TRADING STRATEGY DEVELOPMENT ON GB ELECTRICITY MARKET

KRITI 2025 - LOW PREP

Final Submission Report

Author:
Hostel 57

I. Introduction

The Great Britain (GB) electricity market is a competitive and liberalized system where electricity is traded between generators, suppliers, and consumers. It consists of the wholesale market, where electricity is traded in bulk, and the retail market, where suppliers sell to end consumers. Prices in the market fluctuate due to various factors, including supply and demand, renewable energy generation (such as wind and solar), grid load, and government policies. These price fluctuations create opportunities for intraday trading strategies, which can capitalize on the volatility to generate profits. Understanding these trends is crucial for identifying patterns and developing effective trading strategies

II. Background and Problem Description

A. Background:

This project focuses on analyzing and forecasting electricity prices and demand, particularly within the context of renewable energy sources like wind and solar. It involves data from energy markets, including wind forecasts, temperature, demand, and historical price data. The aim is to utilize machine learning techniques to predict electricity prices, system demand, and renewable generation, while accounting for various complexities like forecast errors, seasonality, and price volatility.

B. Problem Description:

The task at hand is to analyze the intraday electricity price trends in the GB market from October 1, 2022, to December 31, 2024. This involves identifying periods of high and low price volatility and understanding the underlying factors that drive these fluctuations, such as environmental conditions, renewable energy contributions (like wind and solar), grid load, and changes in supply and demand.

The ultimate goal is to develop a simple intraday trading strategy that can take advantage of these price patterns, backtest it, and evaluate its effectiveness using key metrics such as return, drawdown, and risk-adjusted performance. Visualizations are also expected to help demonstrate the strategy's performance over time.

III. Dynamics of GB Electricity Market

The equity market focuses on ownership of companies with financial risk-return dynamics, while the GB electricity market revolves around physical and financial energy transactions shaped by real-time operational needs and policy-driven decarbonization. The former is investor-driven, while the latter balances engineering, economics, and sustainability goals.

The GB electricity market operates with distinct time periods to manage the physical and financial aspects of electricity generation, trading, and consumption. These periods are critical for balancing supply and demand, pricing, and settlement.

IV. Data Acquisition

For this project, we chose the Elexon API for data acquisition due to its consistency and reliability in providing real-time, day-ahead forecasts for wind and solar generation in the UK electricity market. Using a single source ensures data alignment and reduces preprocessing complexity. The large dataset available through the API is crucial for backtesting and training the machine learning model over an extended period.

The dataset includes parameters such as:

- Wind Generation Forecast (Day-ahead)
- Solar Generation Forecast (Day-ahead)
- Electricity Demand Forecast (Day-ahead)
- Market Index Price (Electricity prices)
- Temperature Data (Daily/Hourly)
- Settlement Period Data (Periods 1-48)
- Net Imbalance Volume (NIV) data

While alternatives like National Grid ESO, Renewable Energy Guarantees of Origin (REGO), EIA (US), PJM Interconnection, and Gridwatch exist, Elexon was preferred for its comprehensive renewable generation forecasts, specific to Great Britain, and its API accessibility, making it the ideal choice for this project.

V. Making of the Dataset

We merged multiple datasets to create a unified final dataset for analysis and forecasting. The Elexon API provided day-ahead forecasts for wind generation, solar generation, and electricity demand, all aligned by settlement periods. Temperature data was interpolated to match the half-hourly periods, and market prices were merged based on settlement periods. Net Imbalance Volume (NIV) data was also incorporated to account for price volatility. Missing values and anomalies were addressed using methods like interpolation and forward filling. The final dataset, with all parameters aligned, was then used for exploratory analysis, preprocessing, and machine learning model preparation.

VI. Data Analysis

The Exploratory Data Analysis (EDA) section of the project focuses on understanding the underlying patterns and relationships within the data, identifying anomalies, and deriving insights that can guide the feature engineering process and modeling. Here's a detailed description of the data analysis performed:

A. Problems in Data:

We started by identifying and addressing issues in the dataset, such as missing values, duplicates, and inconsistencies. Anomalies like incorrect settlement periods (e.g., periods 1 and 2 appearing too often) were flagged for correction. Gaps in data, possibly caused by market holidays, DST transitions, or maintenance periods, were also examined to ensure no critical data points were missing or incorrectly aligned.

B. Basic Cleaning and Processing:

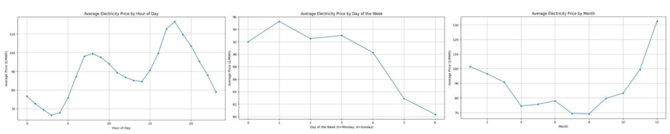
The dataset underwent initial cleaning, where missing values were handled using forward/backward filling or interpolation. Temperature data, for example, was interpolated to match half-hourly settlement periods. Data types were checked and corrected, ensuring that all features (like time, demand, and prices) were correctly formatted for analysis and modeling.

C. Key Insights from Summary Statistics:

Descriptive statistics were computed for key variables like wind generation, solar generation, electricity demand, and prices. This helped in identifying distributions, ranges, and potential outliers. The central tendency (mean, median) and variability (standard deviation, IQR) of the features were analyzed to detect any patterns or unusual trends.

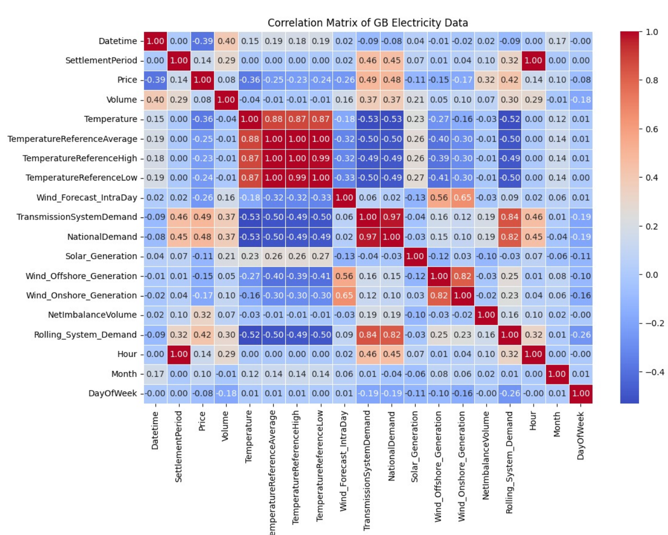
D. Hourly, Monthly, and Weekly Price Trends:

We explored how electricity prices varied across different time intervals. Price trends were examined at hourly, daily, monthly, and weekly levels to understand seasonality and identify peak price periods. The analysis showed that electricity prices tend to rise during high-demand periods and in response to fluctuating renewable generation (e.g., lower



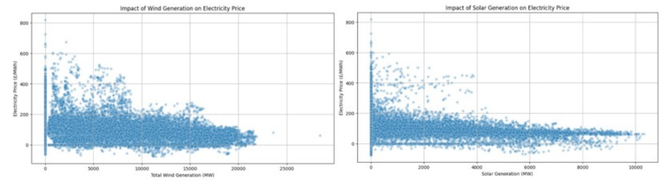
E. Correlation Insights:

Correlation analysis was conducted to understand the relationships between different variables. For example, we looked at the correlation between temperature and demand, price and demand, and renewable generation and prices. Strong correlations were noted, such as higher electricity demand during colder temperatures and higher prices when demand exceeded supply.



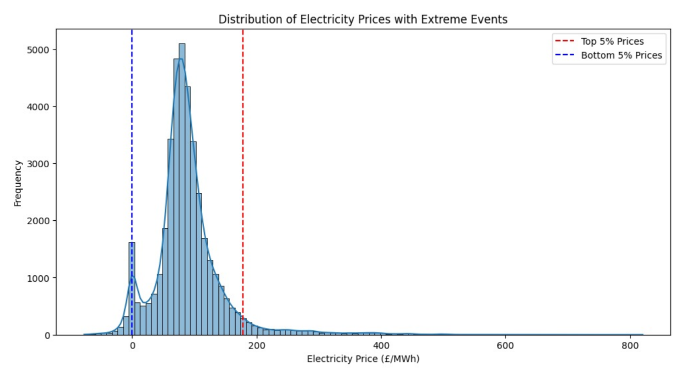
F. Renewable Generation Impact:

We investigated how renewable energy generation (wind and solar) affected electricity prices. It was found that higher renewable generation generally led to lower prices, particularly during off-peak hours. Wind generation, in particular, was a significant factor, as it influenced the balance between supply and demand, impacting price volatility.



G. Insights on Extreme Price Events:

Extreme price events, where prices spiked unusually, were analyzed to determine what factors contributed to these occurrences. It was found that these price spikes often happened during periods of high demand or low renewable generation. Identifying these events helped in understanding price volatility and the conditions under which the market becomes more sensitive to supply-demand imbalances.



H. Price Volatility and Holiday Impact:

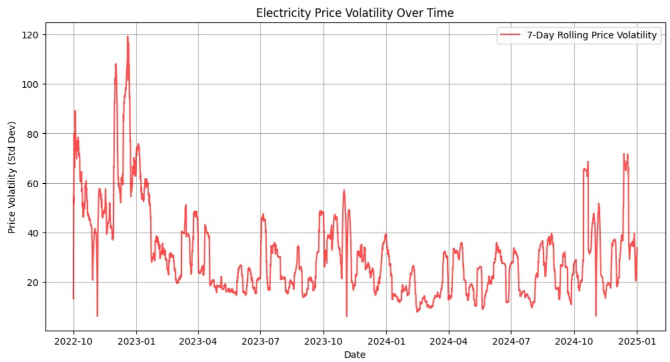
We assessed price volatility and its relationship with external factors like market holidays and system imbalances. Higher volatility was observed during certain months and around holidays when demand patterns shifted unexpectedly. The holiday effect was especially pronounced during periods of reduced trading activity, where prices became more erratic due to lower liquidity.

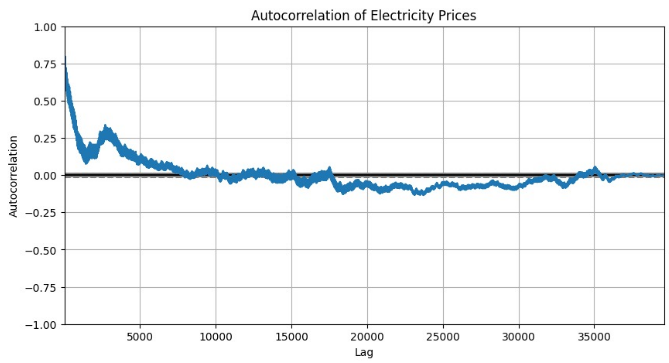
I. Insights from Price Autocorrelation:

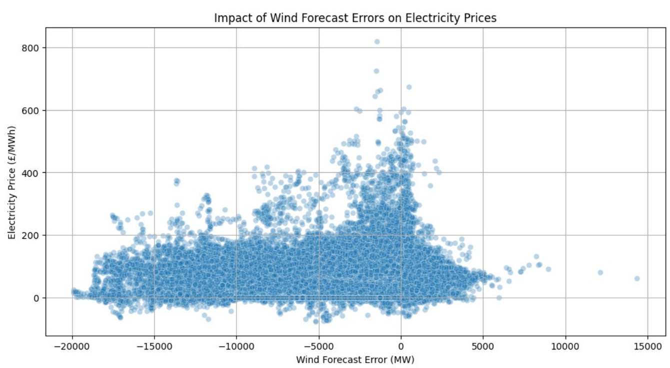
Price autocorrelation was analyzed to understand how past prices influence future prices. This analysis highlighted patterns such as price persistence, where high prices were often followed by high prices and vice versa.

J. Wind Forecast Errors and Price Sensitivity:

We analyzed how errors in wind forecasts (differences between forecasted and actual wind generation) affected electricity prices. Larger forecast errors were linked to higher price volatility as the grid adjusted to supply-demand mismatches.







K. Outlier Analysis:

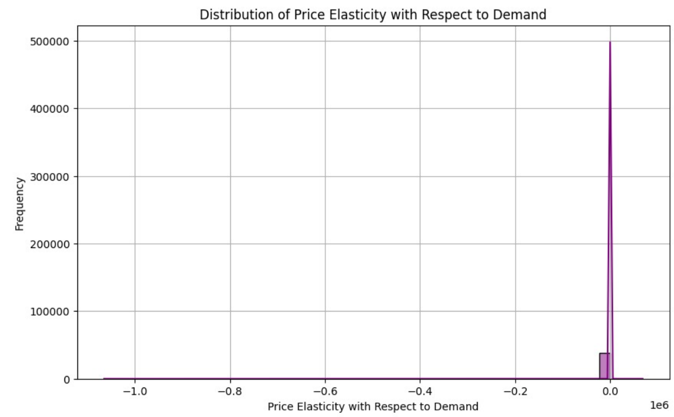
Outliers in price and demand were identified to assess their impact on the model. Extreme outliers, such as unusually high prices or low generation periods, were flagged and analyzed separately to understand their causes. Adjustments to the model were made to ensure these outliers did not unduly influence model predictions.

L. Demand-Driven Price Sensitivity:

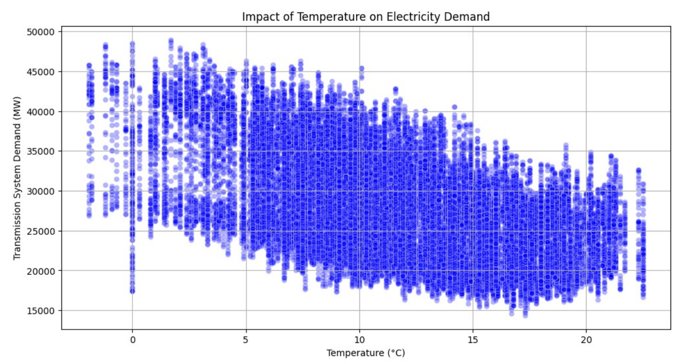
We studied how demand fluctuations impacted electricity prices, particularly during periods of high demand. Price elasticity and its correlation with demand were key focus areas. Higher demand typically led to higher prices, but this relationship was more pronounced when renewable generation was low.

M. Feature Engineering and Implications:

The insights from EDA informed feature engineering, leading to the creation of new variables like rolling averages, lag



features, and interaction terms (e.g., demand and temperature). Additional features like forecast errors, volatility, and demand-price trends were generated to improve model accuracy.



In summary, the EDA process provided a comprehensive understanding of the dataset, highlighting key patterns, correlations, and anomalies. These insights were crucial for building a more effective predictive model, ensuring that the machine learning algorithms could account for the complexities in the electricity market, particularly the influence of renewable generation and weather on electricity prices.

VII. Experimented Approaches

A. NIV based Trading Strategy

The study focuses on predicting Net Imbalance Volume (NIV), which represents the net sum of all balancing actions taken by National Grid to match electricity supply and demand. A positive NIV indicates a shortage of generation (higher prices), while a negative NIV suggests excess generation (lower prices). Accurately forecasting NIV allows traders to anticipate price movements in the intraday electricity market.

A two-stage feedforward neural network model is developed to predict electricity demand and NIV one hour ahead. The first neural network forecasts total transmission system demand, which is then used as an input for the second model to predict NIV. Both networks are trained using historical market and system balancing data, optimized with the Adam optimizer, and fine-tuned for best performance.

A simple trading strategy is implemented based on predicted NIV values:

Buy electricity if $NIV > 0$, expecting prices to rise. Sell electricity if $NIV < 0$, anticipating price drops.

B. Volatility Clustering using PCA and K-Means

We tried to use PCA and K-means clustering to generate different volatility clusters, in order to enhance the trading strategy by reducing dimensionality and grouping similar trading periods. K-Means clustering was applied to PCA-transformed training and testing datasets, with the model fitted on training data to predict test cluster labels. Interactive plots visualized price clusters over time, and key statistics like size, average close price, and volatility provided insights into cluster characteristics.

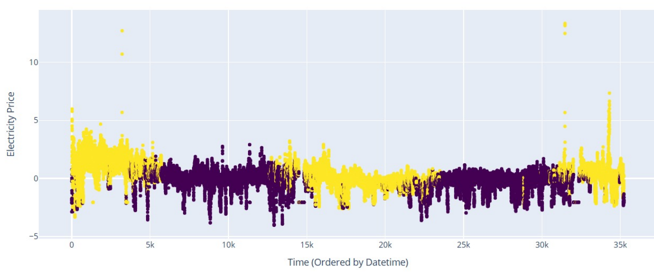


Fig. 1: Yellow is for high volatility and Purple is for low volatility

VIII. Key Approaches used in the Strategy

A. Volatility Regime Identification Using Markov-Switching Model

1) Introduction: Volatility refers to the variation in asset prices over time, with volatility clustering occurring when high volatility follows high volatility, and low volatility follows low volatility. Identifying these periods is crucial for risk management and trading. The Markov-Switching Model (MSM) is a statistical tool that models time series with unobservable shifts between regimes, helping to identify volatility regimes.

2) Theory Behind the Markov-Switching Model: The MSM assumes that a time series is governed by an unobserved state variable s_t that follows a Markov process. Each state corresponds to a different regime (e.g., low or high volatility). The data at time t is related to the regime s_t as:

$$y_t = \mu_{s_t} + \epsilon_t$$

Where:

- μ_{s_t} is the mean of the regime s_t,
- ϵ_t is the error term.

The transition probabilities between regimes are captured by a transition matrix P, where each entry P_{ij} represents the probability of transitioning from state i to state j:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}$$

The sum of each row in the matrix equals 1:

$$P_{11} + P_{12} = 1 \quad \text{and} \quad P_{21} + P_{22} = 1$$

3) Logic and Approach: The Markov-Switching Model classifies time points into volatility regimes based on the likelihood of being in each state. A threshold of 0.5 is applied to classify periods as high or low volatility. The model relies on the Expectation-Maximization (EM) algorithm for parameter estimation and uses the likelihood function:

$$L(\theta) = \prod_{t=1}^{T} P(y_t | s_t, \theta) \cdot P(s_t | s_{t-1}, \theta)$$

Where θ are the parameters, including the transition probabilities and regime-specific means.

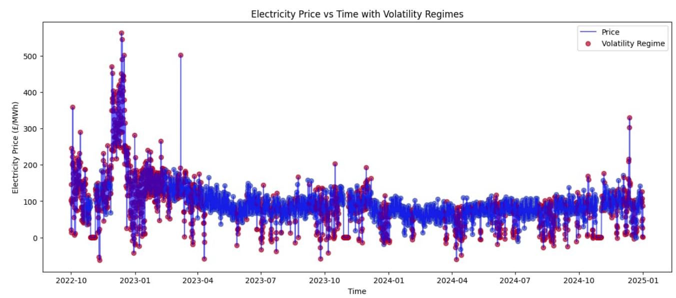


Fig. 2: Red represents High Volatility and Blue represents Low Volatility

B. CUSUM

CUSUM (Cumulative Sum) is a statistical method used to detect shifts in the mean of a process over time. It tracks cumulative deviations from a reference value, where consistent positive or negative deviations indicate potential market shifts. The deviation between each observed value x_i (e.g., price) and the reference value μ_0 (mean of the process) is calculated as:

$$d_i = x_i - \mu_0$$

The cumulative sum at time i is computed by summing these deviations up to that point:

$$S_m = \sum_{i=1}^{m} (x_i - \mu_0)$$

This method helps to identify significant shifts in market conditions when the deviations consistently move in one direction.

IX. Strategies Used

A. CUSUM Strategy

Buy Signal (Long Entry Condition):

- **Regime:** regime = 'bullish' (CUSUM indicates an upward shift in price trends)
- **Volume Condition:** Volume > Rolling Volume Mean (Increased market activity supports upward momentum)
- **Price Condition:** Price < Rolling Price Mean (Buying at a relative discount based on historical prices)

- **Demand Condition:** Demand > Rolling Demand Mean (Higher demand suggests stronger market conditions for price increase)
- **Price Validity:** Price > 0 (Ensuring valid price data)
- **Position Condition:** Not already in a long position (Avoids redundant buy signals when already in a long trade)

Short Signal (Short Entry Condition):

- **Regime:** regime = 'bearish' (CUSUM detects a downward shift in price trends)
- **Price Condition:** Price > Rolling Price Mean (Selling at a relative high before expected decline)
- **Demand Condition:** Demand < Rolling Demand Mean (Lower demand suggests potential price weakness)
- **Price Validity:** Price > 0 (Ensuring valid price data)
- **Position Condition:** Not already in a short position (Avoids redundant short signals when already in a short trade)

Sell Signal (Exit Long Position):

- **Regime Shift:** regime switches from 'bullish' to 'bearish' (CUSUM detects a market shift signaling potential downside)

Exit Short Trade Conditions: The short position is exited when any of the following conditions are met:

- **Regime Shift:** If the market shifts from bearish to bullish, indicating a reversal: regime_i = 'bullish'

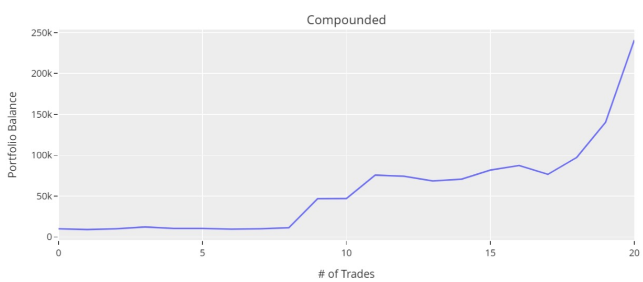


Fig. 3: Portfolio Visualization

Metric	Value
Initial Balance	10,000
Final Balance	240,743.892
Peak Balance	240,743.892
Maximum Dip	-10,788.244
Average Dip	-1,647.896
Lowest Balance	9,106.751
Maximum PnL	100,490.842
Minimum PnL	-10,788.244
Net Return	2,307.439%
Annualised Return	34,785,783.206%
Buy and Hold Return (BTC/USDT)	-90.45%
Maximum Drawdown	-21.296%
Total Transaction Fees	0

TABLE I: Compounding Metrics Summary

B. ML Approach

1) Model Selection: This strategy uses Random Forest to predict next-period price movements, generating trading signals accordingly. Random Forest was selected over XGBoost and Ridge Regression based on its lowest MAE, ensuring higher predictive accuracy and robustness.

2) Signal Generation: Buy (Long) Signal (1): If the model predicts a price increase. Sell (Short) Signal (-1): If the model predicts a price decrease.

3) Trade Execution: Enter a position at the current period's close price based on the model's prediction. The sharpe ratio is less because of high volatility in the price.

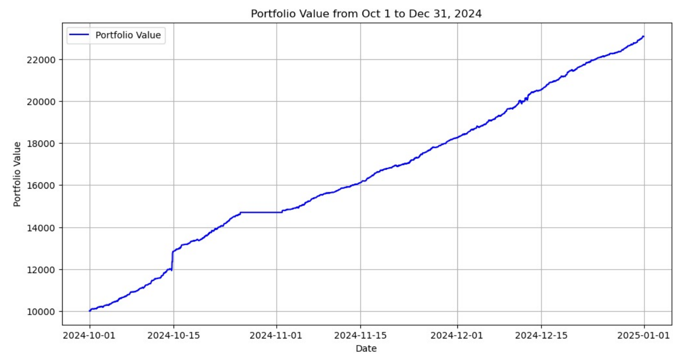


Fig. 4: Portfolio (ML Approach)

C. Time Based Approach

Buy Signal (Long Entry Condition): A long entry is triggered when the following conditions are met:

- **Regime Condition:** regime_i = 'bullish' (CUSUM detects an upward trend continuation)
- **Trend Confirmation:** regime_{i-1} = 'bullish' (Previous period was also bullish, confirming trend strength)
- **Execution Window:** $\text{SettlementPeriod}_i = 9$ (Trade is executed only at a specific time window)
- **Volatility Stability:** $\text{Volatility\_Regime}_i = 0$ (Market volatility is stable, reducing unexpected price swings)
- **Valid Price Check:** $P_i > 0$ (Ensures valid price data and avoids anomalies)
- **Position Constraint:** Current Position = 0 (Avoids re-entering a long position if already active)

Short Signal (Short Entry Condition): A short entry is triggered when the following conditions are met:

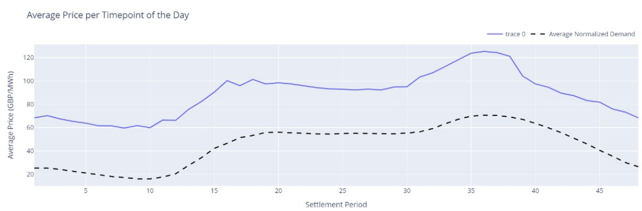
- **Regime Condition:** regime_i = 'bearish' (CUSUM detects a downward trend continuation)
- **Trend Confirmation:** regime_{i-1} = 'bearish' (Previous period was also bearish, confirming trend strength)
- **Execution Window:** $\text{SettlementPeriod}_i = 17$ (Trade is executed only at a specific time window)
- **Volatility Stability:** $\text{Volatility\_Regime}_i = 0$ (Market volatility is stable, reducing unexpected price swings)
- **Valid Price Check:** $P_i > 0$ (Ensures valid price data and avoids anomalies)
- **Position Constraint:** Current Position = 0 (Avoids re-entering a short position if already active)

Exit Long Signal (Closing Long Position Condition): The long position is exited when the following condition is met:

- **Execution Window:** The market reaches a peak in price, signaling an optimal exit point for long positions: $\text{SettlementPeriod}_i = 35$

Exit Long Signal (Closing Short Position Condition): The short position is exited when the following condition is met:

- **Execution Window:** The market reaches a peak in price, signaling an optimal exit point for short positions: $\text{SettlementPeriod}_i = 35$



X. Conclusion

The GB electricity market operates differently from standard financial markets due to its unique supply-demand dynamics, real-time pricing fluctuations, and regulatory influences. Unlike equities or commodities, electricity cannot be stored efficiently, making price movements highly volatile and dependent on grid stability, weather patterns, and consumption trends. To navigate these complexities, we have developed three distinct trading strategies tailored to different aspects of the market—short-term price arbitrage, imbalance forecasting, and algorithmic trend trading—each leveraging different facets of price and demand data. Our dataset includes historical and real-time electricity prices, demand forecasts, imbalance costs, and grid frequency data, acquired from official sources, independent market operators, and API integrations. This comprehensive approach ensures that our models are well-informed and adaptable to the ever-changing electricity trading landscape.

XI. Sources

- https://bmrs.elexon.co.uk/apidocumentation/endpoint/datasets
- Pozzetti, L. (2020). Algorithmic trading in UK power markets using neural networks. BSc thesis, Department of Computer Science, University of Bristol.
- https://research-information.bris.ac.uk/en/publications/trading-electricity-markets-using-neural-networks-2 Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica, 57(2), 357–384. DOI:10.2307/1912559