestamp,
    - Aggregated quarterly data into hourly time intervals to ensure consistent timestamps.
- **Variable Renaming:**
    - Renamed columns to incorporate 'part' of the file names, enhancing clarity given the large number of variables.
- **Outlier Handling:**
    - Removed outliers using a percentile-based threshold to cap extreme values.
- **Missing Data Treatment:**
    - Removed special characters ("-") used to denote missing data,
    - Applied the forward-fill (ffill) method to fill in missing values and maintain model stability.
- **Feature Engineering:**
    - Created lagged features to capture temporal dependencies,
    - Added seasonal (winter, summer) and temporal features (daily, weekly) essential for the forecasting problem,

- Derived new variables for the Generation Feature:
    - **Total Renewables:** Sum of all renewable generation features.
    - **Total Conventionals:** Sum of all conventional generation features, providing a macro-overview of each energy source's impact.
- **Train-Test Split:**
  - Split the dataset into training and testing sets using an 80/20 ratio, ensuring that 80% of the data was used for model training and the remaining 20% for validation and testing.

From the EDA I used the *'Price_DE_LU',* which is the Germany/Luxembourg day-ahead electricity price, as **dependent variable** (the target we are trying to predict). It showed strong correlations with prices in several other countries, making it a solid and representative choice for modelling.

All other variables:

- Actual_cons (actual consumption),
- Residual_load,
- Forecast_cons,
- Total_Renewables,
- Total_Conventionals,
- Net_export_physical,
- Net_export_scheduled.

plus all the derived temporal, lagged, and rolling features are **independent variables** (features used to predict the price).

Detailed breakdown of each model used in the code, along with the calibration and tuning methods applied:

- **Persistence Model:**
  - **Method:**
    - A naive forecasting approach where each predicted value equals the previous observation.
    - For the first test point, the last value from the training set is used as a fallback.
  - **Calibration/Tuning:**
    - No explicit tuning or calibration is performed, as it serves as a baseline for comparison.

- **Linear Regression:**
  - **Method:**
    - Utilizes scikit-learn's LinearRegression to model a linear relationship between features and the target variable.
  - **Calibration/Tuning:**
    - No hyperparameter tuning or calibration is applied; the model is used in its standard.

- **Random Forest:**
  - **Method:**
    - Uses scikit-learn’s RandomForestRegressor to capture nonlinear relationships and complex interactions among features.
  - **Tuning:**
    - **RandomizedSearchCV:**
      - Hyperparameter distributions are defined:
        - n_estimators: [100, 200, 300, 400]
        - max_depth: [3, 5, 7, 10, None]
        - min_samples_split: Random integers between 2 and 15
        - min_samples_leaf: Random integers between 1 and 10
        - max_features: Options include 'sqrt', 'log2', and None
      - A TimeSeriesSplit (with 5 splits) is used for cross-validation to preserve the temporal order.
      - The tuning is set to run 30 iterations, optimizing based on the negative mean squared error.
  - **Calibration:**
    - No additional calibration is performed after tuning; the best estimator from RandomizedSearchCV is directly used for predictions.

- **Quantile Regression with GradientBoostingRegressor (for Prediction Intervals):**
  - **Method:**
    - Two separate GradientBoostingRegressor models are trained:
      - One for the 5th percentile (lower bound) using loss='quantile' and alpha=0,05,
      - One for the 95th percentile (upper bound) using loss='quantile' and alpha=0,95,
    - Both models share hyperparameters such as n_estimators=500, learning_rate=0,1, max_depth=3, and a fixed random state.
  - **Calibration:**
    - **Post-Hoc Calibration:**
      - After initial prediction intervals are obtained, empirical coverage is calculated.
      - If the actual coverage is below the target of 95%, a scaling factor is computed:
        - **Scaling Factor:** target_coverage / current_coverage
      - This factor is used to adjust the half-width of the prediction intervals, thereby recalibrating the interval to achieve the desired coverage.

5. Results & Performance Metrics

5.1 Model Comparison

Performance Metrics:

Model	RMSE	MAE	Directional Accuracy	Volatility Capture	Extreme Precision	Extreme Recall
Persistence	14,02	9,59	71,5%	1,00	0,56	0,56
LinearReg	19,58	15,65	**79,7%**	**0,75**	**0,70**	0,53
RandomForest	27,49	20,32	**79,73%**	0,64	**0,76**	0,47

Key Insights:

- Directional accuracy is stronger in the Linear Regression model (~79,7%), crucial for predicting trends.
- Persistence performs well in capturing volatility because it responds directly to recent changes.
- Random Forest achieves the highest precision for detecting extreme price movements, but this comes with a trade-off in recall.

5.2. Market-Driven Prediction Accuracy and Business Usability & Interpretability

Directional Accuracy:

Both **Linear Regression** and **Random Forest** models demonstrate **high directional accuracy (~79,7%),** meaning they correctly classify price movements (up, down, or stable) most of the time, this is a vital metric for market decision-making.

Volatility Capture:

The models underperform compared to the Persistence baseline when it comes to capturing the magnitude of price variability, Persistence achieves a perfect volatility capture ratio (1,00), while models smooth out extremes (**Linear Regression: 0,75** and Random Forest: 0,64).

Extreme Price Movement Detection:

The **Random Forest model** shows strength in identifying sharp movements (>15% change), with a **precision of 0,76**, However, recall remains moderate at 0,47, indicating some extreme events are missed.

Confidence Intervals & Probability Forecasting:

The **Gradient Boosting model** generates calibrated prediction intervals, with the 95% confidence interval achieving a **post-calibration coverage of 89,93%** (up from 87,2%). This adds significant value for probabilistic forecasting and risk management.

Interpretability & Feature Importance:

SHAP analysis provides transparent insights into feature influence:

- Top features: **Total_Conventionals**, **Residual_load**, and various **lagged features.**
- Beeswarm plots visually show the individual and global impact of these features.

To understand the drivers behind the model's predictions, SHAP (SHapley Additive Explanations) analysis was conducted on the trained Random Forest model. The SHAP results help explain both the overall and individual predictions of the model, showing which features have the biggest impact and in what way.

Key Findings from SHAP Analysis:

- **Total_Conventionals** and **Residual_load** are the most impactful features, indicating that conventional generation and net demand are strong predictors of electricity prices,
- When **Total_Conventionals** and **Residual_load** are high, the model tends to predict higher prices, likely because greater demand or reliance on conventional (and more costly) generation pushes prices up,
- Alternatively, **Total_Renewables** shows a negative relationship, when renewable generation is high, price predictions tend to decrease, aligning with market behaviour,
- Lagged versions of these features also rank highly, confirming the importance of recent past values in price forecasting.

Business Usability & Insights:

- The most important features make sense from a market perspective, which adds confidence that the model is capturing real-world energy dynamics accurately,
- The analysis distinguishes between:
    - Controllable variables (e.g., conventional generation) which can inform operational or trading decisions,
    - Observable/forecastable variables (e.g., residual load, renewable output) which can enhance situational awareness and real-time strategy.
- SHAP values enable scenario testing and “what-if” simulations, supporting proactive decision-making and risk management,

- These interpretability results make the model more transparent, which is valuable for stakeholder communication, regulatory reporting, and internal validation by domain experts.

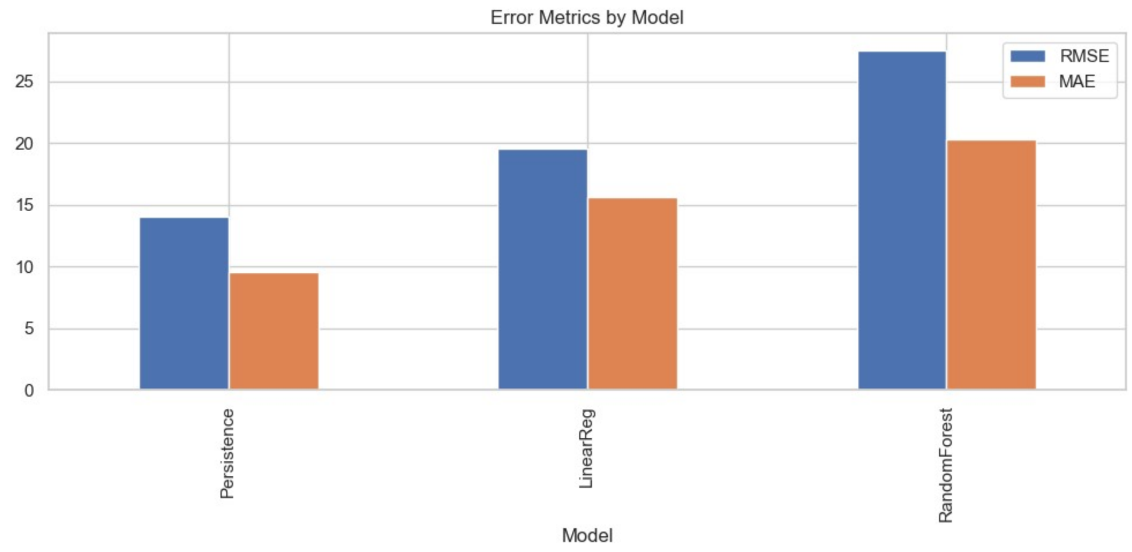
Results Summary:

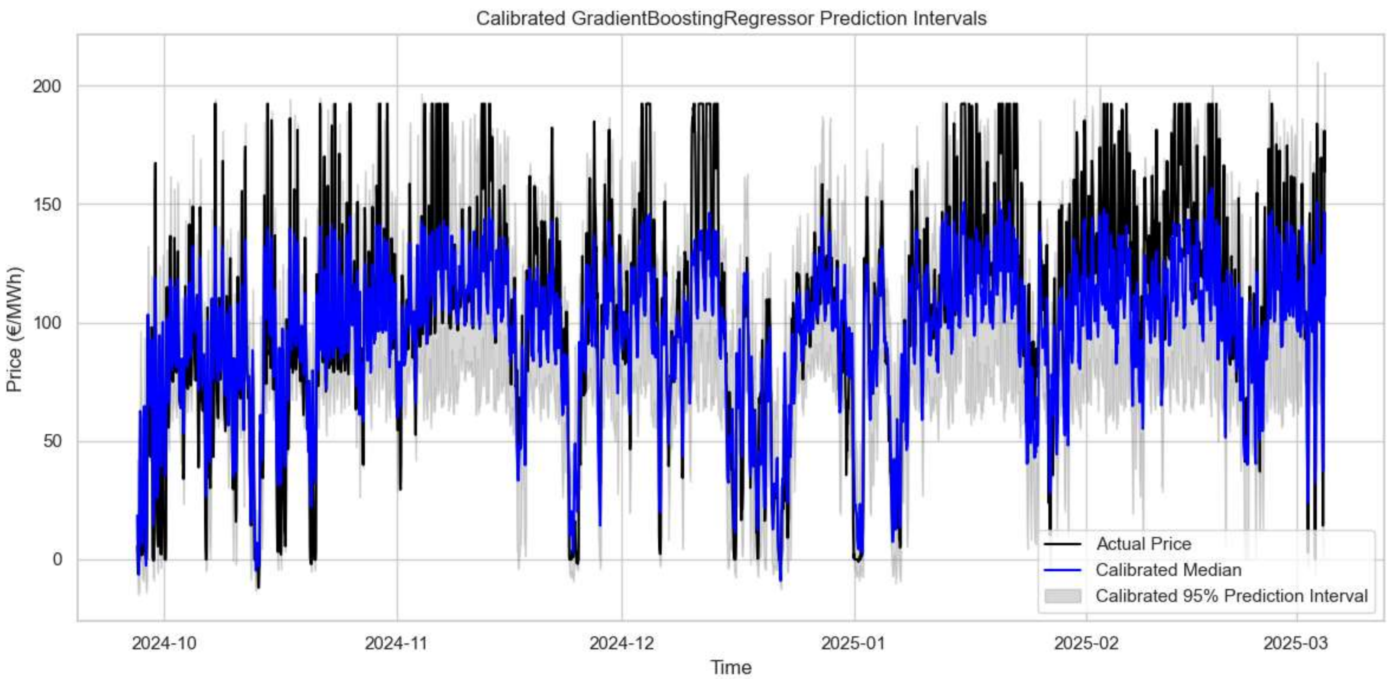
The three forecasting approaches were evaluated: a Persistence baseline, Linear Regression, and a Random Forest model. While the Persistence model had the lowest RMSE (14,02) and MAE (9,59), both Linear Regression and Random Forest significantly outperformed it in directional accuracy, correctly predicting the direction of price changes nearly 80% of the time (79,7% for Linear Regression, 79,73% for Random Forest, compared to 71,5% for Persistence). This is particularly valuable for market-facing decisions.

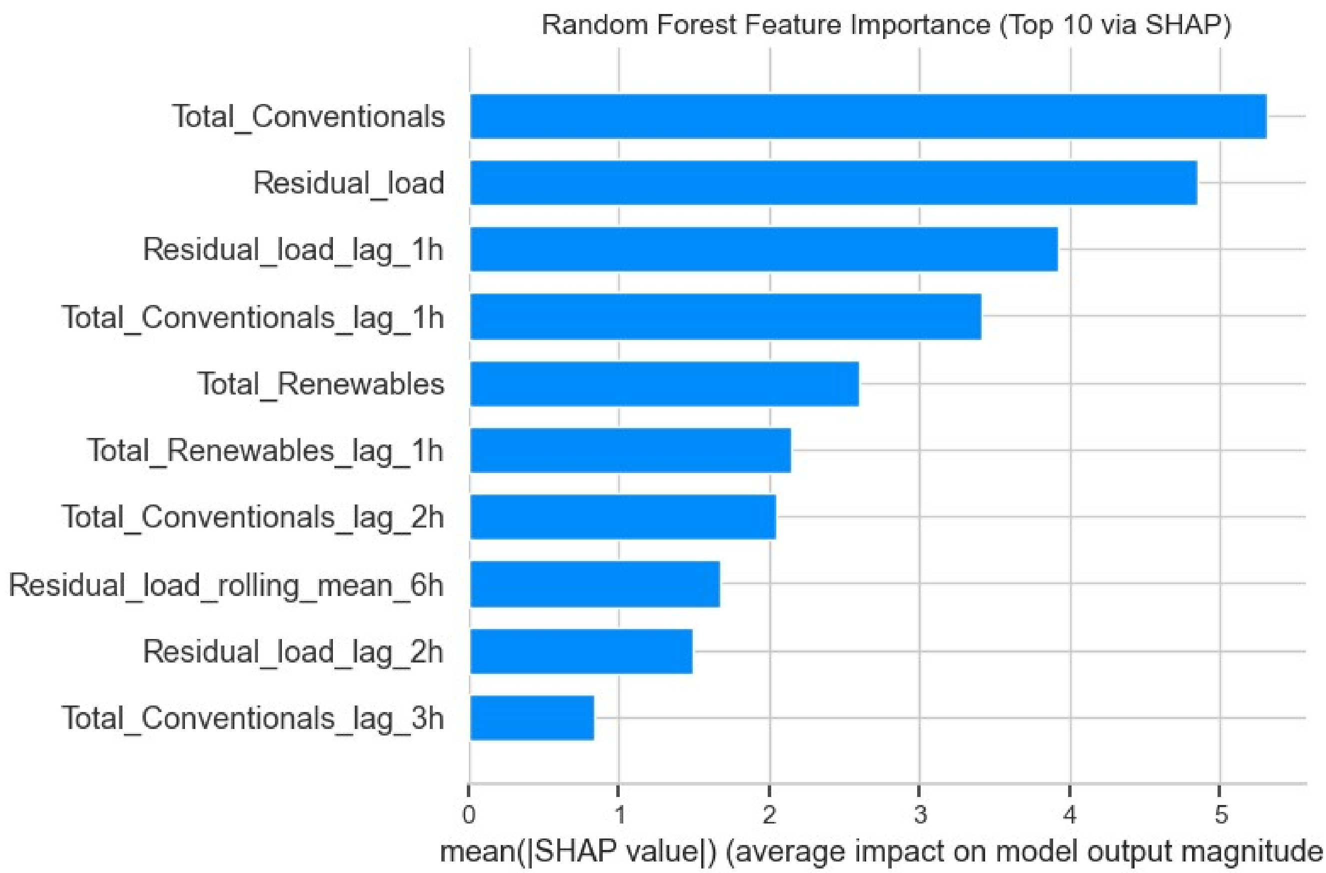
In terms of volatility capture, Persistence performed best with a perfect score of 1,00, as expected. The other models tended to smooth out price extremes, with scores of 0,75 (Linear Regression) and 0,64 (Random Forest). However, Random Forest showed the highest precision (0,76) when detecting large price movements (over 15%), although its recall was lower (0,47), meaning some sharp changes were missed.

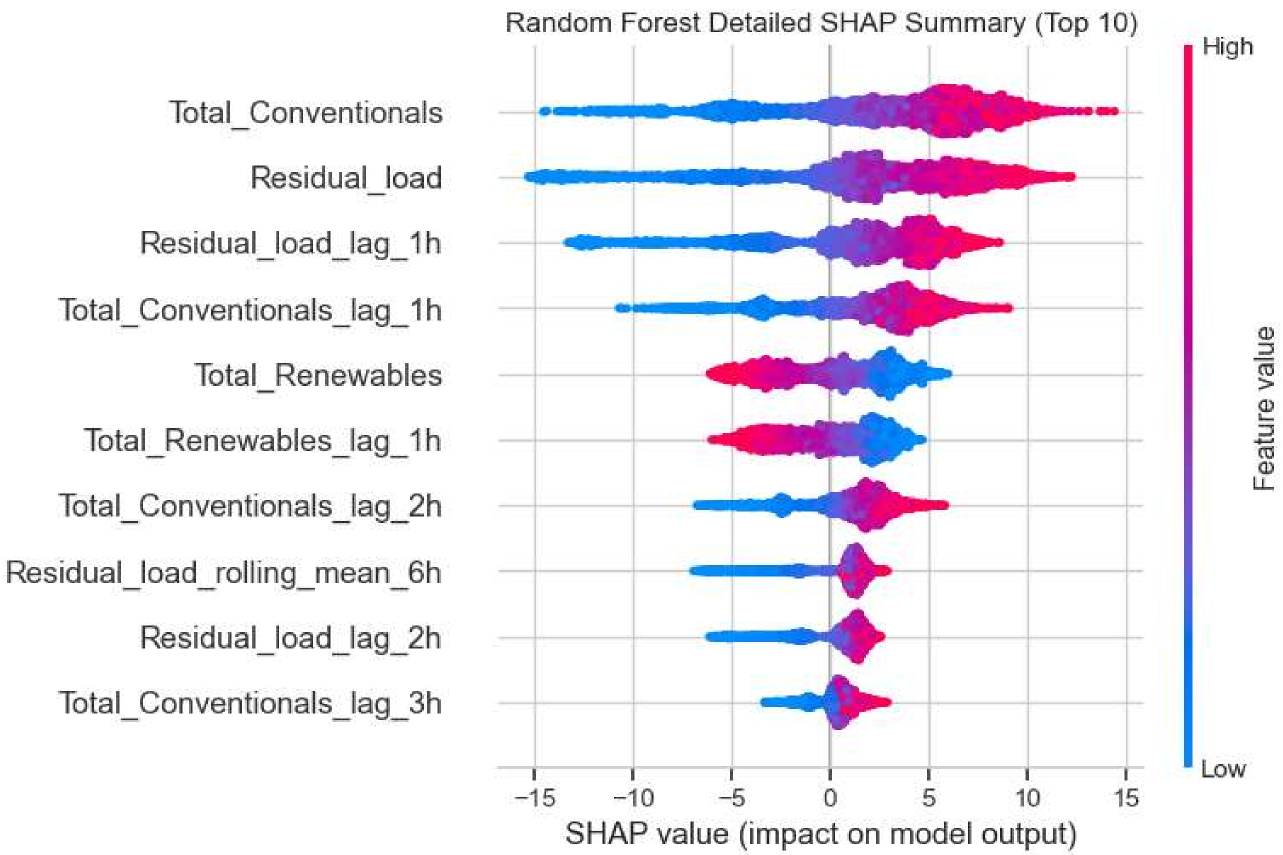
Finally, the Gradient Boosting model was used for probabilistic forecasting. After calibration, its 95% prediction interval achieved 89,93% coverage, up from 87,2%, offering more reliable confidence intervals for risk management.

The SHAP analysis revealed that Total_Conventionals, Residual_load, and their lagged values are the most influential features driving price predictions. High levels of conventional generation and residual load tend to push prices up, while increased renewable output generally lowers them. These findings align well with market fundamentals, adding confidence in the model's behavior. Overall, SHAP helps clarify how the model makes decisions, supporting transparency and practical use in business and regulatory contexts.


Error Metrics by Model
RMSE
MAE
25
20
15
10
5
0
Persistence
LinearReg
RandomForest
Model


Calibrated GradientBoostingRegressor Prediction Intervals
200
150
100
50
0
Price (€/MWh)
Actual Price
Calibrated Median
Calibrated 95% Prediction Interval
2024-10
2024-11
2024-12
2025-01
2025-02
2025-03
Time


Random Forest Feature Importance (Top 10 via SHAP)
Total_Conventionals
Residual_load
Residual_load_lag_1h
Total_Conventionals_lag_1h
Total_Renewables
Total_Renewables_lag_1h
Total_Conventionals_lag_2h
Residual_load_rolling_mean_6h
Residual_load_lag_2h
Total_Conventionals_lag_3h
0
1
2
3
4
5
mean(|SHAP value|) (average impact on model output magnitude


Random Forest Detailed SHAP Summary (Top 10)
Total_Conventionals
Residual_load
Residual_load_lag_1h
Total_Conventionals_lag_1h
Total_Renewables
Total_Renewables_lag_1h
Total_Conventionals_lag_2h
Residual_load_rolling_mean_6h
Residual_load_lag_2h
Total_Conventionals_lag_3h
−15
−10
−5
0
5
10
15
SHAP value (impact on model output)
High
Low
Feature value

6. Business Usability & Key Takeaways

Actionable Insights for Stakeholders:

Energy Traders:

- High directional accuracy and spike precision make the models suitable for short-term trading strategies.
- Confidence intervals aid in risk-adjusted decision-making.

Industrial Consumers:

- Probabilistic forecasts and price direction indicators help optimize energy procurement timing.
- Can align load management strategies with predicted low/high price windows.

Grid Operators:

- SHAP analysis reveals drivers of price surges, improving situational awareness.
- Intervals assist in stress-testing and planning reserve margins.

Strengths:

- Strong trend prediction capability (Directional Accuracy ~80%).
- Model transparency via SHAP.
- Calibrated uncertainty estimation.

Limitations:

- The models underperform Persistence in volatility capture and recall for extreme events.
- Calibration still slightly under 95% target coverage.

7. Conclusion & Recommendations

This study presents a robust electricity price forecasting report utilizing baseline models, linear regression, Random Forest and Quantile Regression with GradientBoostingRegressor and Post-Hoc calibration. Key performance metrics such as RMSE, MAE, directional accuracy, and volatility capture were evaluated. Random Forest demonstrated strong performance in capturing directional trends and price spikes, making it well-suited for strategic trading scenarios focused on trend prediction. On the other hand, linear regression offers a good balance between predictive accuracy and interpretability, making it a solid choice.

Business Implications:

- Stakeholders can leverage different models for specific needs: Persistence/Linear Regression for conservative planning, Random Forest for proactive trading,
- Probabilistic forecasts allow for risk-informed decisions,
- Feature insights improve transparency and stakeholder trust.

Recommendations:

- Apply Random Forest outputs cautiously, especially during expected high volatility,
- Extend the pipeline to include real-time retraining and scenario simulations.

This approach to price forecasting is not only statistically robust but also operationally meaningful. With ongoing refinement and the integration of key market inputs, it has the potential to support both strategic planning and day-to-day decision-making across the energy sector.