# Forecasting Carbon Prices Using Machine Learning: A Comparative Study of ARIMA, Random Forest, and LSTM Models

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## 1. Introduction

The European Union Emissions Trading System (EU ETS) is a climate policy instrument designed to reduce greenhouse gas (GHG) emissions in a cost-effective manner. It was launched in 2005, and is the worlds first and one of the largest carbon markets globally. The EU ETS requires polluters to pay for their GHG emissions, thereby creating a financial incentive for companies to cut emissions and invest in cleaner technologies. Covering emissions from electricity and heat generation, industrial manufacturing, aviation, and recently maritime transport, the EU ETS accounts for roughly 40% of the EU's total GHG emissions [**?** ]. As the EU ETS has evolved, it has undergone four trading phases, each introducing significant reforms aimed at improving its efficiency and effectiveness in reducing emissions [**?** ].

The EU ETS operates under a "cap-and-trade" principle, which involves setting a cap on the total amount of GHG emissions allowed from the sectors covered by the system. This cap is reduced annually to align with the EUs climate targets, ensuring that emissions decrease over time. Emission allowances, which permit companies to emit a certain amount of GHG, are either auctioned or allocated for free, depending on the industry. Companies that emit less than their allowance can trade the excess, while those that exceed their allocation must purchase additional allowances or face heavy fines [**?** ]. This market-based approach not only supports emission reductions but also generates revenues to finance the green transition across the EU [**?** ].

As the EU strives to achieve climate neutrality by 2050, understanding and accurately predicting carbon prices is vital for both policymakers and market participants. The EU ETS cap-and-trade mechanism makes carbon prices inherently volatile and influenced by various factors, such as regulatory changes, economic growth, and energy demand. Forecasting these prices helps stakeholdersincluding governments, businesses, and investorsmake informed decisions about emissions management, risk mitigation, and strategic planning [**?** ]. Reliable predictive models can enhance market stability by allowing for better anticipation of price movements, thus helping companies adapt their strategies to comply with emission regulations cost-effectively.

Moreover, the EU ETS has served as a blueprint for other emissions trading systems worldwide, making research into its market dynamics globally relevant [**?** ]. Understanding how carbon pricing functions in the EU market can provide insights into designing or improving similar systems in other regions. By developing and comparing models such as ARIMA, Random Forest (RF), and Long Short-Term Memory (LSTM) networks, this research aims to identify which methodologies provide the most reliable predictions under varying market conditions. This comparative analysis not only contributes to the academic literature on carbon price forecasting but also offers practical insights that can enhance the efficacy of carbon trading systems,

supporting the overall goal of reducing global GHG emissions in a cost-effective manner.

## 2. Literature Review

The literature on carbon price forecasting has evolved significantly over the past two decades, reflecting the need for more accurate predictive models to cope with the growing complexity of carbon markets. Traditional econometric models, such as ARIMA, have been among the first tools used to forecast carbon prices due to their simplicity and statistical rigor. Zhu et al.[**?** ] highlighted ARIMA's effectiveness in modeling linear components of carbon price time series, especially during the early phases of the EU ETS, when the carbon market exhibited relatively stable and predictable trends. However, ARIMA's limitations in capturing the nonlinear and volatile nature of carbon prices, particularly in the post-2017 EU ETS environment, have prompted researchers to explore more advanced methods [**? ?** ].

Machine learning models have become increasingly popular due to their ability to manage nonlinear relationships and complex patterns in data. Studies have shown that Random Forest (RF) and other machine learning models offer significant improvements in predictive accuracy by handling complex interactions among input variables [**?** ]. RF, for instance, has demonstrated excellent predictive performance, particularly when integrated into hybrid frameworks with other machine learning models. Xu et al. [**?** ] showed that RF consistently outperformed traditional econometric models such as ARMA in predicting carbon returns in China's carbon trading market, suggesting its advantage in managing the complexities of carbon price dynamics. Furthermore, Lu et al. [**?** ] explored multiple machine learning approaches, including extreme gradient boosting and RF, to predict carbon trading volume and price in various Chinese carbon markets, emphasizing the adaptability of RF to different market characteristics.

Deep learning approaches, particularly LSTM networks, have also been extensively utilized due to their strength in modeling sequential data and learning long-term dependencies. Huang et al. [**?** ] used a hybrid GARCH-LSTM model to address volatility in carbon prices under the EU ETS following market reforms in 2017. The hybrid model was capable of outperforming both standalone econometric and machine learning models, with significantly smaller forecasting errors. Zhang et al. [**?** ] introduced a novel hybrid deep learning model, VMD-CNN-BILSTM-MLP, which leveraged variational mode decomposition to effectively handle noise in carbon price data, demonstrating superior performance compared to single models. Additionally, Li et al. [**?** ] used Multivariate LSTM, taking into account multiple

influencing factors, to improve the prediction of carbon prices in China, demonstrating that LSTM outperformed other deep learning models in terms of MAE, MSE, and RMSE metrics.

The importance of combining econometric models and machine learning techniques is emphasized by several hybrid approaches. For instance, Zhu et al.[**?** ] proposed an empirical mode decomposition-based evolutionary least squares support vector regression (EMD-LSSVR) model, which leveraged both linear and nonlinear feature extraction for multiscale forecasting of carbon prices. Their results demonstrated improved statistical accuracy compared to ARIMA and standalone LSSVR models, highlighting the value of incorporating multiscale features for enhancing model robustness. Similarly, Yahcsi et al. [**?** ] noted that the hybrid approach of RF and decision trees was particularly successful in managing the high dimensionality and nonlinear aspects of carbon pricing data.

Past literature has also pointed out the importance of selecting appropriate predictors in carbon price forecasting. For example, Abdi et al. [**?** ] used Bayesian Networks to forecast carbon prices in the Western Climate Initiative market, demonstrating that energy prices and economic growth were the most influential drivers. The incorporation of external influencing factors such as energy markets, macroeconomic stability, and policy changes has been shown to enhance the predictive power of machine learning and deep learning models significantly [**? ?** ].

The contributions of this study are twofold. Firstly, it offers a rigorous comparative analysis of ARIMA, Random Forest (RF), and Long Short-Term Memory (LSTM) models, thereby enhancing the understanding of the performance of different forecasting methodologies within the complex dynamics of the carbon trading market. Secondly, this research elucidates the relative merits of traditional time series models in contrast to advanced machine learning approaches, providing valuable insights for both investors and policymakers. Specifically, the study aims to demonstrate that while ARIMA models may be suitable for relatively stable market conditions, machine learning and hybrid approaches provide superior predictive accuracy in the context of nonlinearities and heightened market volatility. This comparative evaluation serves to determine the optimal models for varying market scenarios and provides a basis for employing these models to effectively manage the uncertainties inherent in carbon price forecasting.

Past literature on carbon price forecasting has made significant advances by utilizing traditional statistical models, machine learning techniques, and hybrid approaches. However, much of the existing research has focused either on individual modeling techniques or lacked a direct, systematic comparison among various models under the same conditions. As a result, there has been limited insight into the

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specific contexts in which each approach might perform best. Furthermore, while hybrid models have shown improved accuracy, the question of which standalone model or hybrid combination is most suitable for specific market conditions has remained largely unexplored.

This study addresses these gaps by providing a comprehensive evaluation of three distinct types of modelsARIMA, RF, and LSTMunder identical market conditions. Unlike previous studies that predominantly concentrated on demonstrating the superiority of a single model or a specific hybrid framework, this research systematically contrasts the performance of traditional time series models, machine learning algorithms, and deep learning networks to offer a clear understanding of their relative strengths and weaknesses. By doing so, it clarifies the scenarios where simpler statistical models might suffice versus those where advanced machine learning models are essential for achieving high accuracy, thereby filling the gap in understanding the contextual effectiveness of different forecasting methods in the carbon trading market.

## 3. Methodology

Our analysis employs three distinct modelsARIMA, Random Forest, and LSTMto forecast carbon prices, using a consistent set of extraneous variables and shared methodologies for cross-validation and rolling forecasts.

Each model integrates a comprehensive set of extraneous variables to capture the impact of external influences on carbon prices. These variables include macroeconomic indicators such as Fit_for_55, Law, Compromise, and the Economic Policy Uncertainty (EPU) index, as well as environmental factors like temperature, precipitation, solar energy, and wind speed. Additionally, we incorporate key energy pricesCrude Oil, Coal, and Natural Gasand major stock indices, including DAX, STOXX, FTMIB, CAC40, AEX, and SPGTCLNT.

For all models, we use a consistent data preparation strategy, splitting the dataset into an 80% training set and a 20% testing set. Time-series cross-validation is applied to preserve the temporal order, ensuring that training and testing data reflect realistic forecasting conditions. Furthermore, we adopt a rolling forecast strategy, updating each model iteratively with newly observed data.

### 3.1. ARIMA Model

Our methodology leverages the ARIMA model, which combines autoregressive (AR), differencing (I), and moving average (MA) components to capture temporal patterns in time series data. We denote this model as ARIMA$(p, d, q)$, where $p$

indicates the autoregressive order, $d$ represents the differencing degree required to achieve stationarity, and $q$ specifies the moving average order. The ARIMA model is expressed mathematically as:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{m} \beta_k X_{t-k} + \varepsilon_t$$

where $y_t$ represents the forecasted carbon price at time $t$, $c$ is a constant, and $\phi_i$, $\theta_j$, and $\beta_k$ are the coefficients for the AR terms, MA terms, and extraneous variables, respectively, while $\varepsilon_t$ denotes the error term.

We began by conducting a preliminary analysis to assess trends and autocorrelations in the carbon price data, using diagnostic tools such as the autocorrelation function (ACF) and partial autocorrelation function (PACF) to inform our choice of parameters $p$, $d$, and $q$. And we then uses maximum likelihood estimation (MLE) to determine the parameters. This process iteratively adjusts parameters to maximize the log-likelihood function:

$$\text{LogL} = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

where $\hat{y}_t$ represents fitted values, and $\sigma^2$ denotes residual variance.

To address multicollinearity, we applied Principal Component Analysis (PCA) to two feature groupsstock indices (DAX, STOXX, FTMIB, CAC40, AEX, SPGT-CLNT) and energy prices (Crude Oil, Coal, and Natural Gas). This dimensionality reduction allowed us to condense these variables into two principal components, $PCA_{Stock\_Index}$ and $PCA_{Energy\_Prices}$, which we then included as exogenous variables in the ARIMA model. Before conducting PCA, we standardized the data using a StandardScaler to maintain uniform scaling and prevent any single feature from disproportionately influencing the resulting components.

*3.2. Random Forest*

We also employ the Random Forest (RF) methodology to forcast carbon price as an ensemble-based predictive model for forecasting carbon prices. Random Forest operates on the principle of Bootstrap Aggregating (Bagging), where multiple datasets are created from the original training set through bootstrap sampling. This sampling technique, involving random selection with replacement, generates subsets where individual instances may repeat or be excluded. The RF algorithm constructs a sequence of decision trees $(T_1, T_2, \ldots, T_N)$ during the training process. For each regression task, a tree $T_i$ is trained on a bootstrap sample $D_i$, drawn with replacement

from the complete training dataset $D$. During tree construction, a random subset of $m$ features is selected at each node for splitting. Given a new input $x$, each tree $T_i$ yields a prediction $y_i$, and the RF's final prediction $\hat{y}$ for input $x$ is calculated as the average of these predictions:

$$\hat{y}(x) = \frac{1}{N} \sum_{i=1}^{N} y_i(x)$$

Within each tree, the learning objective is to minimize prediction error, quantified by mean squared error (MSE), as shown by:

$$\text{Err}(t) = \frac{1}{n_t} \sum_{D_t} (y_i - k_t)^2$$

where $n_t$ represents the number of instances in node $t$, and $k_t$ is the average of instances within each node.

We applied two variations of the Random Forest model in this study: one using the original undifferenced carbon price data and another using a differenced series to address non-stationarity. Differencing was performed by subtracting the previous value of the time series from the current value:

$$y_t' = y_t - y_{t-1}$$

where $y_t'$ represents the differenced carbon price at time $t$, and $y_t$ and $y_{t-1}$ are the current and previous carbon prices, respectively. This transformation removed trends and other non-stationary components, preparing the series for machine learning. The variables used as extraneous variables were not differenced.

To implement the Random Forest model effectively, we optimize several hyper-parameters, including the number of trees (`n_estimators`), maximum tree depth (`max_depth`), minimum samples required to split a node (`min_samples_split`), minimum samples required at a leaf node (`min_samples_leaf`), and the number of features considered at each split (`max_features`). Hyperparameter tuning is conducted via grid search based on minimizing Mean Squared Error (MSE), with time-series cross-validation applied to capture the temporal structure of the data and minimize overfitting. Each decision tree is trained on a bootstrap sample, and the models final predictions were obtained by averaging outputs across individual trees.

*3.3. LSTM Model*

LSTMs are designed to capture long-term dependencies in time-series data, addressing challenges associated with vanishing gradients in traditional RNNs. An

LSTM cell includes memory units that retain information across sequences, regulated by three gates: the forget gate ($f_t$), input gate ($i_t$), and output gate ($o_t$). These gates operate as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, y_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, y_t] + b_i)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, y_t] + b_o)$$

$$c_t = \tanh(W_c \cdot [h_{t-1}, y_t] + b_c)$$

$$h_t = o_t * \tanh(c_t)$$

where the hidden state $h_t$ and cell state $c_t$ manage information retention and update across time steps. This architecture enables the LSTM to effectively capture dependencies within sequences, which is crucial for modeling the temporal behavior of carbon prices.

To configure the LSTM model, we perform hyperparameter tuning using `RandomizedSearchCV`, optimizing batch size, epochs, optimizer, and learning rate. This search yield an optimal multi-layer LSTM configuration with dropout layers for regularization and either the `Adam` or `RMSprop` optimizer, contingent on the chosen learning rate.

For model training, we preprocess the carbon price data by normalizing features and target values, then structure the dataset with a look-back period of 1 time steps to capture relevant historical patterns. Using backpropagation through time, we train the LSTM model to update its weights based on the sequential structure of the data. The training process employ early stopping, with `mean_absolute_error` as the loss function to optimize prediction accuracy.

## 4. Descriptive Statistics

In the analysis of carbon pricing trends within the European Union's Emissions Trading System (EU ETS), this study draws upon a meticulously compiled dataset encompassing the period from January 1, 2021, to January 31, 2024. During this time frame, a total of 763 data points were collected, providing a granular view of carbon price movements. The carbon price data, sourced from Investing.com, is critical for understanding the economic implications of regulatory shifts and market dynamics under the EU's climate policy framework.

This timeframe is deliberately aligned with the initiation of Phase 4 of the European Union's Emissions Trading System (EU ETS), marking a significant transition from the system's previous phases. The focus on this specific period is due to the

substantial regulatory shifts introduced in Phase 4, which differ markedly from the earlier phases in terms of emissions reduction targets and allowance allocation mechanisms.

Notably, in Phase 3 of the EU ETS (2013-2020), the Union-wide cap for stationary installations was subject to an annual decrease by a linear reduction factor of 1.74%, with the 2013 cap determined based on the average total quantity of allowances issued annually during 2008-2012. Conversely, Phase 4 (2021-2030) introduces a more aggressive approach to emissions reduction, with the cap on emissions decreasing annually at an increased linear reduction factor of 2.2%. This heightened ambition reflects the EU's commitment to achieving more substantial emissions reductions and necessitates an in-depth analysis of carbon pricing trends under the new regulatory framework. The study aims to isolate the impacts of these changes on carbon pricing, underscoring the importance of understanding the dynamics introduced by Phase 4's enhanced regulatory measures.

The descriptive statistics for the dataset, which includes carbon pricing trends within the European Union's Emissions Trading System (EU ETS) from January 1, 2021, to January 31, 2024, are presented in Table **??**. These statistics provide insights into the behavior of the carbon market during Phase 4 of the EU ETS. The carbon price exhibits a mean of 72.98 and a standard deviation of 16.45, reflecting market volatility over the 763 observations in the dataset.

Table 1: Descriptive Statistics of the Dataset

| Variable | Mean | Standard Deviation | Maximum | Minimum |
|---|---|---|---|---|
| Carbon | 72.98 | 16.45 | 98.01 | 31.96 |
| Coal | 176.47 | 93.46 | 439.00 | 63.75 |
| Crude Oil | 83.82 | 14.26 | 127.98 | 51.09 |
| Natural Gas | 72.45 | 54.61 | 339.20 | 15.53 |
| Fit_for_55 | 0.83 | 0.38 | 1 | 0 |
| Law | 0.22 | 0.41 | 1 | 0 |
| Compromise | 0.25 | 0.43 | 1 | 0 |
| EPU | 276.88 | 69.80 | 418.62 | 141.39 |
| DAX | 14980.43 | 1082.54 | 16972.34 | 11975.55 |
| SPGTCLNT | 1699.21 | 295.68 | 2720.79 | 1088.34 |
| FTMIB | 25692.05 | 2414.81 | 30744.24 | 20352.98 |
| CAC40 | 6722.63 | 526.14 | 7677.47 | 5399.21 |
| AEX | 732.69 | 44.97 | 827.57 | 630.58 |
| STOXX | 448.01 | 22.92 | 494.35 | 382.89 |
| Temperature | 12.94 | 6.64 | 31.1 | -3.2 |
| Precipitation | 1.53 | 4.05 | 36.03 | 0.0 |
| Solar Energy | 6.75 | 5.88 | 27.1 | 0.1 |
| Wind Speed | 11.39 | 3.82 | 30.7 | 3.8 |

The time series plot of the carbon price, depicted in Figure **??**, emphasizes the fluctuations over the observed period. Furthermore, the study will explore the patterns in related energy commodities, policy indicators, European stock indices, and weather variables, all of which could influence emission levels and subsequently, carbon market dynamics.
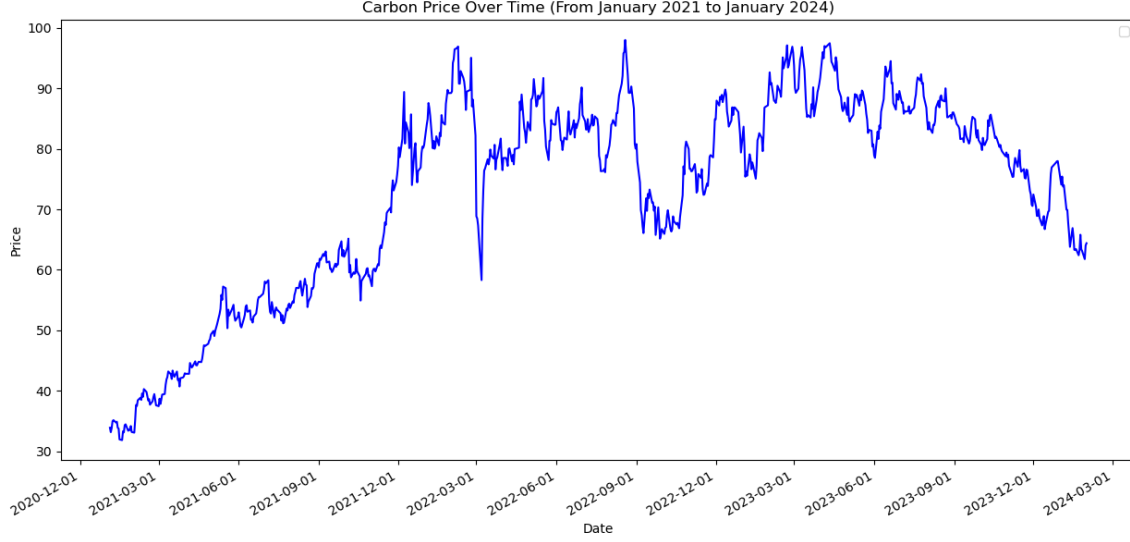
Figure 1: Time Series Plot of Carbon Price from January 2021 to January 2024.

## 5. Performance and Results

### 5.1. Evaluation Criteria

To evaluate the accuracy and reliability of our predictive models in forecasting carbon prices, we utilize several statistical metrics. The primary measure is Root Mean Squared Error (RMSE), which captures the magnitude of prediction errors:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2}$$

where $y_t$ represents the observed value, $\hat{y}_t$ the forecasted value, and $n$ is the number of observations. RMSE is complemented by Mean Absolute Percentage Error (MAPE), offering insights into the relative error size:

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

To capture additional dimensions of forecast accuracy, we also include Mean Absolute Error (MAE) and Mean Squared Error (MSE):

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t|$$

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$$\text{MSE} = \frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2$$

The MAE provides the average absolute error, while the MSE further emphasizes larger errors due to its quadratic form. We also assess model fit with the Coefficient of Determination ($R^2$), which quantifies the proportion of variance explained by the model:

$$R^2 = 1 - \frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2}$$

where $\bar{y}$ is the mean of actual values $y_t$. An $R^2$ value closer to 1 indicates a better fit.

*5.2. Model Performances*

The performance of the ARIMA(1,1,1) model and the Random Forest models for forecasting carbon prices are summarized in Table **??**. The ARIMA model, augmented with exogenous variables such as PCA-transformed stock indices and energy prices, displayed strong in-sample and out-of-sample predictive capabilities. The in-sample RMSE, MAPE, and MAE values were low, with a high $R^2$ of 0.986, while the out-of-sample evaluations indicated the models robustness with an RMSE of 1.46 and an $R^2$ of 0.967.

The model trained without differencing performed well in the in-sample evaluation, achieving an $R^2$ value of 0.991, indicating that it captured the majority of the variance in the training data. However, when tested out-of-sample, the models performance decreased, with a higher RMSE of 3.33 and an $R^2$ of 0.826, suggesting some overfitting. The error metrics indicate that while the undifferenced model could explain most of the variance in the training data, its generalization ability was limited in out-of-sample forecasts.

On the other hand, the differenced Random Forest model demonstrated strong generalization, with an out-of-sample RMSE of 1.54 and an $R^2$ of 0.963, reflecting a better ability to forecast carbon prices in previously unseen data. The in-sample performance remained robust, with an RMSE of 2.22 and an $R^2$ of 0.984. The relatively balanced performance across both in-sample and out-of-sample tests suggests that differencing helped stabilize the model and prevent overfitting to the training data.

Table **??** presents a comparative summary of the performance metrics for all models.

Table 2: Performance Summary of ARIMA(1,1,1) and Random Forest Models

| Model | Metric | In-Sample | Out-of-Sample |
|---|---|---|---|
| **ARIMA(1,1,1)** | RMSE | 2.07 | 1.46 |
| | MAPE | 2.08% | 1.53% |
| | MAE | 1.50 | 1.19 |
| | MSE | 4.28 | 2.13 |
| | $R^2$ | 0.986 | 0.967 |
| **Random Forest (No Differencing)** | RMSE | 1.69 | 3.33 |
| | MAPE | 1.58% | 3.60% |
| | MAE | 1.17 | 2.72 |
| | MSE | 2.85 | 11.11 |
| | $R^2$ | 0.991 | 0.826 |
| **Random Forest (With Differencing)** | RMSE | 2.22 | 1.54 |
| | MAPE | 2.17% | 1.55% |
| | MAE | 1.56 | 1.21 |
| | MSE | 4.93 | 2.37 |
| | $R^2$ | 0.984 | 0.963 |

The figures comparing actual and predicted carbon prices for in-sample and out-of-sample periods illustrate the models' performance. The ARIMA models predictions closely matched actual data, with minor deviations in out-of-sample forecasts, which were within acceptable margins. Similarly, the differenced Random Forest model demonstrated consistent alignment with actual prices, underscoring its efficacy for time series with non-stationary characteristics.
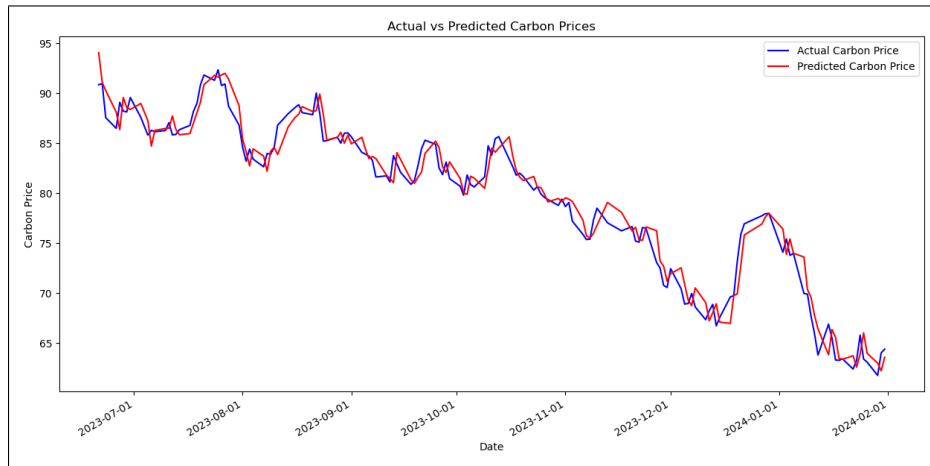
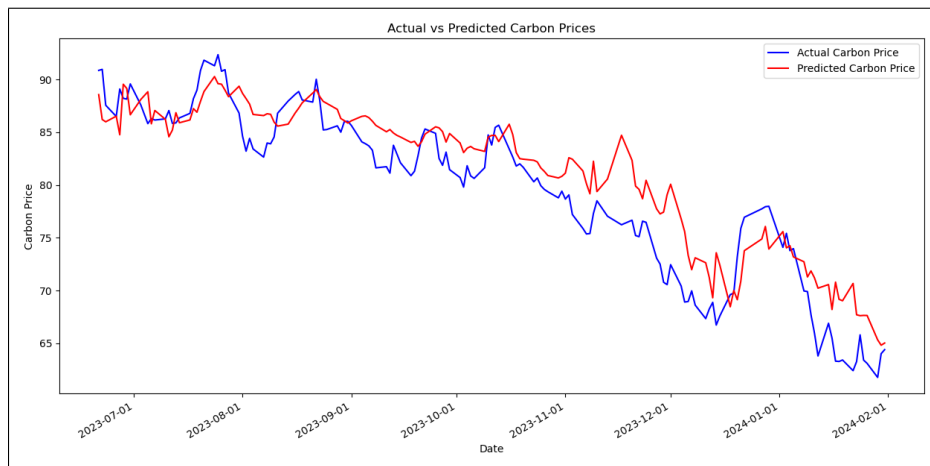Figure 2: Out-of-sample Actual vs Predicted Carbon Prices using ARIMA(1,1,1).



Figure 3: Out-of-sample Actual vs Predicted Carbon Prices using Random Forest (Without Differencing).
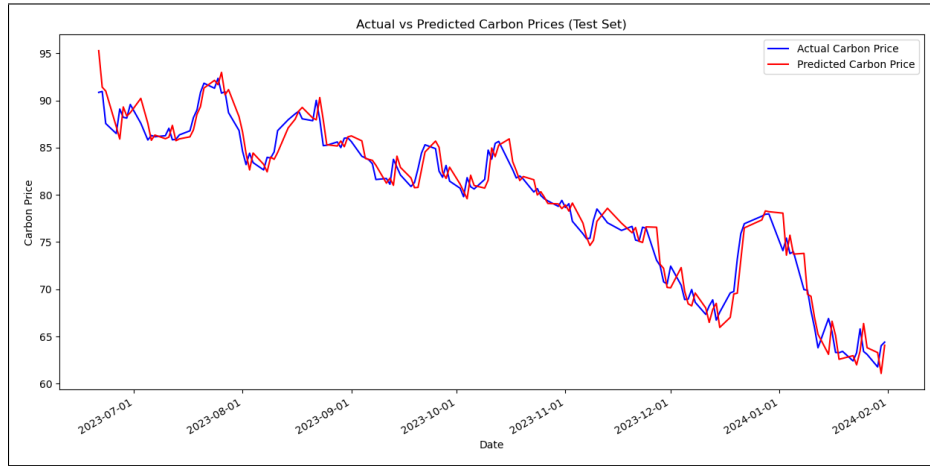
Figure 4: Out-of-sample Actual vs Predicted Carbon Prices using Random Forest (With Differencing).

## 5.3. Discussion

Discuss the results, implications, and any observed trends or anomalies.

## 6. Conclusion

Summarize the findings, their implications for

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