# Vaibhav Gupta

amy227557@iitd.ac.in (official) | vaibhav19m345@gmail.com (personal)

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This proposal outlines a trading strategy for the electricity market in GB, focusing on leveraging intraday price dynamics observed during the first week in December. The strategy combines insights from data analysis and weather-driven factors to optimize electricity trading for **profit maximization** and **risk mitigation**.

## [A] Weekly Dataset:

02-12-2024 to 09-12-2024 (day-ahead and intraday)

[GB_dayahead_pricedata.csv and GB_intraday_pricedata.csv]

## [B] Data Analysis:

I have visualized the different types of temporal patterns in the electricity data for the day-ahead and intraday sets after preprocessing and cleaning the dataset.

### 1. Day-ahead GB electricity price data

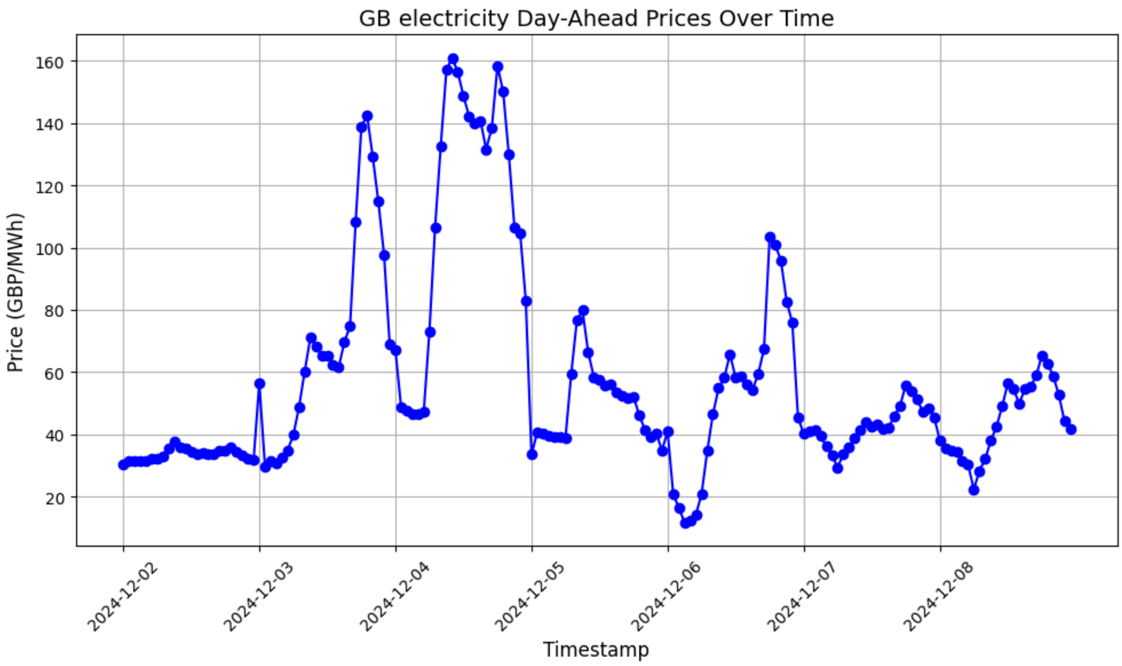


*Figure 1: day-ahead prices over time*

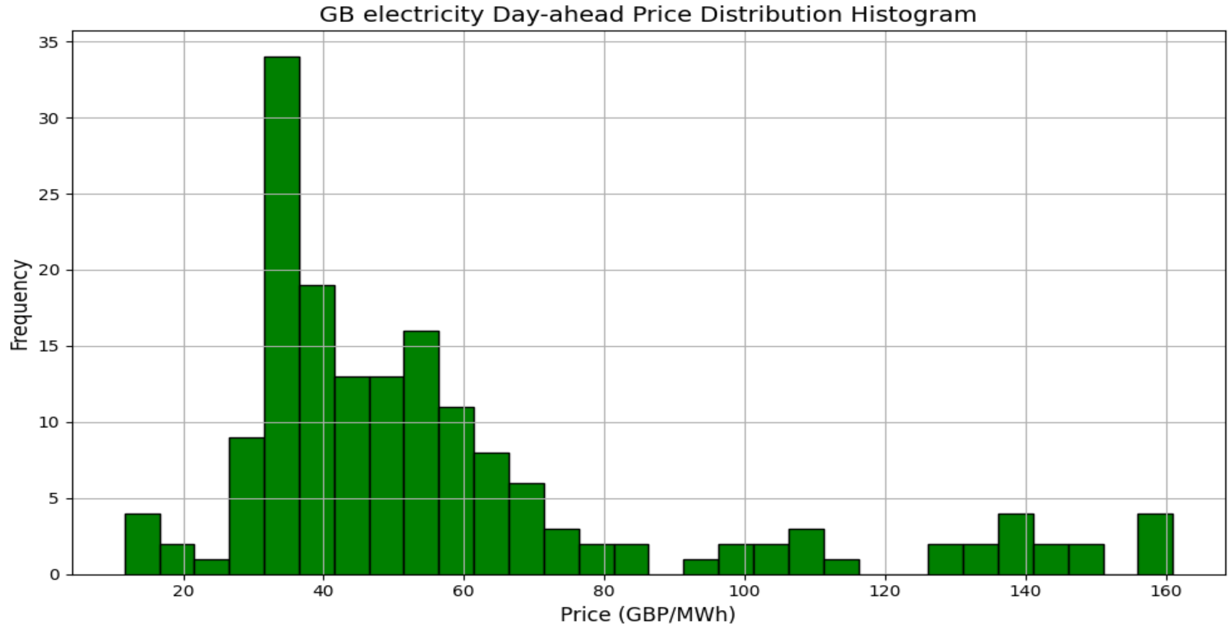

Figure 2: day-ahead price distribution histogram

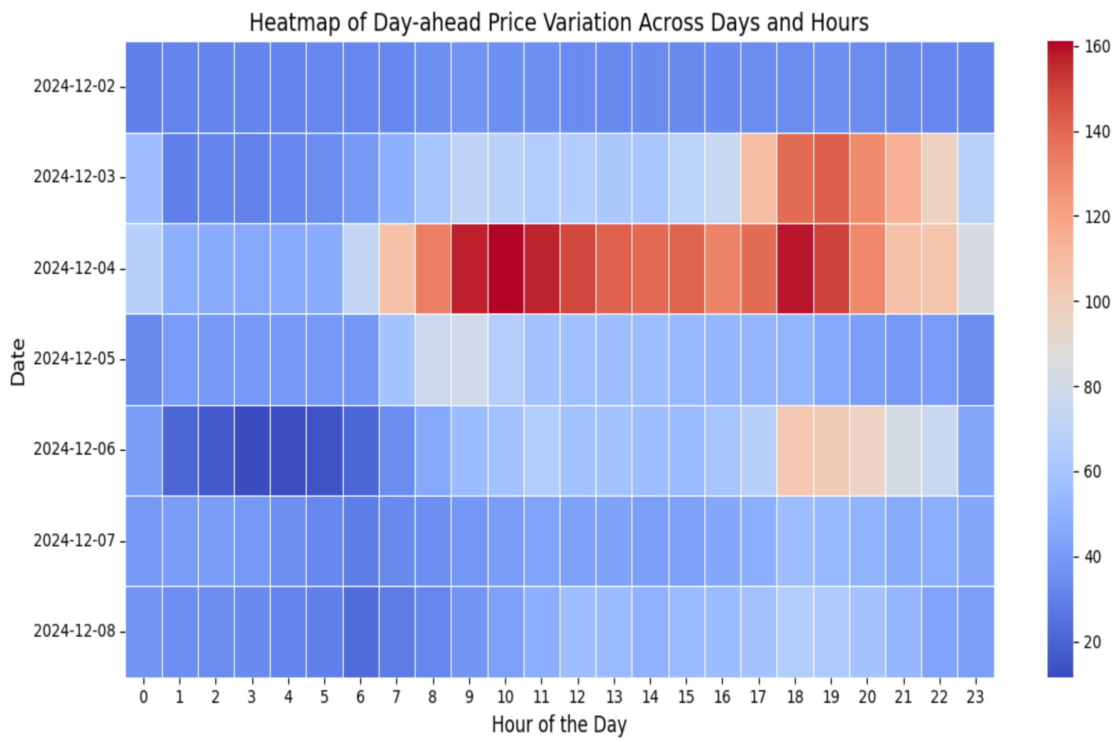

Figure 3: day-ahead price heatmap

## 2. Intraday GB electricity price data

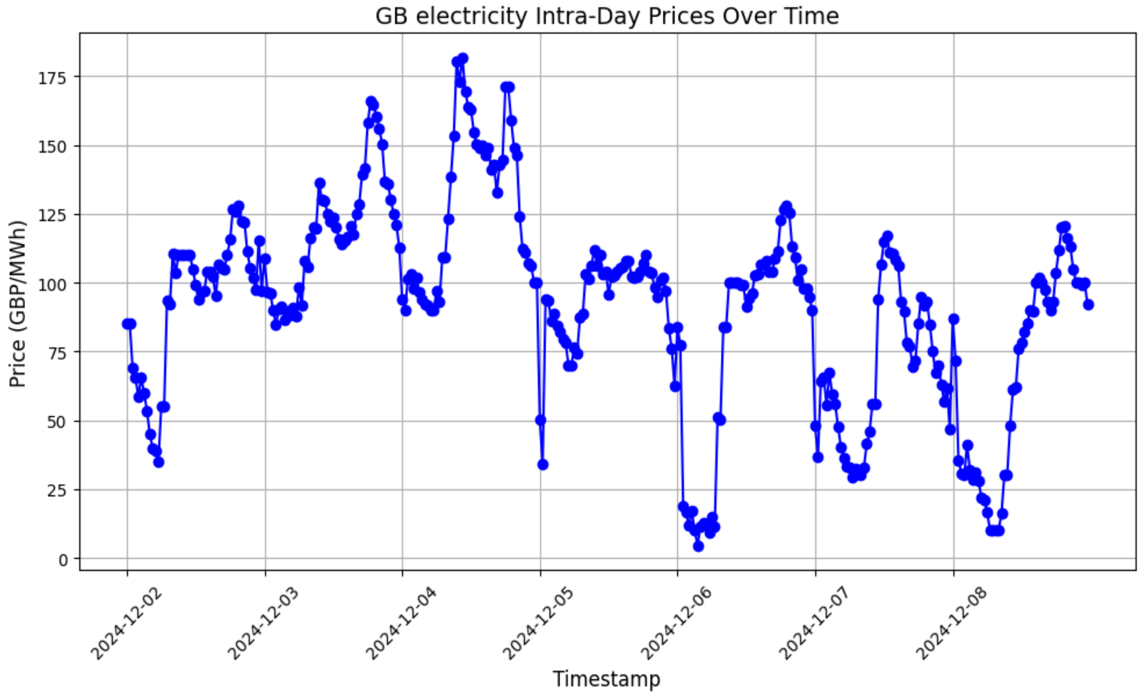


*Figure 4: intraday price over time*

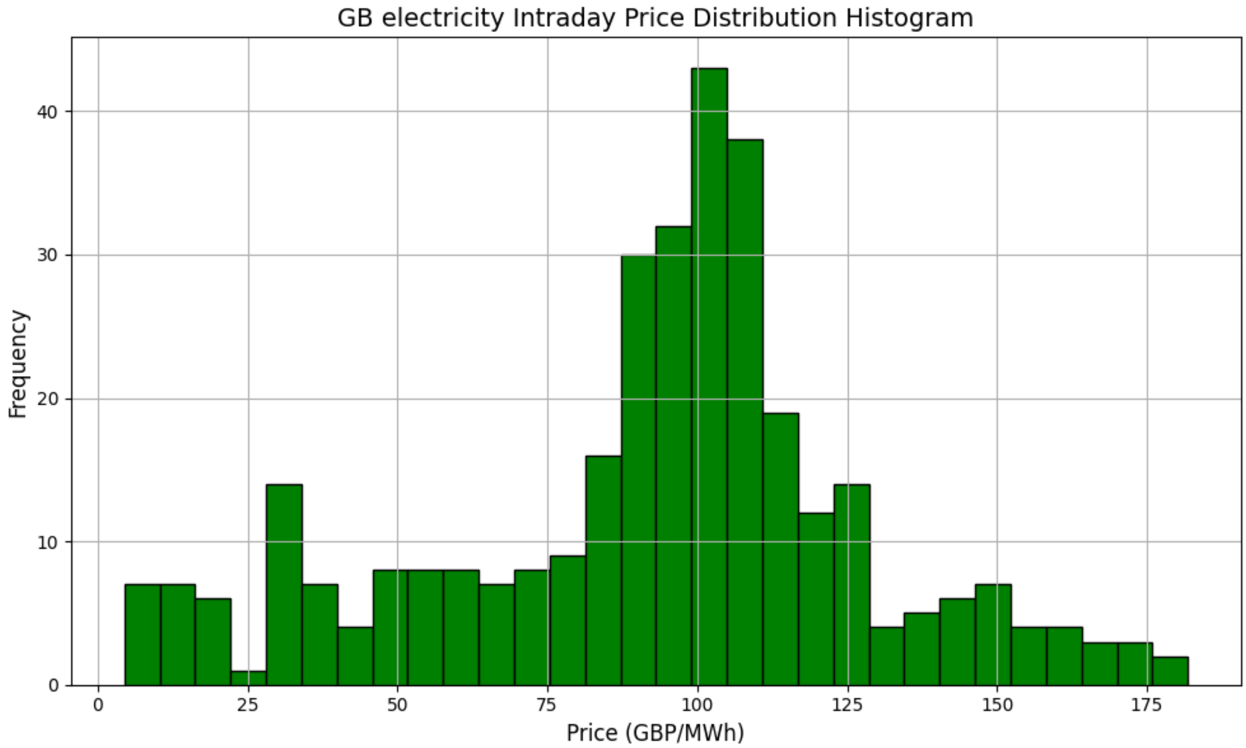


*Figure 5: Intraday price distribution histogram*

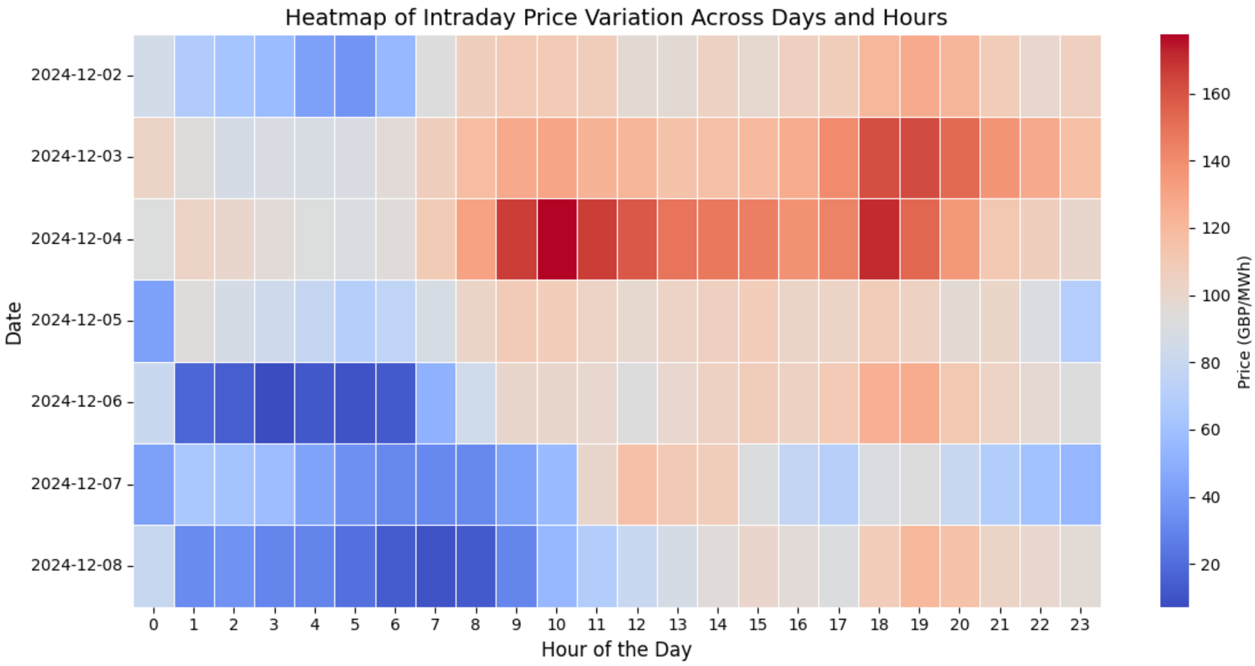


*Figure 6: Intraday price heatmap*

## *2.1 More analysis on intraday dataset:*

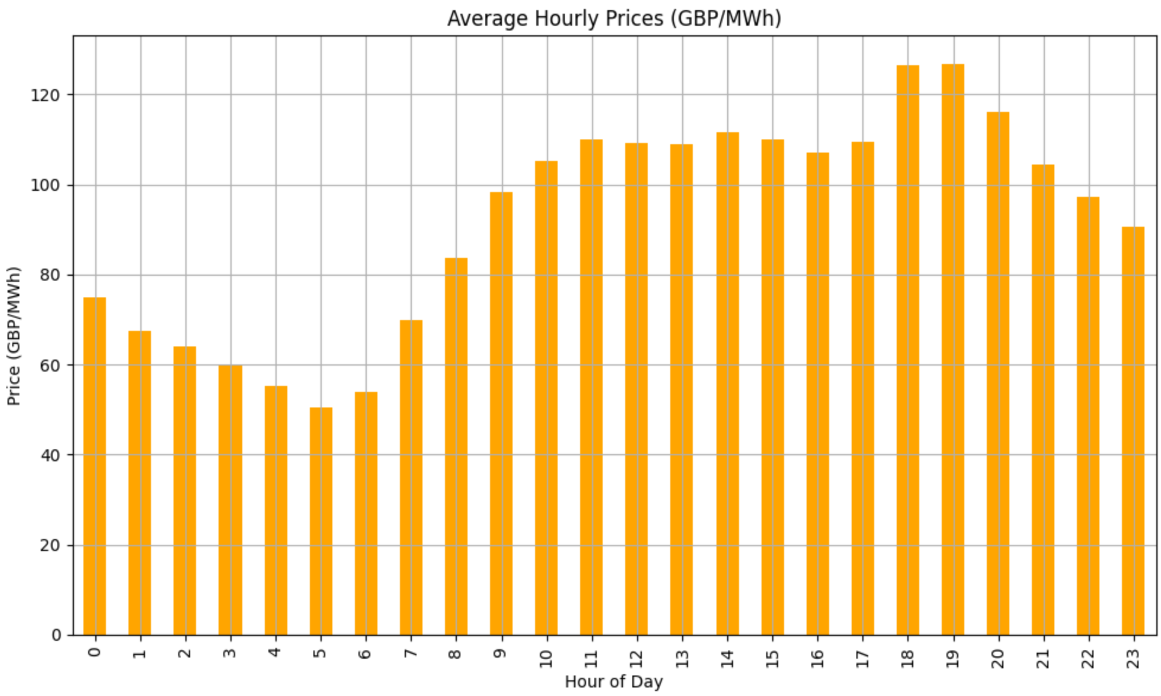


*Figure 7: Intraday avg hourly price histogram*

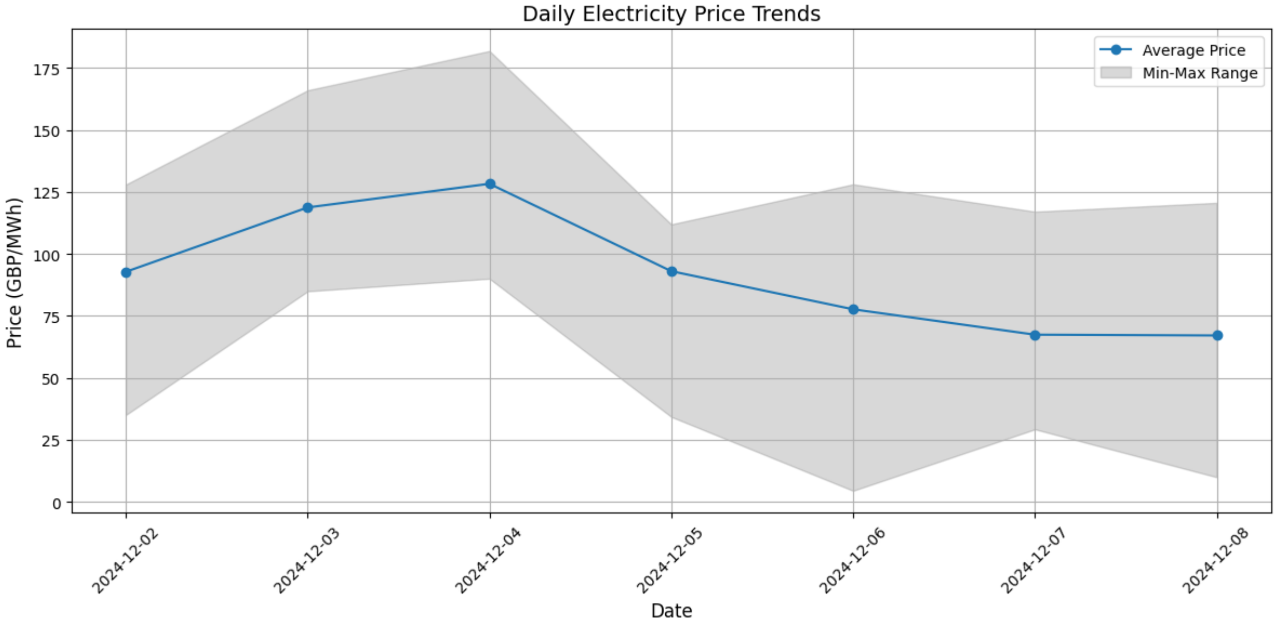


*Figure 8: Intraday daily electricity price trend*

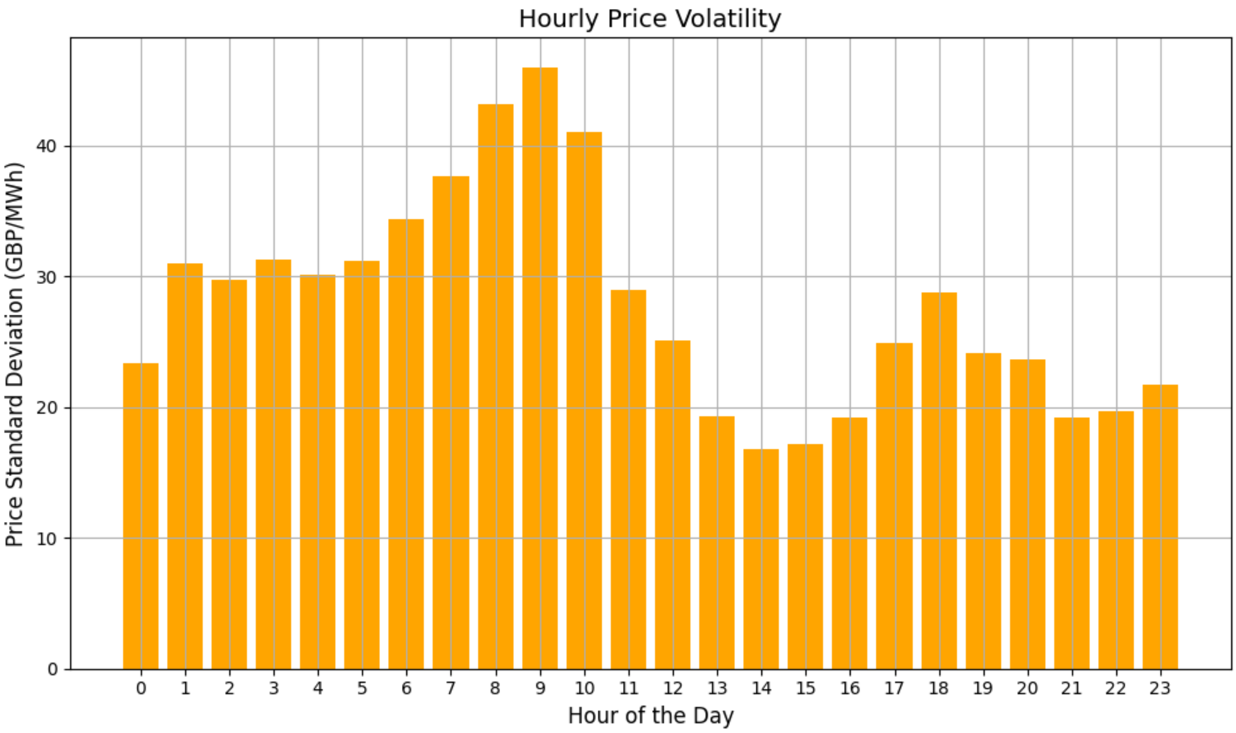


*Figure 9: Intraday hourly price volatility*

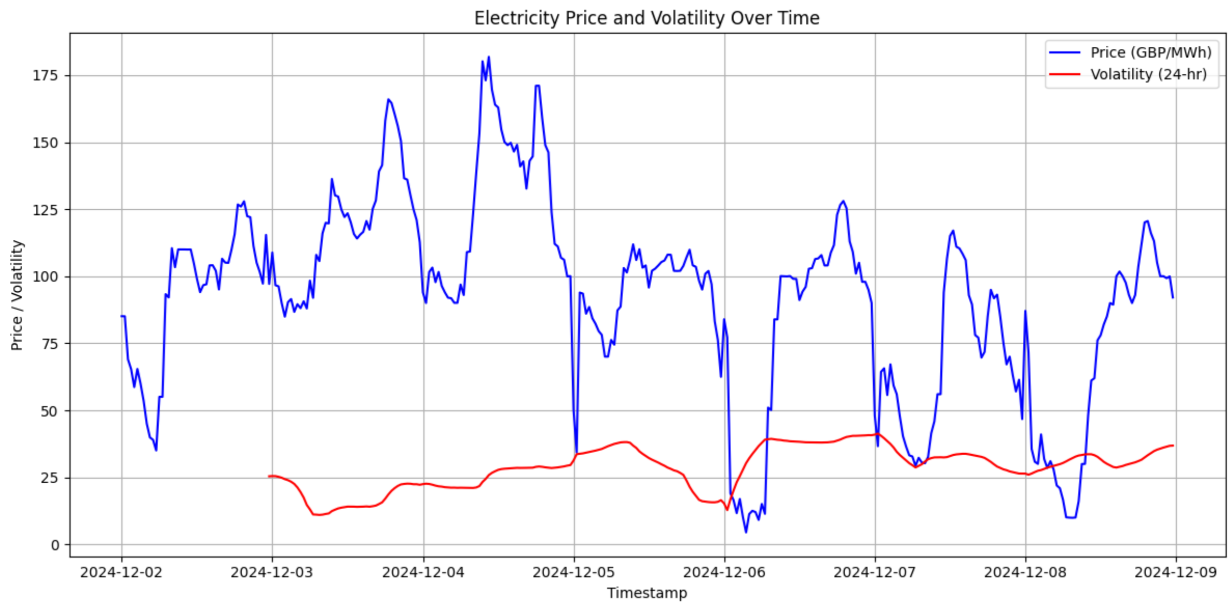


*Figure 10: Intraday volatiliy over time*

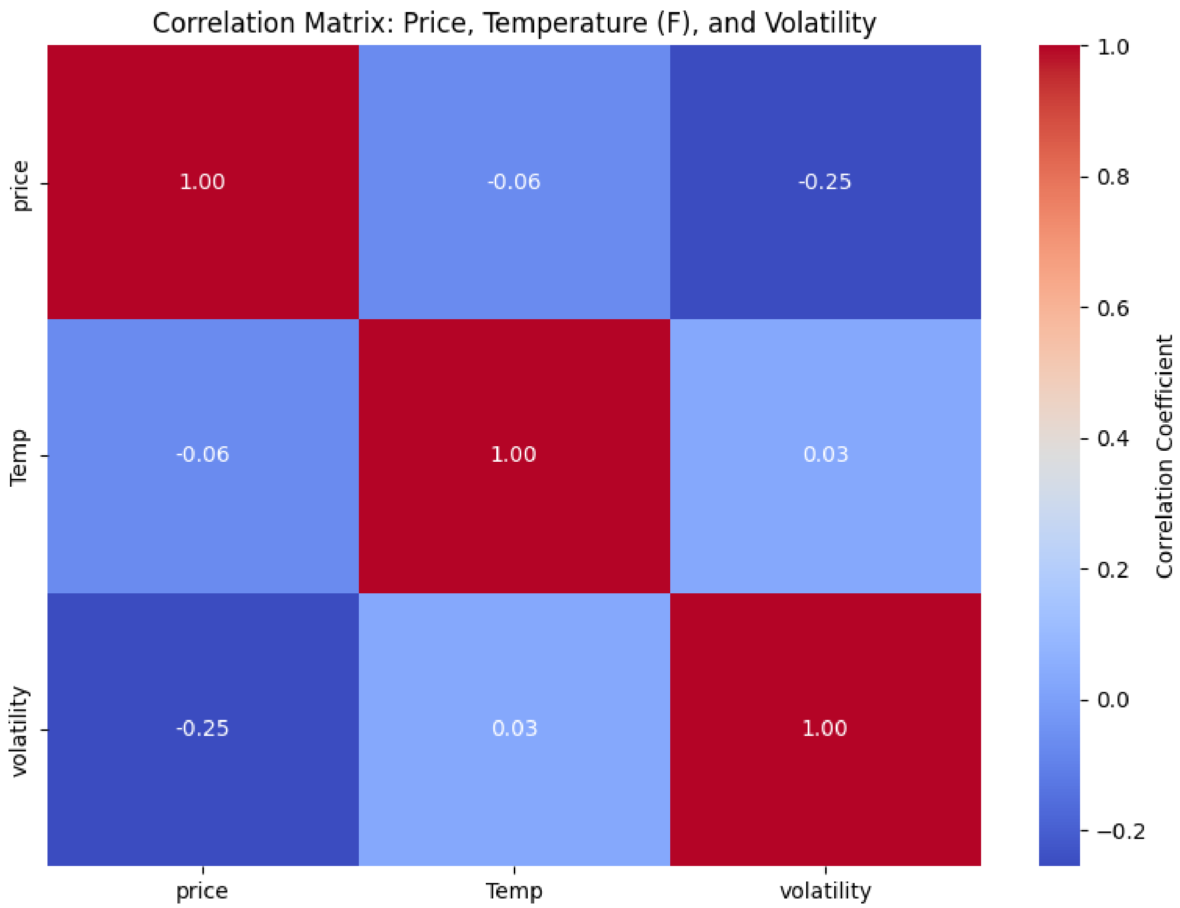


*Figure 11: Correlation matrix over price, temp and volatility*

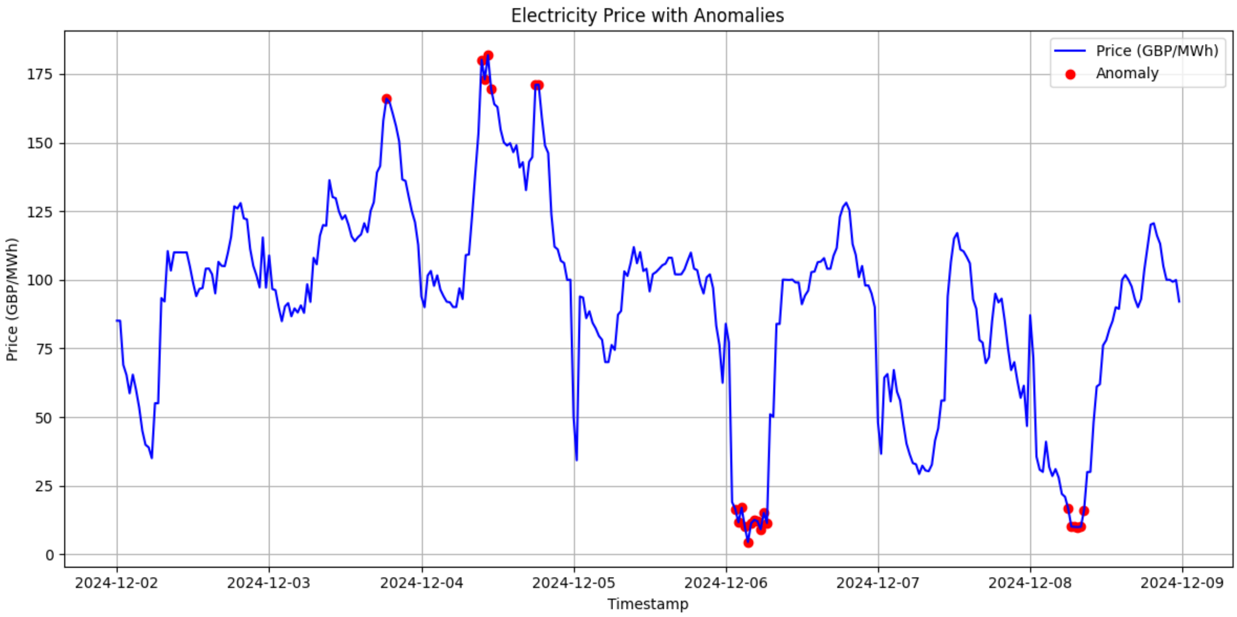


*Figure 12: Intraday price anomalies*

## [C] Assumptions:

1.The analysis is based on intraday electricity price data for the first week in december [a] and synthetic half-hourly weather data (temperature in Fahrenheit scale) [b].

2. December is characterized by high electricity demand due to heating needs, shorter daylight hours, and colder temperatures. December weather can be unpredictable, with possibilities of storms, snow, or frost, which may cause supply disruptions and add to price volatility.

3. December is known for the Christmas festival and New Year celebrations, which lead to higher electricity demand compared to other months due to decorations and other arrangements [d].

3. Observed correlations between price, temperature, and volatility hold true for similar weather and market conditions.

4. Traders can participate in both day-ahead and intraday electricity markets but I am analyzing the intraday price data and all reasonings are related to it.

5. Trading costs are negligible for this analysis but can be integrated into the model.

6. For this study, I have only included wind and solar power as the renewable energy sources.

# [D] Summary:

## #Key Findings:

### 1. Price Trends:

- The frequent price in the day-ahead market is around 30 GBP/MWh [Figure 2], while in the intraday market it is around 100 GBP/MWh [Figure 5]. Additionally, the intraday price distribution resembles a normal distribution, reflecting real-time prices. The higher prices suggest that electricity demand is elevated during the month [d].
- If we observe the heatmaps for both day-ahead and intraday data [Figures 3 and 6], it is evident that electricity prices were abnormally high on the 3rd and 4th of December. One possible reason for this could be the forecast of a storm at the end of the first week of December [c], which likely caused a spike in electricity consumption. As a result, demand exceeded supply, driving prices higher. However, the news [c] indicated that the storm occurred around the 7th of December. This raises the question of why prices were not higher just before the 7th. A potential explanation is that during or just before the storm, many industries and workplaces were closed, leading to lower electricity demand than initially anticipated. Additionally, the news suggested that around 94% of households experienced power cuts, which further reduced demand. Consequently, electricity generation from renewable sources also decreased, although the supply from other sources (gas and coal) likely remained similar.
- Higher prices are observed during the evening peak hours (6-8 PM) and lower prices during late-night hours (4-6 AM) [Figure 7]. Additionally, around the 6th of December, there is greater variation in electricity prices [Figure 8]. This could be due to a mismatch between demand and supply caused by the storm, as mentioned earlier. It is also evident that night-time hours typically have lower prices compared to daylight hours, which is expected.

### 2. Temperature Correlation:

- There is a negative correlation (−0.06) between temperature and price [Figure 11], meaning that lower temperatures drive increased demand for heating, which in turn raises electricity prices. This is consistent with seasonal energy trends, where colder days are associated with higher prices.

### 3. Volatility Patterns:

- There is a positive correlation (+0.03) between volatility and temperature [Figure 11]. High volatility may arise due to constrained supply during peak winter periods, as energy generation adjusts to increased demand. However, the correlation is weak, as indicated by its low numerical value.

- There is a negative correlation (-0.25) between volatility and price [Figure 11]. This suggests that during predictable, cold periods (e.g., steady high demand for heating), prices remain consistently high but stable.
- Volatility spikes during rapid temperature changes, from 7-10 AM [Figure 9] and between 12-4 PM, it is likely less volatile and more stable.
- The electricity prices were more volatile around the 6$^{th}$ of December, as seen in [Figure 10]. This can be attributed to the storm [c], as explained earlier.

## #Proposed Strategies

### 1. Intraday Trading

- Objective: Respond to real-time price fluctuations within the trading day.

- Approach:

  - Monitor live temperature and demand forecasts using real data/APIs.
  - Execute trades when prices deviate significantly from day-ahead predictions.
  - Buy during late-night off-peak hours and sell during morning and evening peaks to make profit. From [Figure 7] we can observe that the cheapest hour was 5:00 AM with average price of 50.45 GBP/MWh and the most expensive hour was 7:00 PM with average price of 126.69 GBP/MWh.

- Alert System:

  - Flag trades when hourly prices differ by more than predefined threshold (like 10% from forecasts).

### 2. Volatility-Based Scalping

- Objective: Leverage price fluctuations for short-term profits.

- Approach:

  - Trade smaller volumes during volatile periods.
  - Use stop-loss and take-profit thresholds.

- Implementation:

  - Compute a real-time volatility index using price standard deviation.

- Trade only when volatility exceeds a predefined threshold.

**3. Seasonal Arbitrage**

- Objective: Exploit seasonal trends and cold snaps for long-term gains.
- Approach:
  - Pre-buy electricity contracts ahead of forecasted cold periods.
  - Sell these contracts during peak price days.

## #Risk Assessment

1. Market Risks:
   - Use stop-loss orders to cap potential losses.
   - Diversify trades across peak and off-peak hours.
2. Weather Variability:
   - Incorporate live weather updates into intraday strategies.
3. Regulatory Risks:
   - Adhere to market regulations for electricity trading in GB.
   - It is advisable to avoid trading during periods associated with anomalies, as these periods carry the highest risk, as clearly seen in [Figure 12]. In this case, we consider prices that are more than twice as volatile as the mean prices to be risk points (anomalies)

## #Reflection

- The study relied on basic statistical techniques and assumptions (like using temperature as the sole weather factor) without leveraging advanced ML models, limiting the depth of insights.
- The analysis was constrained to one week of electricity price data, which does not capture seasonal variations or long-term market trends.
- Future work can focus on integrating ML models, expanding the dataset across seasons, and developing dynamic trading strategies using real-time market data.

# Sources:


a) Nord Pool Group. "GB Half-Hour and N2EX Day-Ahead Data." Accessed December 15, 2024. https://data.nordpoolgroup.com/

b) Weather Underground. "Daily Weather History: London City Airport Station, England, UK." Accessed December 15, 2024. https://www.wunderground.com/history/daily/gb/london/EGLC

c) The Guardian. "Storm Darragh: Two Men Killed by Falling Trees in UK Weather." December 8, 2024. Accessed December 16, 2024. https://www.theguardian.com/uk-news/2024/dec/08/storm-darragh-two-men-killed-by-falling-trees-uk-weather


> There were gusts of nearly 100mph in some parts of the country on Saturday and more than a quarter of a million people were left without power in the west of England and Wales.
>
> By 7pm on Sunday, 94% of homes that had suffered power outages had been reconnected the Energy Networks Association said, leaving 118,000 people without power.
>
> The rail network was blighted by delays and cancellations, with Southeastern and Thameslink services particularly badly affected and all lines closed between Wolverhampton and Stafford due to a tree blocking the line.


d) GreenMatch. "Christmas Lights: Costs, Energy Consumption, and Alternatives." April 24 2024 Accessed December 16, 2024. https://www.greenmatch.co.uk/christmas-lights


# Appendix:

**Volatility:** it measures the fluctuation of prices over a certain period. It is commonly calculated using the standard deviation.

$$\sigma=\sqrt{\frac{\sum_{i=1}^{n}(P_i-\mu)^2}{n}}$$

Where:

- Pi: Price at time i
- μ: Mean price over the time period
- n: Number of time interval