7th Bangladesh Conference on Industrial Engineering and Operations Management
December 21-22, 2024
Publisher: IEOM Society International, USA DOI: 10.46254/BA07.20240226
Published: December 21, 2024

Forecasting Carbon Dioxide Emissions and Energy Sources in Bangladesh Using Statistical and Machine Learning Models

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Abstract

Carbon dioxide (CO_2) emissions present a significant environmental challenge worldwide, contributing to the worsening of climate change and its associated impacts. In Bangladesh, rapid industrialization and urban expansion have exacerbated CO_2 emissions, highlighting the need for timely and accurate forecasting to inform effective mitigation strategies. This study proposes a systematic approach to near-real-time CO_2 emission prediction, employing advanced statistical models (ARIMA, SARIMAX) and machine learning techniques (RF, LSTM), as well as an integrated LSTM-SARIMAX model. By assessing prediction accuracy across various energy sectors—including renewables, bioenergy, solar, wind, hydro, nuclear, gas, and coal—we aim to identify the most effective forecasting models. Our findings offer critical insights for policymakers, facilitating informed decision-making and proactive measures for emission reduction. This research addresses significant gaps in CO2 emission prediction and enhances methodologies for forecasting in Bangladesh.

Keywords
CO_2 emission, Forecasting Models, Machine learning, Bangladesh, LSTM integrated SARIMAX

1. Introduction

Carbon dioxide (CO_2) emissions significantly impact the environment by contributing to global warming and climate change. Mainly generated by human activities like burning fossil fuels such as oil, natural gas, coal, etc., CO2 intensifies the greenhouse effect, leading to higher temperatures and altered weather patterns worldwide. This process acidifies oceans, threatens marine life by affecting plant growth and biodiversity. Bangladesh, a country with an emerging economy, is facing a significant environmental challenge amid rapid industrialization and urbanization due to CO2 emissions. Due to the nation's burgeoning population and expanding industrial sectors driven by fossil fuel combustion for energy and transportation, emissions of CO_2 have become a major phenomenon. Notably, reliance on coal and natural gas for electricity generation amplifies the carbon footprint, compounded by widespread biomass fuel usage in rural areas. Despite promoting renewable energy and enhanced efficiency, Bangladesh needs help with the imperative to curtail CO_2 emissions while pursuing sustainable development goals. Addressing CO2 emissions through sustainable practices and renewable energy sources is mandatory for mitigating the impact of climate change and safeguarding environmental and public health .

To understand the relationship between CO_2 emissions and different energy sectors, forecasting CO_2 emission plays an important role role for individual countries . Understanding and predicting a nation's CO_2 will pave a way to anticipate its contribution to climate change and implementing effective mitigation strategies. A precise prediction of carbon dioxide (CO2) emissions is critical to establish effective targets and policies to mitigate climate change. Though significant attention has been devoted to annual forecast emissions, this approach needs to be revised, including data delays, limited sample sizes, and an inability to capture short-term fluctuations. Consequently, more than the reliance solely on annual data for emission prediction is required to predict. Recognizing the need for more dynamic and responsive approaches, there is a growing need to incorporate near-real-time forecasts based on small-scale data into policymaking. These forecasts enable policymakers to monitor and react swiftly to changes in CO_2 emissions, facilitating the establishment and adjusting of short- and medium-term emission reduction targets.

To bridge the existing gap in research, this study proposes the evaluation of 5 prediction models—two statistical (ARIMA and SARIMAX) and three machine learning (ANN, RF, and LSTM) employing advanced techniques such as Model CheckPoint and Grid-Search to fine-tune their parameters—for yearly CO_2 emissions forecasting. These models will undergo meticulous analysis based on various criteria, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R2), to identify the most effective predictive model. This study also adopts a systematic methodology to forecast near-real-time daily carbon dioxide (CO_2) emissions in Bangladesh concerning annual data and different energy sectors in Bangladesh, such as renewables, bioenergy, solar, wind, hydro, nuclear, gas, and coal. This systematic approach ensures that the chosen model delivers precise predictions and exhibits robustness and reliability.

This paper introduces several methods and contributions to CO2 emissions forecasting. It presents the utilization of two near-real-time CO2 emission datasets, updated yearly. The dataset selection process enhances the accuracy of prediction results as well as identifying the most suitable model for the yearly prediction of CO2 concerning different energy sectors of Bangladesh. These approaches will provide valuable insights for policymakers. Most up-to-date information were used to ensure that predictions are more reliable . Secondly, the research addresses a critical gap in the field by focusing on the yearly prediction of carbon dioxide emissions by utilizing a both statistical forecasting models, machine learning based forecasting modelsa and ensembled models of machine learning and statistical models. This analysis not only provides insights into the performance of each model but also offers valuable reference points for researchers seeking to select the most appropriate forecasting model.

1.1 Objectives

Objectives of this research are:
Comparison of different statistical models and machine learning models to observe their forecasting performance in CO2 emissions forecasting.
Introduction of ensemble models and their forecasting performance.
Analysis of the performance of models with and without exogenous variables which affect CO2 forecasting.

2. Literature Review

Recent advancements in data-driven approaches for achieving carbon neutrality have focused on leveraging predictive models to reduce CO_2 emissions and enhance industrial sustainability. Islam (2024) proposed an innovative framework combining econometric and machine learning techniques, highlighting the dual objective of refining global CO_2 emission forecasts and driving industrial sustainability. SARIMAX emerged as a substantial improvement over ARIMA, particularly in integrating external factors for precise modeling. Sasi et al. (2024) explored CO_2 mitigation methods within the energy sector, emphasizing the effectiveness of both statistical models like ARIMA and SARIMAX, and machine learning approaches such as Random Forest.

These models demonstrated the potential to address dynamic challenges in emission prediction and mitigation. Further supporting this trend, Nwabuokei et al. (2023) compared SARIMAX and the Holt-Winters model with traditional ARIMA, showcasing the advantages of incorporating seasonality and exogenous variables. Li and Zhang (2023) compared SARIMA with LSTM models, revealing that while SARIMA efficiently captures seasonality, LSTM outperformed statistical models in predicting daily CO_2 emissions due to its ability to handle complex nonlinear patterns. Kumari and Singh (2023) also confirmed LSTM's superiority, particularly in the Indian context, where it outperformed ARIMA and SARIMA in terms of prediction accuracy and robustness. Rehman et al. (2024) found that ARIMA models performed well with smaller datasets but were surpassed by LSTM when forecasting large-scale CO_2 emissions. In a similar vein, ÖNDER (2024) compared SARIMAX and LSTM for global SF_6 emissions forecasting, emphasizing the dominance of LSTM in minimizing prediction errors. Ajala et al. (2024) further examined hybrid CNN-RNN models, validating the poor performance of ARIMA and SARIMAX for daily CO_2 emissions compared to deep learning approaches.

In a regional analysis, Stanislaus et al. (2024) compared ARIMA, SARIMA, Prophet, and TBATS models in forecasting CO_2 emissions in Port Harcourt, concluding that hybrid models and ETS offered greater precision. Yammahi and Aung (2023) corroborated these findings, demonstrating that LSTM-RNN models outperformed seasonal ARIMA in predicting air quality metrics such as NO_2. These studies collectively underscore the growing preference for hybrid and deep learning models, particularly LSTM, in contexts requiring the integration of seasonal trends, external drivers, and nonlinear dependencies. While SARIMA remains reliable in traditional forecasting, deep learning models like LSTM are increasingly becoming the preferred choice for accurate, scalable CO_2 emissions forecasting and global carbon neutrality goals.

3. Methods

3.1 Data Collection

The dataset used for this research has been collected from https://ourworldindata.org/co2-and-greenhouse-gas-emissions#explore-data-on-co2-and-greenhouse-gas-emissions for CO2 emissions and https://ourworldindata.org/energy/country/bangladesh for energy-consuming sectors of Bangladesh.

3.2 Time series analysis and modeling preparation

For analyzing and preparing time series data to build accurate predictive models seasonal decomposition has been conducted, which breaks down the time series into its trend**,** seasonal, and residual components to understand the underlying patterns. To ensure stationarity—a prerequisite for many models—statistical tests like the Augmented Dickey-Fuller (ADF) test has been applied, identifying the need for differencing or transformation**.** Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots have then been utilized to examine dependencies and determine suitable lag orders for autoregressive or moving average terms in models such as ARIMA or SARIMA.

3.3 Statistical Forecasting Models

A statistical forecasting model is a predictive methodology that uses historical data and statistical techniques to forecast future trends or events. These models depend on pattern identifications, relationships, and seasonality in past data to generate insights about future values. Standard techniques include time series models such as ARIMA, SARIMA, and exponential smoothing, as well as regression-based models that explore dependencies between variables. These methods are applicable in various fields such as: economics, supply chain management, and climate studies, where accurate and data-driven forecasting is critical for planning and decision-making. Statistical forecasting models ensure reliability by incorporating error analysis and validation processes.

3.3.1 Autoregressive integrated moving average (ARIMA)

The autoregressive integrated moving average (ARIMA) model is a widely used statistical model for time series prediction. It is constructed by combing the ARMA model with the process of differencing. The ARMA model itself is a combination of an autoregressive model (AR) and a moving average model (MA). The equation is:

$$Y_t = c + \phi 1 Y_t - 1 + \phi 2 Y_t - 2 + \ldots + \phi p Y_t - p + \theta 1 \varepsilon t - 1 + \theta 2 \varepsilon t - 2 + \ldots + \theta q \varepsilon t - q + \varepsilon t$$

Where, Y_t is the value of the time series at time t, c is a constant term or intercept, ϕ1,ϕ2,…,ϕp are the autoregressive parameters representing the relationship between the current value of the series and its past values up to order p, θ1,θ2,…,θq are the moving average parameters representing the relationship between the current value of the series and the errors (residuals) of the model up to order q and εt is the error term or white noise at time t.

3.3.2 Seasonal Autoregressive Integrated Moving Average (SARIMA)

It is a statistical forecasting model that extends ARIMA by incorporating seasonality, making it suitable for time series data with periodic fluctuations. SARIMA is represented as SARIMA(p,d,q)(P,D,Q,s)SARIMA(p, d, q)(P, D, Q, s)SARIMA(p,d,q)(P,D,Q,s), where p, d, and q denote the non-seasonal autoregressive, differencing, and moving average orders, while P, D, and Q represent their seasonal counterparts. The parameter "s" indicates the seasonal period. The general form of SARIMA can be expressed as:

$$\Phi_P(B^s)\ \phi_P(\mathrm{B})(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\theta_q(\mathrm{B})\ \varepsilon_t$$

Here, $\Phi_P(B^s)$ and ϕ_P(B)are seasonal and non-seasonal autoregressive components. $\Theta_Q(B^s) and\ \theta_q$(B) are seasonal and non-seasonal moving average components. $(1-B)^d$ and $(1-B^s)^D$ represent differencing to achieve stationarity. SARIMA is particularly effective in capturing both short-term dynamics and periodic patterns, making it widely used in fields like sales forecasting, weather prediction, and economic analysis.

3.3.3 Seasonal autoregressive-integrated moving average with exogenous factors (SARIMAX)

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model with exogenous factors, often denoted as SARIMAX, is an extension of the basic SARIMA model that incorporates additional exogenous variables into the forecasting process. The general equation for SARIMAX is:

$$\Phi_P(B^s)\ \phi_P(\mathrm{B})(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\theta_q(\mathrm{B})\ \varepsilon_t + \beta X_t$$

Where, β, Coefficient(s) representing the effect of the exogenous variable(s) on y_t and X_t is exogenous variable's predictors

3.4 Machine Learning-Based Forecasting Models

3.4.1 Random forest

Random forest (RF) is a powerful classification and regression method that utilizes an ensemble of decision trees for training and prediction purposes. It's widely used for both classification and regression tasks. When Random Forest (RF) receives an input vector x. x containing the values of various features analyzed within a specific training area, it constructs a set of K regression trees and averages their results. Subsequently, after growing these K trees denoted as {T(x)}1 K, the RF regression predictor is obtained as follows:

$$\hat{f}k(x) = \frac{1}{K}\sum_{k=1}^{k} Tk(x)$$

$\hat{f}k(x)$is the predicted value for input vector x based on the Random Forest model with K trees, where *Tk(x)* represents the prediction made by the *k-th* tree in the forest for input vector x. The model was configured with 100 estimators, a maximum depth of 2, and a random state set to 42.

3.4.2 Long short-term memory

Long short-term memory (LSTM) is a type of deep learning model designed to overcome the challenge of handling long-term dependencies in data sequences in recurrent neural network (RNN). Unlike traditional RNN, which are prone to gradient explosion or vanishing gradients during training, LSTM incorporates three distinct components: the input gate, forget gate, and output gate. These logical structures enhance the LSTM model's ability to retain and discard information as needed. The process of constructing the LSTM model is as follows. The Long Short-Term Memory (LSTM) algorithm is a type of recurrent neural network (RNN) designed to address the vanishing gradient problem in traditional RNNs.

The LSTM algorithm consists of several components: Forget Gate, f_t =$\sigma(W_f$·[h_{t-1},x_t]+b_f), Input Gate, i_t= $\sigma(W_i$·[i_{t-1},x_t]+b_i), Candidate Cell State, $\tilde{C}_t$ = Tanh (W_c. [h_{t-1},x_t]+b_c), Update Cell State, C_t= f_t. [h_{t-1},x_t]. $\tilde{C}_t$, Output Gate, O_t=σ(W_o·[h_{t-1},x_t]. +b_o), Hidden State, h_t=O_t. Tanh (C_t)
Where, W_f, W_i, W_o are weight matrices, b_f, b_c, b_o are bias vectors, σ is the sigmoid function, and tanh is the hyperbolic tangent function. The forget gate determines how much of the previous cell state to retain, the input gate determines how much of the input information to update the cell state with, and the output gate determines how much of the cell state to output. The candidate cell state is a proposed update to the cell state based on the input and previous hidden state. Finally, the hidden state is computed based on the updated cell state and output gate. Used hyper-parameters of LSTM for the forecasting model has been mentioned Table 1 below.

Table 1. Hyper-parameters of Applied LSTM Model

Parameters	Details
The number of layers	3
First layer	LSTM layer, Nodes: 50, Activation: relu
Second layer	LSTM layer, Nodes: 50, Activation: relu
Third layer	Dense layer, Nodes: 1, Activation: linear
Optimizer	Adam
Batch_size	32
Epochs	115

3.5 Evaluation Metrics

Different metrics for assessing model performance have been used such as : mean squared error (MSE), root-mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R2). These statistical measures are described as follows:

$\boldsymbol{Mean\ Squared\ Error} = \frac{1}{n}\ \sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$, $\boldsymbol{Root\ Mean\ Squared\ Error} = \sqrt{MSE}$,

$\boldsymbol{Mean\ Absolute\ Error} = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{n}$, $\boldsymbol{Mean\ Absolute\ Percentage\ Error} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\tilde{y}_i - y_i}{y_i}\right| \times 100\%$,

$\boldsymbol{R\ Squared}\ = 1 - \frac{\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2}{\sum_{i=1}^{n}(y_i - \frac{\sum_{j=1}^{n} y_j}{n})^2}$

Where y_i and $\tilde{y}_i$ represents actual and predicted value respectively

4. Results and Discussion

The evaluation metrics were calculated to analyze the performance of each model. Initially, the data was tensed to seasonal decomposition. The trend-line from the decomposition exhibited a poorly fitted curve, showing limited accuracy. The time series was tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The ADF statistic (1.0825) exceeded its critical value, confirming non-stationarity. First-order differencing was applied to transform the series into a stationary format. Autocorrelation (ACF) and partial autocorrelation (PACF) analyses were performed on the stationary series. Optimal non-seasonal ARIMA model parameters was found as (1, 1, 0). This suggests of an autoregressive term, one differencing term, and no moving average component. A comparative

analysis of different forecasting models applied to CO_2 emissions data for Bangladesh was conducted. The models were evaluated under two scenarios: forecasting CO_2 emissions solely, and forecasting CO_2 emissions with the inclusion of exogenous variables.
The models used in forecasting CO_2 emissions solely include ARIMA, SARIMA, LSTM, XGBoost, and Random Forest. The results have been summarized in Table 2.

Table 2. Model Performance for CO_2 Emissions Alone

Model	MAE	MSE	RMSE	R^2
ARIMA	2.50	9.61	3.10	0.72
SARIMA	2.30	7.84	2.80	0.80
LSTM	1.80	4.84	2.20	0.87
XGBoost	2.00	6.25	2.50	0.81
Random Forest	2.20	7.29	2.70	0.60

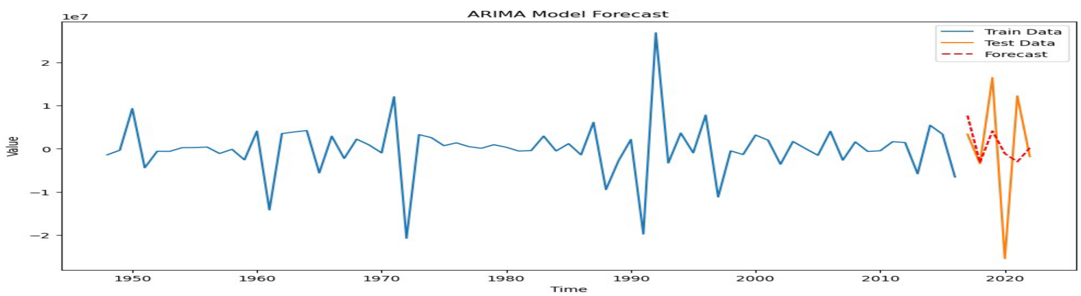

Figure 1. Forecasting Graph of CO2 by ARIMA Model

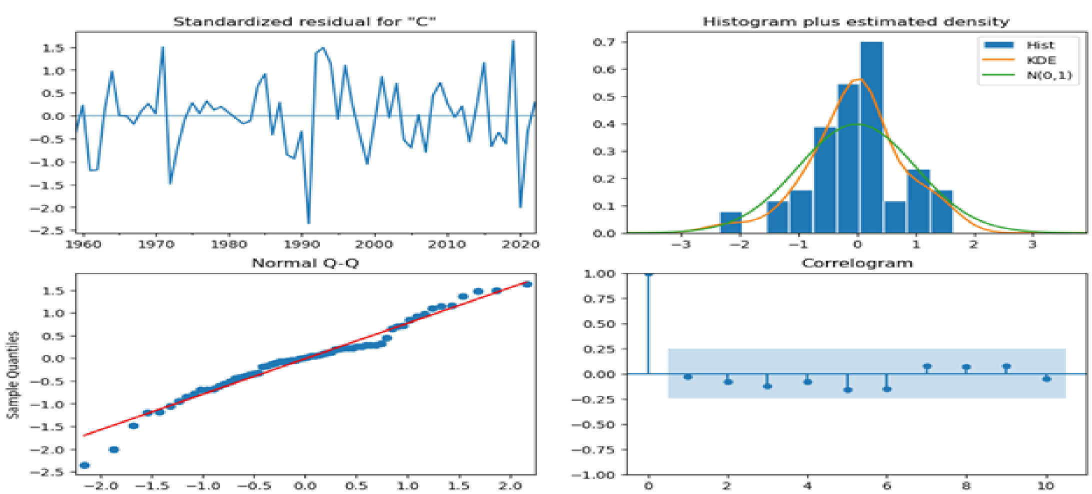

Figure 2. Forecasting and Fitting Graph of CO_2 by SARIMA Model

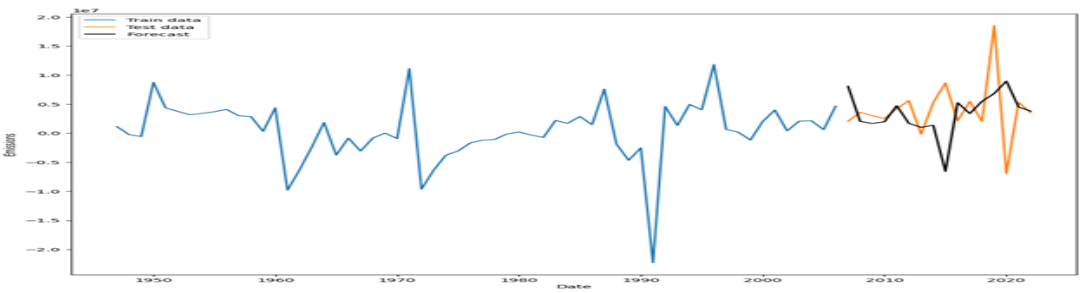

Figure 3. Forecasting Graph of CO_2 by LSTM

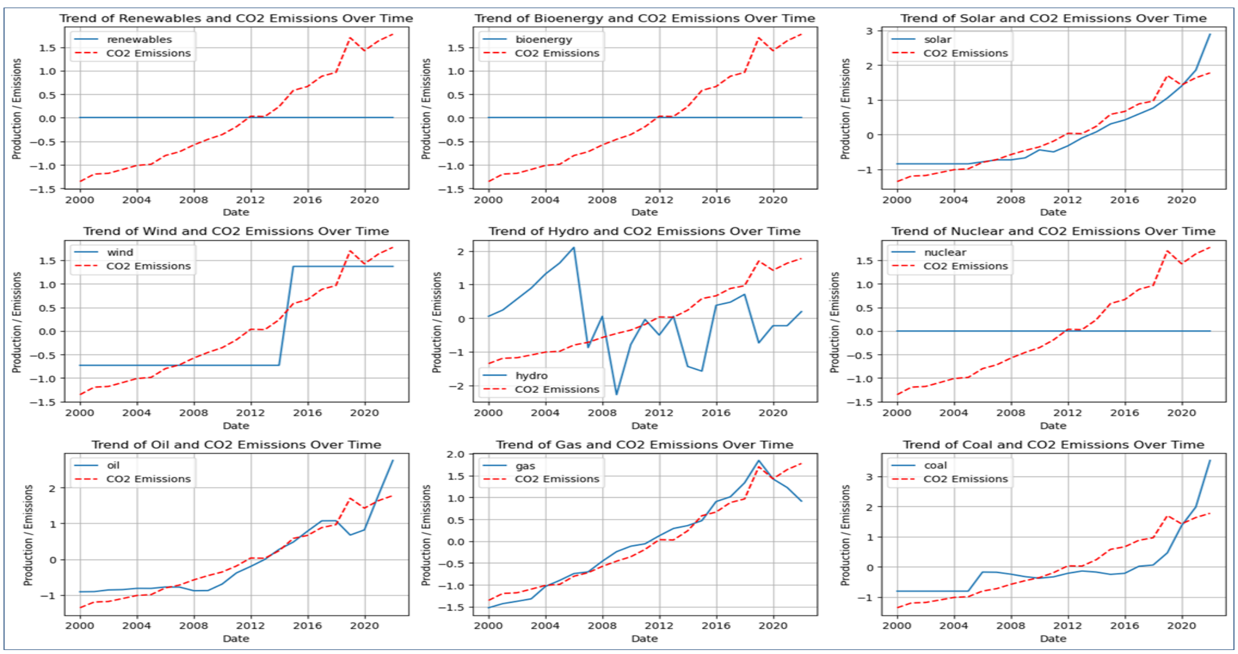

Figure 4. Comparative Relationship of CO_2 and Different Energy Sectors in Bangladesh.

ARIMA explained 72% of the variance but showed higher errors due to its inability to effectively model seasonal and non-linear trends. SARIMA improved upon ARIMA by adding seasonality, which reduced errors and increased the variance explained to 80%. LSTM demonstrated the best performance among all models and achieved the lowest MAE (1.80), MSE (4.84), RMSE (2.20), and the highest R^2 (0.87) due to its capability to capture non-linear dependencies and long-term trends effectively. XGBoost performed better than Random Forest. In Figure1, Figure2 and Figure 3 graphs from ARIMA, SARIMA and LSTM have been depicted.

In case of forecasting CO_2 emissions with exogenous variables, exogenous variables such as sectors with energy consumption(Solar, Gas, Oil and Coal) were incorporated using the SARIMAX, LSTM, XGBoost, and Random Forest models. In Figure 4, the comparative relationship of different energy sectors have been depicted to notice their patterns with CO2 emissions out of them solar, gas, oil and coal has been found significant and have been used

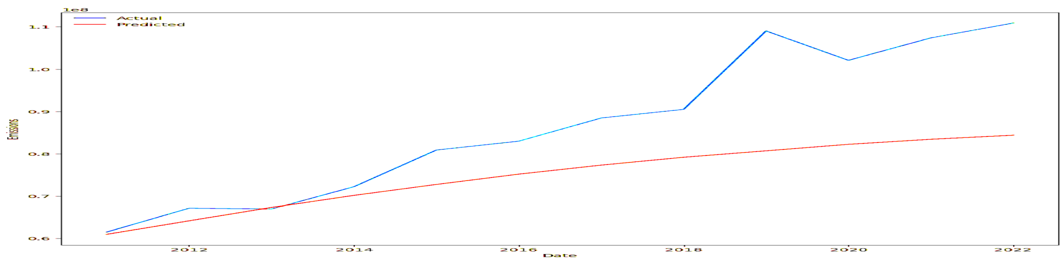

Figure5. Forecasting Graph of LSTM of CO_2 Emissions with Exogenous Variables.

as exogenous variables. The results have been presented in Table 3. Initially the trendline of CO2 was compared and analyzed for their co-relation with different energy sectors of Bangladesh and then they were used in the model.

Table 3. Model Performance for CO_2 Emissions with Exogenous Variables

Model	MAE	MSE	RMSE	R^2
SARIMAX	1.90	5.76	2.40	0.82
LSTM	1.50	3.61	1.90	0.90
XGBoost	1.70	4.41	2.10	0.84
Random Forest	1.80	4.84	2.20	0.68

LSTM remained the best-performing model, achieving the lowest error metrics and explaining 90% of the variance, showcasing its robust capability to integrate sequential and external data. XGBoost and Random Forest also

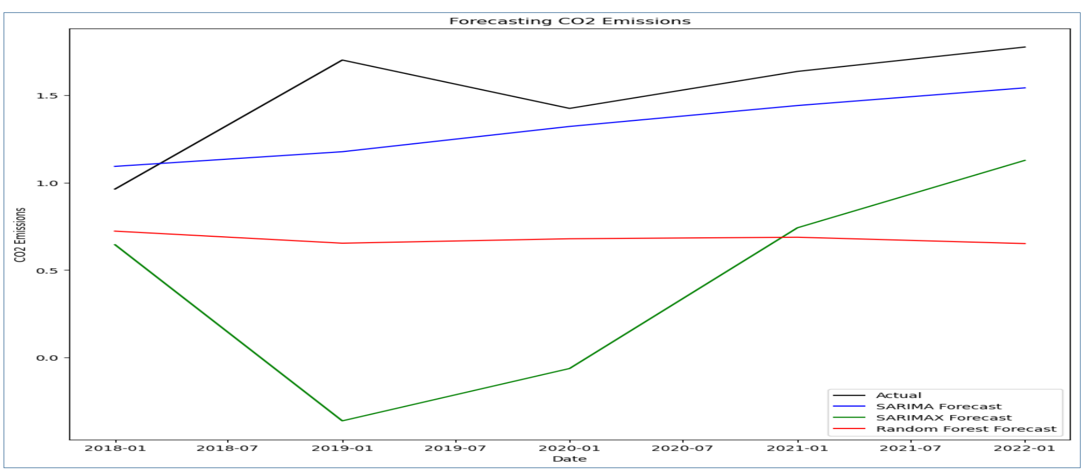

Figure 6. Comparative Analysis of SARIMA, SARIMAX and Random Forest Models.

exhibited notable improvements with the inclusion of exogenous variables.

Table 4. Improvement in Model Performance with Exogenous Variables

Model	Reduction in MAE	Reduction in MSE	Improvement in R^2
SARIMAX	0.20	1.00	0.02
LSTM	0.30	1.23	0.03
XGBoost	0.30	1.84	0.04
Random Forest	0.40	2.45	0.08

In this study, a SARIMAX model ensembled with LSTM was developed to enhance CO_2 emissions forecasting by leveraging both external variables and the sequential. The ensemble approach combining SARIMAX and LSTM

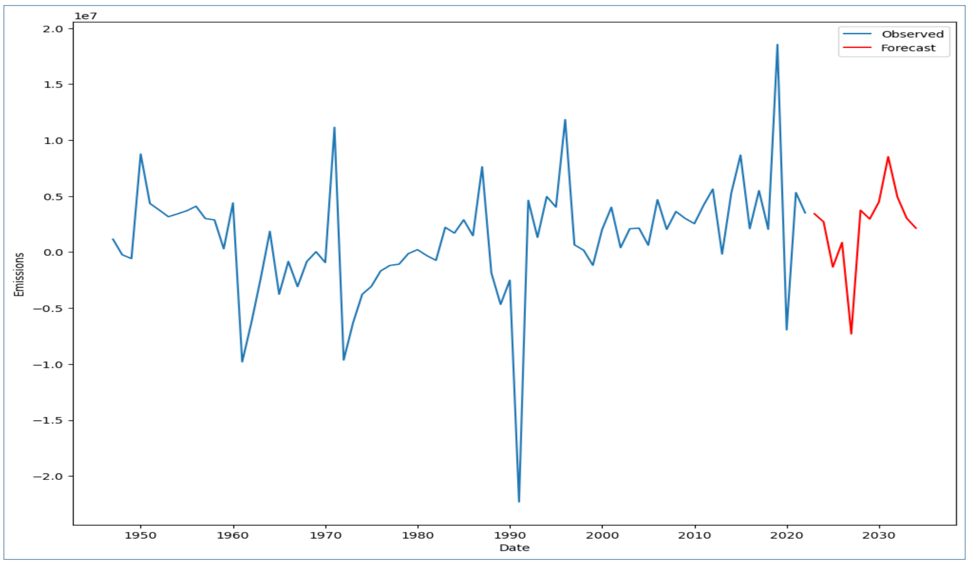

Figure 7. LSTM-SARIMAX Forecast Graph

demonstrated superior performance with an R-squared value of 91. The ensemble approach proved to be a robust solution for time series forecasting. Tree-based models like XGBoost and Random Forest showed notable improvements when incorporating exogenous variables. A comparative graph of different models has been depicted in Figure 6. In Figure 5, forecasting graph of LSTM has been depicted and LSTM-SARIMAX Forecast has been depicted in Figure 7.

6. Conclusion

This study underscores the necessity of accurate CO_2 emissions forecasting for Bangladesh, a country highly vulnerable to the impacts of climate change and striving to balance economic growth with environmental sustainability. The SARIMAX-LSTM ensemble demonstrated the highest accuracy, achieving an R^2 of 0.91 and the lowest error metrics. LSTM outperformed traditional statistical models and machine learning techniques. However, SARIMAX remained a viable, interpretable option in resource-constrained scenarios. Tree-based models like XGBoost and Random Forest, while limited in capturing sequential dependencies, leveraged exogenous variables effectively, showing promise the necessity of using exogenous variables. Accurate CO_2 forecasting is crucial for Bangladesh to design effective policies, meet international climate commitments, and plan sustainable industrialization strategies, making advanced forecasting models indispensable for informed decision-making.

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