Automated electricity trading strategy

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2023

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Abstract

This report outlines a machine learning-based methodology to forecast energy futures prices and volume and develop a trading algorithm to maximize profits in the volatile energy market. The study uses historical auction data from the UK energy market to train and evaluate the models' performance. The approach involves four main stages: data preprocessing, price forecasting, trading decision-making, and backtesting and evaluation. The report highlights the importance of accurate price forecasting and presents different techniques, including ARIMAX, XGBBoost, linear regression, Lasso, MLPRegressor, and Model Averaging, to achieve this. Next, the most suitable model for predicting auction prices was selected based on a comparative analysis of the results obtained from these models, which is Model Averaging in this task. Finally, the trading decision was made after predicting the auction prices, and the strategy's performance was evaluated using backtesting and evaluation.

1 Introduction

Electricity trading has become an essential element of modern power systems as it provides a mechanism to balance supply and demand, ensuring grid stability and preventing blackouts. However, with the increasing share of renewable energy in the electricity grid, volatility and uncertainty in power production have increased, making it challenging to balance supply and demand. To address these challenges, grid-scale energy storage systems, such as battery energy storage systems, have become an optimal fit for the short-term nature of electricity markets, providing additional flexibility.

In the electricity market, there are different types of trading, with physical trades being supported by assets like power plants or renewable energy sources. On the other hand, non-physical trades depend solely on the market's price, without providing or receiving energy. In this context, we will focus on non-physical financial trades, which have become increasingly popular in the Great Britain market.

In the Great Britain market, traders can buy and sell electricity without owning an asset, meaning they do not need to generate or store electricity physically. Instead, they trade electricity as a financial commodity based on market prices. These trades are based on contracts for difference (CFDs), a type of financial derivative that allows traders to speculate on the price movements of an underlying asset, in this case, electricity. CFDs enable traders to take long and short positions, meaning they can profit from rising and falling electricity prices.

The non-physical financial trades provide a flexible and efficient way to manage risk in the electricity market, allowing market participants to manage their exposure to price volatility without owning a physical asset. They also enable market participants to benefit from market movements in different time frames, from short-term intraday trading to long-term hedging strategies. However, non-physical trades come with complexities, which market participants must carefully consider.

Overall, non-physical electricity trading has become an essential element of modern power systems, providing a flexible and efficient way to manage risk in the electricity market. Moreover, as the share of renewable energy continues to grow, non-physical financial trades are expected to become even more important in ensuring grid stability and facilitating the integration of renewable energy sources into the grid.

2 Methodologies

The methodology consists of four steps: data preprocessing, price forecasting, trading decision, and backtesting and evaluation, as shown in Figure 1. In the data preprocessing step, the collected data is cleaned, transformed into time series data, and split into training and testing sets. Then, the price forecasting step involves applying various machine learning and statistical models to predict future prices. Next, trading decisions are made based on the predicted prices. Finally, backtesting and evaluation are performed to evaluate the trading strategy's performance. These steps are essential for successful electricity trading and accurate price forecasting.

Figure 1: The figure shows the four main steps of the methodology used in electricity trading. These steps include data preprocessing, price forecasting, trading decision, and backtesting and evaluation.

2.1 Data Preprocessing

Electricity price forecasting is an essential task in energy trading, which involves predicting the price of electricity in the future. This prediction depends on the accuracy of the preprocessed data used for analysis. Thus, cleaning the data is the first step in preprocessing the time series data for electricity price forecasting. This step involves removing any unwanted data points that can affect the forecasting models' accuracy.

After cleaning the data, the next step is to remove any duplicate timesteps in the dataset. This step is necessary as it helps to reduce the problems with the model's training process. For example, duplicate data can lead to overfitting, where the model fits the training data too closely, resulting in poor performance on new, unseen data. Duplicate data occur when the same information is represented in multiple timesteps in the dataset. Therefore, removing duplicate data is essential for improving the forecasting model's accuracy.

With the absence of data for certain timesteps, the forecasting model may produce inaccurate predictions. Thus, the third step in preprocessing the time series data for electricity price forecasting is to interpolate any missing timesteps using linear interpolation. Linear interpolation is a method used to estimate missing values by fitting a straight line between two adjacent data points. This step ensures that the dataset is complete and that the forecasting model can accurately predict the price of electricity at every timestep.

Finally, splitting the dataset into training and testing sets is critical in evaluating the forecasting models' performance. This step involves dividing the preprocessed dataset into two sets, training and testing sets. The training set is used to fit the forecasting model, while the testing set is used to evaluate the model's accuracy. In addition, the dataset should be split based on a specific date. For example, the training set can include data up to a specific date, and the testing set can include data after that date, which is the end of February 2022, in this task. That ensures the forecasting model can generalize to new data and produce accurate predictions for future electricity prices.

In conclusion, preprocessing the time series data for electricity price forecasting involves several crucial steps, including cleaning the data, removing duplicate columns, filling in any missing timesteps using linear interpolation, and splitting the dataset into training and testing sets. These steps are necessary for ensuring the forecasting models' accuracy and generalizing the model to new data. Thus, careful attention should be paid to these steps to produce reliable and accurate predictions for electricity prices in the future.

2.2 Forecasting Model

Price forecasting is a crucial aspect of energy trading which involves predicting future electricity auction prices using historical data and other relevant factors. Therefore, accurate price forecasting is essential for making informed and profitable trades in the energy market. To achieve this, various techniques are employed, including statistical models, machine learning, and deep learning. In this report, we have utilized five of the most renowned regression models, namely ARIMA, XGBBoost, LinearRegression, Lasso, MLPRegressor, and Model Averaging, to forecast future electricity auction prices. Each model has its strengths and weaknesses, making it essential to select the appropriate method for the specific task. By comparing and analyzing the results obtained from these models, we aim to determine the most suitable method for electricity auction price forecasting.

The first model utilized for price prediction is the ARIMA model with exogenous variables, also referred to as ARIMAX, which is a prevalent time-series model. The ARIMA model applies the autoregressive model, which employs the previous values of the variable being forecasted to anticipate future values. Additionally, it utilizes the moving average model, which takes into account the unpredictable fluctuations in the data. Moreover, the ARIMAX enables the incorporation of external variables that may impact the predicted time series. These external variables are known as exogenous variables and can be employed as predictors to enhance the accuracy of the prediction. Hence, ARIMAX is a powerful method for capturing trends, seasonal patterns, and other time-related factors influencing electricity auction prices.

The second model is XGBBoost (Extreme Gradient Boosting), which is a gradient-boosting algorithm widely used in machine learning. XGBBoost works by combining multiple weak models to create a strong ensemble model that can make more accurate predictions. The model is trained on historical data, and the resulting model is used to make future predictions. The advantage of XGBBoost is its ability to handle large datasets, feature selection, and high accuracy in making predictions.

The third model used is linear regression, which is a simple linear regression model that employs a linear relationship between the input and output variables. Linear regression is a fundamental model that is simple to implement and interpret, making it a good starting point for price forecasting. However, it may not capture the complexity of the data.

The fourth model applied in this study is Lasso, a regularization method specifically designed to refine the performance of linear regression models. Lasso imposes a penalty on the model when it comprises numerous features, as excess features can result in overfitting. However, by curtailing the number of features employed, Lasso is useful for selecting the most important ones, thereby enhancing the accuracy of linear regression models. Moreover, Lasso is known to be highly effective in handling high-dimensional data, making it an ideal choice for datasets with many features.

The fifth model used is MLPRegressor (Multilayer Perceptron Regressor), which is a neural network-based model. MLPRegressor creates a layered network of artificial neurons that can learn complex relationships between inputs and outputs. This model is adept at capturing nonlinear patterns in data and is especially suited for handling large datasets. However, the MLPRegressor model can be challenging to interpret and requires substantial computational resources compared to other models. Despite this, MLPRegressor remains a popular and influential model for tackling complex regression tasks in machine learning.

An additional approach to forecasting electricity auction prices is by using the average of multiple model predictions, known as model averaging. Model averaging is a technique used in statistical modeling and machine learning where multiple models are combined to form a more accurate model. This is done by taking the average of the predictions made by each model. Model averaging is particularly useful when the performance of individual models varies widely, as it can help reduce the impact of poorly performing models and improve overall prediction accuracy. It can also help prevent overfitting, where a model fits too closely to the training data and performs poorly on new data. Model averaging is a simple yet powerful technique that can be used with other forecasting methods to achieve more accurate forecasts.

In conclusion, auction price forecasting is critical in electricity trading, and various techniques are available for making accurate predictions. The five models discussed in this report are just a few examples of the many models used for price forecasting. The model selection depends on the data's complexity, the available computational resources, and the desired level of accuracy. Therefore, it is crucial to evaluate the performance of each model using backtesting and other evaluation metrics to select the most suitable model for electricity trading.

2.3 Trading Decision

Once auction price forecasts are obtained, a trading strategy can be employed to make profitable trades. However, the trading strategy should consider various factors such as risk appetite, market conditions, and trading objectives.

It is crucial to emphasize that our trading is non-physical, meaning we do not have any assets to generate or consume electricity. As a result, we kept the difference between trading volumes at each timestep between both auctions at zero to avoid extra fees. Despite the lack of physical assets, our proposed trading strategy is uncomplicated yet efficient in identifying lucrative trades in the energy market. The strategy considers various factors, such as the predicted price, taxes, and fees, to determine when to sell or buy electricity in the auction market.

We propose a simple trading strategy based on comparing the forecasted price of two auctions. This comparison allows for the initial trading decision to be made concerning the first auction. If the predicted price, including taxes and fees, of the first auction is lower than that of the second auction, it is advisable to buy electricity in the first auction. Conversely, if the forecasted price in the first auction is higher than in the second, along with taxes and fees, selling electricity in the first auction. In cases where neither of these conditions is met, holding off on any trading is best.

Given that the auctions occur in a sequence, it is important to note that the first auction results are obtained before the second auction starts. This implies that bids must be created for the first auction, which includes details such as trading volume, price, and action. The trading volume is determined by taking the minimum anticipated trading volume between the two auctions, which is computed by the same forecasting model used to predict the auctions' prices.

Next, the trading price is set based on the expected price projected by the forecasting model. This expected price is then adjusted by adding a risk percentage of the expected profit for buying and subtracting this same percentage for selling. The anticipated profit is calculated as the difference between the forecasted price of the first and second auctions multiplied by the trading volume. Finally, the action of whether to sell, buy, or hold is determined by comparing the forecasted price of both auctions, as explained earlier.

The first auction's results are used to determine the bids of the second auction. The trading volume and action for the second auction are based on the accepted offers from the first auction. The trading volume for the second auction is equal to that of the first. The trading action, on the other hand, is the opposite of the first auction for buying and selling, while the hold remains the same. The price for selling electricity in the second auction is set at half the buying price of the first auction, while the buying price for the second auction is twice the selling price of the first auction. This price selection is intended to mitigate losses due to unexpected changes. For instance, if the buying price in the second auction is too high, the bidders may suffer a significant loss, but setting the price based on the first auction results can help them reduce this issue.

In conclusion, we have proposed a simple yet effective strategy for non-physical trading in the energy market. The strategy considers various factors, such as predicted prices, taxes, and fees, to make profitable trades. We have highlighted the importance of comparing the forecasted prices of two auctions to determine whether to buy, sell or hold. Furthermore, we have explained the process of creating bids for the second auction based on the first auction results, which involves determining trading volume, action, and price. This strategy is designed to mitigate potential losses due to unexpected changes and efficiently identify lucrative trades.

2.4 Evaluation Metrics

To evaluate the effectiveness of both the trading strategy and the forecasting, we will utilize several metrics, including the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R-squared), to gauge their performance.

Mean Squared Error (MSE) is a commonly used evaluation metric that measures the average squared difference between the predicted and actual values. This metric provides a way to measure the accuracy of regression models and gives equal weight to both the overestimation and underestimation of predicted values. It is a valuable tool for evaluating the performance of forecasting models because it provides a quantitative estimate of the degree to which the model's predictions differ from the actual values.

Root Mean Squared Error (RMSE) is the square root of the MSE and measures how close the predicted values are to the actual values in the same units as the original data. It is sensitive to outliers and larger errors, making it ideal for determining the accuracy of the forecast. The RMSE is a popular metric because it provides an estimate of the forecast error that is easy to interpret and can be used to compare the accuracy of different models.

Mean Absolute Error (MAE) calculates the average of the absolute difference between the predicted and actual values, providing an estimate of the model's forecast error in the same units as the original data. It is less sensitive to outliers than the MSE and provides a more robust error estimation. The MAE is also more intuitive and easier to explain than the MSE, making it a helpful tool for evaluating the trading strategy's performance.

The Coefficient of Determination (R-squared) is a statistical measure that determines how well the model fits the data. It measures the ratio of the variation in actual values that predicted values can explain. It ranges from 0 to 1, where a higher value indicates a better fit of the model to the data. The R-squared is an essential metric for evaluating the overall performance of the trading strategy and can help identify whether the model is overfitting or underfitting the data.

In conclusion, using multiple evaluation metrics such as MSE, RMSE, MAE, and R-squared can help accurately measure a trading strategy's performance and forecasting models. The MSE and RMSE measure the degree of difference between predicted and actual values, with RMSE being more sensitive to larger errors and outliers. The MAE provides a robust error estimation that is less sensitive to outliers and is more intuitive to explain than MSE. Finally, the R-squared measures how well the model fits the data, with a higher value indicating a better fit. By utilizing these metrics, we can gain insights into the effectiveness of our trading strategy and forecasting model and identify areas for improvement.

3 Result

In order to generate a prediction for the second auction price, six different models are examined. These models include ARIMA, XGBBoost, Linear Regression, Lasso, MLPRegressor, and Model Averaging, where the mean of the predictions from the five models is computed in Model Averaging. Table 1 presents a comparison of the performance of these six regression models based on various metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-squared.

Table 1: Performance Comparison of Various Regression Models For the Second Auction Price. The table shows the mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-squared values for six different regression models, namely ARIMA, XGBBoost, Linear Regression, Lasso, MLPRegressor, and Model Averaging, where the average prediction of the five models is computed. The lower the error values, the better the performance of the model. The highest R-squared value indicates the model's ability to explain the variation in the data.

	MSE	RMSE	MAE	R-squared
ARIMA	2145.95	46.32	33.13	0.82
XGBBoost	3445.24	58.70	40.22	0.72
LinearRegression	2059.50	45.38	32.68	0.83
Lasso	2026.00	45.01	32.35	0.83
MLPRegressor	2861.02	53.49	41.36	0.76
Model Averaging	1768.73	42.06	29.87	0.85

Among the six regression models, Model Averaging performs the best with the lowest MSE of 1768.73, indicating that it makes the lowest errors in its predictions. Lasso follows closely with an MSE of 2026.00, while Linear Regression and ARIMA also have close MSE values of 2059.50 and 2145.95, respectively. On the other hand, XGBBoost and MLPRegressor have higher MSE values of 3445.24 and 2861.02, respectively, making more prediction errors than the other models.

Regarding RMSE, which is a more interpretable measure of the error since it is in the same units as the target variable, Model Averaging again performs the best with an RMSE of 42.06. Lasso follows closely with an RMSE of 45.01, while ARIMA and Linear Regression also have relative RMSE values of 46.32 and 45.38, respectively. XGBBoost and MLPRegressor have relatively higher RMSE values of 58.70 and 53.49, respectively, indicating that they are less accurate than the other models.

In terms of MAE, which is another commonly used measure of error, Model Averaging has the lowest value of 29.87, indicating that it makes the least amount of absolute errors in its predictions. Lasso and Linear Regression have an MAE of around 32, while ARIMA has an MAE of 33.13. MLPRegressor has a higher MAE value of 41.36, and XGBBoost has an MAE of 40.22.

R-squared measures how well the models fit the data and ranges from 0 to 1, with higher values indicating a better fit. The Model Averaging again performs the best with an R-squared of 0.85. Linear Regression, Lasso, and ARIMA also perform well with R-squared values of 0.83, indicating that they fit the data well. MLPRegressor and XGBBoost have relatively lower R-squared values of 0.76.

In conclusion, Model Averaging is the best model among the six regression models evaluated based on all performance measures. It consistently performs better than the other models, with the lowest MSE, RMSE, and MAE values, indicating that it makes the lowest prediction errors. Additionally, it has the highest R-squared value, indicating a better fit to the data. Lasso, Linear Regression, and ARIMA also perform well with relatively close performance measures, while XGBBoost and MLPRegressor have higher errors and lower R-squared values. Overall, Model Averaging is recommended for predicting auction prices in this scenario.

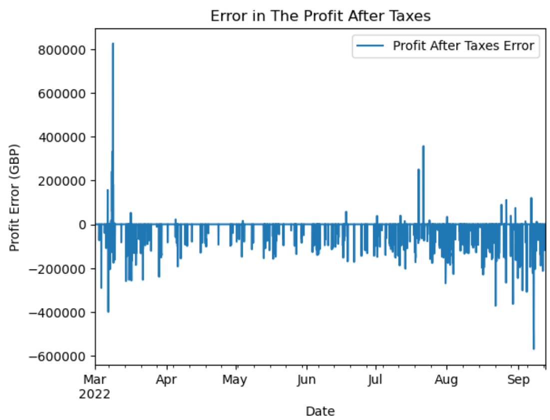
Based on the Model Averaging forecasting of the second auction price and the given forecasting of the first auction price, the trading algorithm's estimated auction profit before taxes amounts to an impressive 61 million GBP, indicating its immense potential for generating substantial returns on investment. However, it is crucial to bear in mind that the actual profits could vary from the anticipated amount, and the algorithm's performance could be affected by various factors. Even after accounting for taxes, the expected auction profit remains significant, standing at 42 million GBP. Despite the minor decrease, the algorithm still holds tremendous potential for generating substantial profits, even after paying taxes.

However, the actual auction profit generated by the algorithm fell short of the expected amount, earning only about 13 million GBP before taxes. While this is still a positive return on investment, it highlights the need to evaluate the algorithm's performance and investigate the reasons behind the deviation from the expected profit. Therefore, it is crucial to identify the factors responsible for the lower-than-expected profits and develop effective measures to address them. Furthermore, after accounting for taxes, the algorithm incurred an unexpected net loss of -5,6 million GBP, making it imperative to conduct a thorough investigation to determine the underlying causes for the deviation. Consequently, it is crucial to thoroughly evaluate the algorithm's functioning to identify the factors affecting its performance and take appropriate actions to enhance its capacity to generate profits.

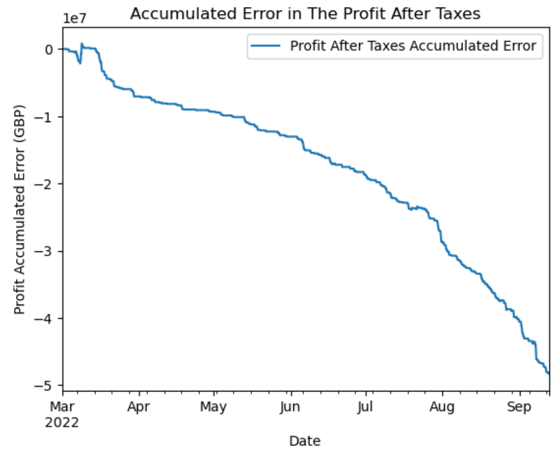
Figure 2a illustrates that the error mainly presents a negative value, indicating that the actual profit falls short of the predicted amount. Moreover, Figure 2b demonstrates the accumulation of this error, which continuously decreases and results in negative values due to the predominantly negative nature of the error.

It is apparent from the graphical representations that the trading algorithm's performance is deviating from the anticipated results, resulting in negative errors and reduced profits. The persistently negative error trend highlighted in Figure 2a implies that the algorithm's predicted profit may be overestimated, and corrective measures must be taken to improve its performance.

The accumulated error in Figure 2b provides a comprehensive view of the magnitude of the deviations from the expected profits, emphasizing the need to identify the underlying factors responsible for the negative trend. Therefore, reviewing and adjusting the algorithm's strategy, parameters, or data sources is imperative to minimize errors and enhance its capacity to generate profits.



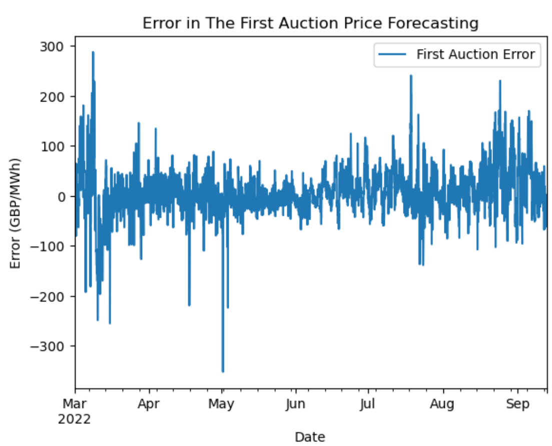
(a) The error in the profit.



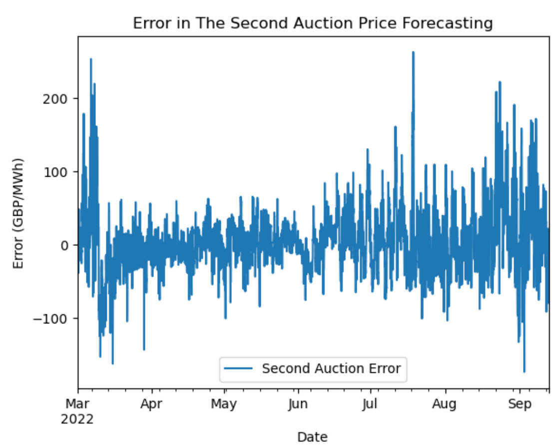
(b) The accumulated error in the profit.

Figure 2: The x-axis represents the date, while the y-axis represents the error between the expected and actual profit in GBP. The figure on the left shows the error at each time step, whereas the figure on the right illustrates the accumulated error.

In order to comprehend and identify the root cause of the discrepancy between the actual and anticipated profits, a meticulous examination of the forecasted auction prices is necessary. These prices represent a core variable determining the trading design and expected profit. Unfortunately, as shown in Figure 3, there is a significant disparity between the actual and predicted auction prices for both the given and algorithm-generated forecasts. Therefore, the accuracy of both auction forecasts is subject to error, which inevitably impacts the performance of the trading algorithm.



(a) The error in the first auction price forecasting.



(b) The error in the second auction price forecasting.

Figure 3: The x-axis represents the timeline, whereas the y-axis represents the error between the expected and actual auction prices in GBP/MWh. The chart on the left depicts the error observed in every step for the provided forecast of the first auction, while the one on the right demonstrates the error for the forecast produced by the algorithm for the second auction.

4 Discussion

As explained earlier, the profitability of the trading heavily relies on accurately predicting the auction prices. In order to delve deeper into this matter, we will examine the results of three specific trading instances conducted during timesteps 18:00:00, 19:00:00, and 20:00:00. These trading prices are depicted in Figure 4.

Figure 4: The figure shows the actual and forecasted prices for the two auctions. The x-axis represents the date, while the y-axis represents the price in GBP/MWh.

Moreover, Table 2 provides a comprehensive breakdown of the actual and forecasted prices for the first and second auctions in three different timesteps (18:00:00, 19:00:00, and 20:00:00), along with the expected and actual difference between the first and second auctions based on the trading design. In addition, the trading decision for the first auction based on the auction price forecast is also shown.

Table 2: This table presents detailed information on the actual and forecasted prices in GBP/MWh for two auctions and the trading decision for the first auction based on the price forecast. In addition, the expected and actual price difference between the first and second auctions based on the trading design is also shown. The difference is set to zero when the trading is stopped.

	18:00:00	19:00:00	20:00:00
Actual price for the first auction	501.00	500.00	499.00
Actual price for the second auction	402.54	399.96	371.59
Actual difference based on the trading design	0.00	-100.04	127.41
Forecasted price for the first auction	405.17	337.30	372.33
Forecasted price for the second auction	412.31	358.45	345.65
Expected difference based on the trading design	0.0	21.145	26.68
The trading decision for the first auction based on the price forecast	Hold	Buy electricity	Sell electricity

The actual auction price for the first and second auctions at the first timestep (18:00:00) was 501.00 GBP/MWh and 402.54 GBP/MWh, respectively. Therefore, buying electricity at the first auction and selling it at the second auction is the optimal strategy based on the actual prices. However, it was decided to stop trading based on the forecasted prices, as the difference between the expected prices for the first and second auctions was lower than 10 GBP/MWh, which is the tax cost. The forecasted auction price for the first auction was 405.17 GBP/MWh, and the forecasted auction price for the second auction was 412.31 GBP/MWh. Therefore, trading was stopped, and the expected and actual differences were set to zero.

In the second timestep (19:00:00), the actual auction price for the first auction was 500.00 GBP/MWh, and the second auction was 399.96 GBP/MWh. Therefore, as per the actual prices, it was profitable to sell electricity in the first auction and buy it back in the second auction, resulting in a profit of 100.04 GBP/MWh. However, the forecasted auction price for the first and second auctions was 337.30 GBP/MWh and 358.45 GBP/MWh, respectively. Therefore, the expected difference was 21.145 GBP/MWh, with the forecasted price of the second auction being higher than that of the first. Hence, the decision was made to buy electricity in the first auction and sell it in the second, resulting in a loss of 162.70 GBP/MWh.

At the third timestep (20:00:00), the actual price of electricity at the first auction was 499.00 GBP/MWh, while the price at the second auction was 371.59 GBP/MWh. Therefore, based on the actual prices, selling electricity in the first auction and buying in the second auction was profitable, resulting in a profit of 127.41 GBP/MWh. However, the forecasted price for the first and second auctions was 372.33 GBP/MWh and 345.65 GBP/MWh, respectively. Thus, the expected difference was 26.68 GBP/MWh, with the forecasted price of the first auction being higher than that of the second. Therefore, the decision was made to sell electricity in the first auction, resulting in a profit of 126.33 GBP/MWh.

Overall, Table 2 and Figure 4 show that the profit is highly dependent on the accuracy of the price forecast. In the first timestep, the holding was the best decision for the first auction based on the forecasted price, while in the second and third timesteps, buying and selling were the best decisions, respectively. It is worth noting that the actual prices were not always in line with the forecasted prices, which can lead to unexpected outcomes. Therefore, correct price forecasting is crucial for making informed and profitable trading decisions.

5 Conclusion

This report presented a methodology for electricity trading that consisted of four main stages: data preprocessing, price forecasting, trading decision-making, and backtesting and evaluation. In the data preprocessing stage, various activities were performed, including data cleaning, duplicate removal, missing data interpolation, and splitting the dataset into training and testing sets. The report utilized different techniques to achieve accurate price forecasting, including ARIMAX, XGBBoost, linear regression, Lasso, MLPRegressor, and Model Averaging. The most suitable model for predicting auction prices was selected based on a comparative analysis of the results obtained from these models, which is Model Averaging in this task. After predicting the auction prices, the trading decision was made, and the strategy's performance was evaluated using backtesting and evaluation.

In conclusion, inaccurate price forecasting led to significant losses. The trading algorithm relied on inaccurate price forecasting, which led to overestimation or underestimation of the auction price. As a result, the actual profit after taxes did not meet the expected amount, causing financial losses. This had a detrimental effect on the trading algorithm's performance and the investor's confidence in the system, potentially leading to reputational damage and a loss of trust.