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The Application of Time Series Forecasting Model for Carbon Emissions Prediction in Electrical Grid: A Step Toward Climate Action

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Abstract - This study evaluates the forecasting performance of three models of Autoregressive Integrated Moving Average (ARIMA), Prophet, and Bi-directional Long Short-Term Memory (BiLSTM) in predicting CO₂ emissions from the electricity grid in the United States. Using a real dataset from the California Independent System Operator (CAISO) that records CO₂ emissions at five-minute intervals between 2018 and 2020, the data underwent preprocessing steps including outlier removal, missing value imputation, and feature selection before model training. ARIMA parameters were determined using statistical tests such as ACF, Partial Autocorrelation Function (PACF), and Augmented Dickey Fuller (ADF), while Prophet addressed seasonality and calendar effects. BiLSTM, a deep learning model, was applied to capture complex temporal dependencies and non-linear relationships in the dataset. The models were evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. The results show that BiLSTM achieved the lowest error values (MAE: 266.726; RMSE: 429.228), outperforming ARIMA (MAE: 1728.797; RMSE: 2203.464) and Prophet (MAE: 831.346; RMSE: 1102.884). These findings indicate that BiLSTM is more effective in modeling and forecasting highly variable and long-term CO₂ emission data. The study provides valuable insights for researchers and energy sector practitioners by demonstrating that machine learning-based forecasting can support carbon reduction initiatives and improve decision-making for electricity grid management. Moreover, the inclusion of a near-real-time alert system and dashboard design enhances the study's practical relevance. Despite being limited to U.S. grid data, this research underscores the potential of BiLSTM models in achieving environmentally sustainable energy operations through accurate and timely CO₂ emission forecasting.

Keywords— Time Series Forecasting, ARIMA, Prophet, BiLSTM, CO₂ Emissions, Carbon, Electricity Grid, Climate Action

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1. INTRODUCTION

1.1 Overview

Nowadays, carbon emissions have had a significant effect on global climate change. This raises awareness among governments and other experts about monitoring and predicting carbon emissions to ensure global environmental sustainability. Consequently, accurate predictions and near real-time monitoring are essential in reducing carbon emissions. This study introduces a Carbon Emission Prediction Dashboard that aims to provide nearly real-time monitoring of carbon emissions and predictive analytics that enable the person in charge to make informed decisions in resolving this issue [1]. The objective of the dashboard is to identify suitable historical carbon emissions related data, enabling the predictive models to predict based on the data. Besides, time-series or regression machine learning algorithms will be integrated into the dashboard for predictive analysis. The trends in carbon emissions can also be visualized over time. Finally, the users of the dashboard will be alerted if the carbon emissions exceed the thresholds through email. The dashboard may be integrated with either the ARIMA, Prophet, or Long Short-Term Memory (LSTM) models for predictive analysis. There will be some search algorithms implemented in the models to enhance their accuracy. In a nutshell, the dashboard enables the stakeholders to interact with the carbon emissions data and gain comprehensive knowledge about near real-time data, enabling them to come up with mitigation strategies to overcome the issues.

1.2 Background Studies

In the twenty-first century, carbon emissions due to electricity generation are growing, attracting more attention from the public. Fossil fuel-based power generation is the main cause of pollution. Based on the Paris Agreement, utilising renewable energy in national grids is one of the ways to solve the pollution issue because it is believed that this way is more cost-effective than fossil fuels by 2030 [2]. In China, their goal is to reduce carbon emissions per unit of Gross Domestic Product (GDP) by 18% by 2020, using 2015 as the baseline year. This goal can be achieved through predictive modelling such as LSTM to help stakeholders make informed decisions [3]. Besides, the increase in global energy demand also increases air pollution. This issue can be overcome through the implementation of Artificial Intelligence (AI) and big data that allow accurate predictions and analyses of carbon emissions by the energy systems based on various significant factors [4]. Leerbeck et al. mentioned that predictive models are important in ensuring high operational efficiency for planning and scheduling in the electricity grid. The grid can operate efficiently based on the demand, reducing pollution caused by unnecessary operation [5]. The net-zero carbon emissions by 2050 goal can be achieved through collaboration between various parties to resolve the issue of excessive carbon emissions. The research study aims to predict carbon emissions from electricity consumption in the U.S. under the Greenhouse Gas (GHG) accounting protocol and then visualize the information in a dashboard. Consequently, the excess carbon emissions can be determined in near real-time through the email alert system, enabling the stakeholders to make informed decisions to reduce the carbon emissions to below the predefined threshold. The business plan is to employ three models: ARIMA, Prophet, and Bidirectional Long Short-Term Memory (BiLSTM), to predict carbon emissions from electricity consumption in the U.S., then select the best model that has the highest forecasting accuracy for future studies.

1.3 Problem Statement

Carbon emissions generated by the electricity grid due to power generation by fossil fuels in the twenty-first century have attracted the attention of the public and government. Hence, the transition to renewable energy is essential to promote the carbon-free goal in the future. Utilising AI, particularly time series forecasting models, may help in strategies making by predicting CO₂ emissions in the electricity grid. The existing and traditional models are poor in predicting non-linear data, resulting in poor capture of the trend or pattern of CO₂ emissions in the electrical grid [6]. Besides, existing and traditional time series forecasting models are poor in long-term forecasting, which is important for informed decision making [7]. Moreover, high-resolution datasets are seldom collected and used to train and test the time series forecasting models, which is important for developing a real-time prediction system [8]. Comparison

among the popular time series forecasting models: ARIMA, Prophet, and BiLSTM is not done in any existing research paper.

1.4.3 Research Hypothesis

- H1 (Theoretical): Prophet and BiLSTM have lower MAE and RMSE than ARIMA, suggesting they may be better in handling non-linear data. Based on the literature review, Prophet and BiLSTM are believed to handle non-linear data, providing accurate predictions in CO2 emissions from the electricity grid.
- H2 (Practical): BiLSTM is theoretically better for capturing temporal dependencies because it learns from both past and future directions. Based on the literature review, BiLSTM can capture long-term dependencies more efficiently by processing the data in both forward and backward directions, although its advantage for long-term forecasting was not directly tested in this study due to limited computational resources.
- H3 (Sustainability): Using high-resolution data (every 5 minutes) is expected to improve forecasting accuracy. Based on the literature review, time series forecasting models trained and tested on higher-resolution datasets have shown lower error compared to those trained on lower-resolution datasets, as higher resolution retains more information for the model to learn from. In this study, the 5-minute resolution data achieved a lower MAE and RMSE than the hourly and daily resolutions; however, because these metrics are reported on each resolution's raw scale, normalized RMSE or MAPE was used to confirm the comparison is scale-independent before this result can be considered as directly supporting H3.
- H4 (Management): Using BiLSTM in power systems can help managers act earlier with better predictions and alerts. Based on the literature review, BiLSTM can handle non-linear data and capture the patterns of complex data better. Hence, a more accurate prediction of carbon emissions could be obtained and managers could be alerted on time.

1.5 Research Framework

The research framework used to develop the study is Cross Industry Standard Process for Data Mining (CRISP-DM). The CRISP-DM methodology provides a structured and comprehensive framework for guiding data mining and analytics studies.

As depicted in Figure 1, there are six clearly defined phases in this methodology, which are Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. This methodology is popular for its simplicity, flexibility, and comprehensiveness, offering a systematic approach to navigating the complexities of predictive modelling. CRISP-DM is more popular compared to other data mining processes, such as Knowledge Discovery in Databases (KDD), which includes nine steps, and Sample, Explore, Modify, Model, and Assess (SEMMA), which comprises five steps. A comparative study by Shafique and Qaiser in 2014 highlights the CRISP-DM's completeness and accuracy over SEMMA, proving that CRISP-DM is more suitable for research and practical applications in data mining [9].

1.6 Scope

The study is aimed at monitoring the carbon emissions from the electricity grid in near real-time and providing predictive analytics to help in making informed decisions for environmental sustainability. This objective can be achieved by the visualisation of the carbon emissions on the dashboard and the email alert system that alerts the stakeholders once the carbon emissions exceed the predefined threshold. The standard protocol followed in this study is the GHG protocol, which is globally admitted for GHG emissions accounting and tracking. This protocol is suitable for this study because carbon falls into one category of GHG gases. However, our focus for this study is on CO2, other gases are not considered. The dashboard will be updated as soon as the new data is fed into it, and the email alert system will also function as it does. The visualisation graphs can be exported as PDF formats to ease the reporting purpose. In conclusion, this is the scope of the study that covers the constraints and deliverables.

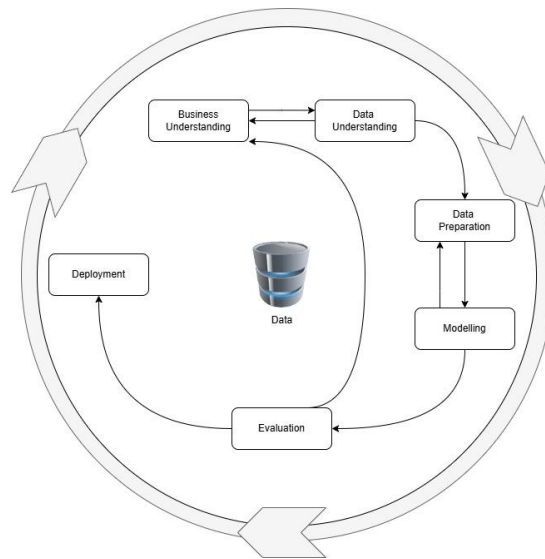


Figure 1. Research Framework

2. LITERATURE REVIEW

2.1 Introduction

Time series forecasting models are important in reducing carbon emissions in various industries by predicting carbon emissions, aiding in informed decision making and strategy making. The differences of the 3 forecasting models are compared as shown in **Error! Reference source not found.**

2.2 The State of the Art in Time Series Forecasting Models

Advancements in time series forecasting models have improved our understanding of machine learning capabilities, particularly the analysis and interpretation abilities of complex datasets. However, there are still limitations for these models. BiLSTM model consists of Forward LSTM and Backward LSTM in its structure to perform dual-direction processing, which is important for handling long-term dependencies. Forward LSTM processes the sequence from the beginning to the end step-by-step, gathering information from previous data points for future predictions. Backward LSTM processes the sequence from the end to the beginning. It starts with the final data point and moves backwards, allowing it to capture insights, such as the influence of certain factors from future data points in the sequence on any previous point [10]. The Prophet model excels in environments with incomplete information, providing high prediction accuracy without interpolating missing values. This makes it user-friendly and efficient because it does not require prior data handling and can automatically detect seasonal patterns in the dataset. Prophet is known for its powerful and fast forecasting capabilities, making it ideal for analysing major trends of time series data. Additionally, it requires less intensive parameter adjustments, making it highly flexible and efficient in examining seasonal patterns and long-term trends in time series data [7], [8].

2.3 Application and Impact of AI and Time Series Forecasting Models in Electrical Grid

The application of AI technologies and time series forecasting models in the electrical grid includes many aspects like grid maintenance, load forecasting, forecasting of meteorological data, and others. The use of time series forecasting

models like BiLSTM in electrical grid settings is still developing, but will promote operational efficiency, cost-effectiveness, and optimisation of resources in the future. This section aims to offer an overview of how time series forecasting models affect different aspects of the electrical grid. BiLSTM, a model that enhances the capabilities of traditional LSTM by integrating a dual-directional structure, has the potential to improve efficiency in the electrical grid. For instance, a hybrid model like BiLSTM and Convolutional Neural Network (CNN) with an Attention mechanism could be used for short-term power load forecasting by utilising the strengths of CNN, BiLSTM, and Attention. The attention mechanism focuses on significant features, CNN extracts spatial features, and BiLSTM captures the bidirectional temporal dynamics [11].

Table 1. Comparison of Three Forecasting Models

Framework	Problem Statement	Objective	Methodology	Contribution	Limitation	Perspective
ARIMA	Difficulty in forecasting non-linear data patterns in CO2 emissions for U.S. electricity grids.	To determine the efficacy of ARIMA in predicting CO2 emissions by examining linear trends.	Utilization of PACF and ACF plots to establish ARIMA parameters p and q .	Provides insights into ARIMA's capability to manage linear aspects of time series data.	ARIMA struggles with non-linear data patterns, limiting its forecasting accuracy.	ARIMA may not be sufficient alone for complex, non-linear forecasting needs in environmental contexts.
Prophet	Inadequacy in handling long-term dependencies and non-linear data in CO2 emissions forecasting.	Assess Prophet's performance in capturing long-term trends and seasonality in CO2 emissions forecasting.	Application of Prophet model to analyse seasonal trends without intensive parameter adjustments.	Highlights Prophet's robustness in dealing with seasonality and its user-friendly nature with minimal need for tuning.	Limited by its less effective handling of non-linear complexities compared to BiLSTM	Demonstrates the importance of choosing models that can effectively handle specific data complexities in environmental forecasts.
BiLSTM	Existing models fail to capture long-term dependencies and non-linear data in CO2 emissions accurately.	To evaluate BiLSTM's capability in handling long-term and non-linear data for forecasting CO2 emissions.	Scaling data for BiLSTM processing to improve model learning from complex, non-linear patterns.	Shows BiLSTM's superiority in forecasting CO2 emissions with the lowest error values among the studied models.	The model's complexity could lead to higher computational demands.	Supports the use of BiLSTM for enhanced accuracy in environmental decision-making, promoting better carbon management strategies.

Moreover, Leerbeck et al. studied how to predict CO2 emissions in European electrical power grids by employing an ARIMA and three linear regression models combined using a Softmax-weighted average. The models were trained and tested using data from many entities. The data underwent variable selection and regularization using the Least Absolute Shrinkage and Selection Operator (LASSO) technique, which improved the interpretability of the data. The forward feature selection process was followed by the LASSO technique, which repeated the significant features as long as the accuracy of the models in predicting carbon emissions kept increasing. The data was also cleaned by handling missing data and correcting errors. The three models performed the first prediction to capture the correlation

of the features. The ARIMA model improved the prediction results by correcting the mistakes in the first prediction results. Cross-validation techniques were utilized to prevent overfitting in the models [5].

2.4 Application and Impact of AI and Time Series Forecasting Models in Grid Maintenance

One of the applications of AI and time series forecasting models in grid maintenance is that it promotes predictive maintenance. For instance, analysis of historical data with significant factors from different grid components, such as transformers, cables, and insulators, is used to train Artificial Neural Networks (ANNs), allowing reliable and accurate prediction of component failures before they occur. This ensures effective maintenance planning, extending the lifespan of the components [12]. The time series forecasting models can forecast potential faults in the electrical grid based on the analysis of historical data. These models can be integrated with advanced technologies like smart non-wire alternatives, which could greatly improve the safety and security of the grid through digital applications and innovative solutions. Consequently, maintenance could be planned earlier during off-peak hours to reduce its influence on the public. The operational costs can also be reduced due to early fault detection of the components [12].

2.5 Application and Impact of AI and Time Series Forecasting Models in Load Forecasting

Implementation of AI and time series forecasting models into load forecasting increases the prediction accuracy, leading to a wiser and better energy distribution process. Hence, the usage of resources could be optimized and reduce the likelihood of power outages. Besides, the grid could be managed dynamically based on the demand [13]. A deep learning approach, a Deep Neural Network (DNN), is introduced to forecast time series data accurately with a hierarchical structure. The forecasts from different hierarchical levels are merged during the DNN training process, preventing additional processes from merging the forecasts from different levels after forecasting, which will introduce error to the forecasts' results. DNN can train and test with several datasets simultaneously and study the relationship between the datasets, improving the forecast results [13].

2.6 Application and Impact of AI and Time Series Forecasting Models in Forecasting of Meteorological Data

The values of meteorological data like wind speed and solar radiation are significant features that can be used to forecast electricity generated from these renewable energy sources [14]. Forecasting the meteorological data is important because it affects the accuracy of prediction on electricity generation. This leads to better business planning on the power system, enabling integration of renewable energy into the electricity generation be carried out seamlessly and reducing the reliance on non-renewable energy sources like fossil fuels. Moreover, excess electricity generated can be stored when the demand is low, which is financially beneficial [14].

2.7 Application and Impact of AI and Time Series Forecasting Models in CO2 Emissions Prediction

The advancements in the time series forecasting models have brought a lot of improvements in the CO2 emissions prediction with higher accuracy. They can study the correlation among the features of datasets, the weights of the features, and output the CO2 emissions prediction. The following points are about the characteristics and strengths of the algorithms used to predict CO2 emissions. The raw datasets collected are usually complex and multivariate, requiring essential data preprocessing steps to improve the quality of input data. Advanced models like Singular Spectrum Analysis (SSA) and an Attention mechanism with LSTM as well as CNN and an Attention mechanism with BiLSTM could handle the complex data well by integrating multiple data handling and preprocessing techniques to manage dataset that include temporal dependencies and multivariate inputs [15]. Advanced models like BiLSTM and LSTM can be integrated into IoT devices for continuous monitoring on the CO2 emissions by the industry. Immediate feedback can be given to the stakeholders, and responsive strategies could be made to overcome the issues like excess CO2 emissions [16]. Immediate feedback on the real-time CO2 emissions allows the policymakers to react to the changes dynamically, enabling informed decision making supported by statistical data, making the decision more convincing to the public [16]. Real-time visualization of CO2 emissions in the electrical grid could raise the awareness of the public and improve their engagement in cultivating environmentally friendly activities. They can view their efforts in real-time, which is a motivation to encourage the public to go green [16]. Based on the literature reviews, it

has been proven that AI and time series forecasting models have the capabilities to contribute to the improvement of prediction accuracy for CO₂ emissions. However, there are still a lot of improvements to enhance the existing models to achieve more satisfying results.

3. RESEARCH METHODOLOGY

3.1 Overview

The CRISP-DM methodology provides a structured and comprehensive framework for guiding data mining and analytics studies. There are six clearly defined phases in this methodology, which are Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. This methodology is popular for its simplicity, flexibility, and comprehensiveness, offering a systematic approach to navigating the complexities of predictive modelling. In this study, the end-to-end methodological workflow is illustrated by Figure 2, providing clear view of the workflow. This study focuses on predictive performance rather than model interpretability or robustness. Therefore, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used as the primary evaluation metric. Sensitivity analysis, which examines the influence of input or parameter variations on model output, is not included as it is out of the scope of this study.

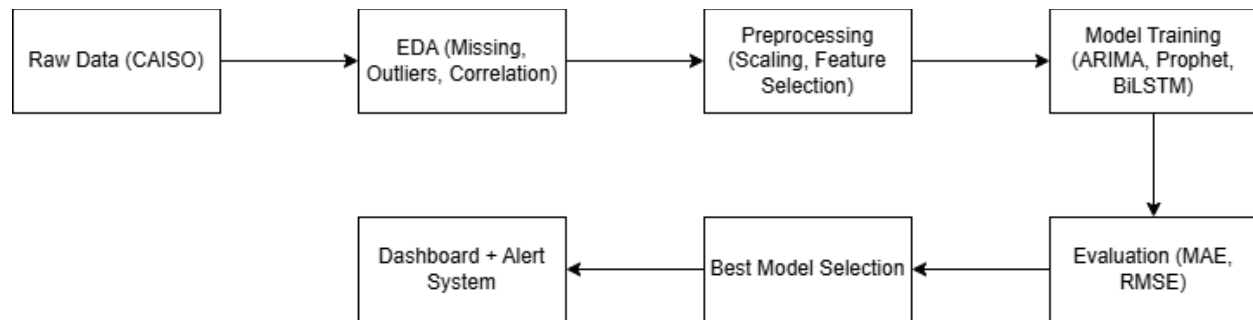


Figure 2. End-to-end Methodological Workflow

3.2.1 Business Understanding

Business understanding is the first phase of CRISP-DM, and it is important to identify whether the study objectives could help resolve or reduce the issues encountered in the real world. The net-zero carbon emissions by 2050 goal can be achieved through collaboration between various parties to resolve the issue of excessive carbon emissions. The research study aims to predict carbon emissions from electricity consumption in the U.S. under the GHG accounting protocol and then visualize the information in a dashboard. Consequently, the excess carbon emissions can be determined in near real-time through the email alert system, enabling the stakeholders to make informed decisions to reduce the carbon emissions until below the predefined threshold. The business plan is to employ three models: ARIMA, Prophet, and BiLSTM, to predict carbon emissions from electricity consumption in the U.S., then select the best model that has the highest forecasting accuracy for future studyions.

3.2.2 Data Understanding

Data understanding is the second phase of CRISP-DM, and it is important to determine whether the dataset selected is suitable for the study objective or not. The dataset used for this study is publicly available and obtained from CAISO. The dataset contains 5-minute-resolution grid-level data for electricity demand, generation by sources including wind, solar, natural gas, coal, biomass, geothermal, large and small hydro, battery storage, nuclear, and imports, together with their corresponding CO₂ emissions from 12 April 2018 to 12 April 2020. The dataset contains 33 columns and 210550 rows with NA values. The EDA is performed on the dataset to analyse and interpret the patterns in the dataset, smoothing the data preprocessing steps. The EDA steps that will be used in this study are outlier analysis using modified z-score, identifying missing values, studying the correlation between the features, identifying the data types for all features, data segmentation by visualising the trend of CO₂ emissions during weekdays and weekends by plotting a heatmap with hour versus weekday, stationarity testing and lastly checking for duplicated data.

3.2.3 Data Preparation

Data preparation is the third phase of CRISP-DM, and it involves data cleaning, which is important to improve the quality of the dataset, enabling the dataset to better suit the models. The data cleaning steps that will be carried out are handling missing values, feature selection, and outlier removal. The missing values within the dataset will be imputed with the median values. The scale of the data will also be standardized to make it suitable for the BiLSTM model, which is sensitive to the scale of the data. Moreover, outliers will also be removed from the dataset to reduce their negative impacts on the forecasting accuracy. Feature selection will also be carried out to reduce the dimensionality of the dataset but remove the less significant features within the dataset. Lastly, the dataset with selected features will be split into training, testing, and unknown sets in 80%, 19%, and 1%, respectively.

3.2.4 Modelling

Modelling is the fourth phase of the CRISP-DM methodology and describes the forecasting models used to predict carbon emissions resulting from electricity consumption across various sectors in the United States. The models employed are ARIMA, Prophet, and BiLSTM, which are trained and tested using a dataset spanning from 12 April 2018 to 12 April 2020 with a temporal resolution of five minutes. The dataset is divided into 80% training data, 19% testing data, and 1% unknown data. ARIMA is a widely used time series forecasting model that has demonstrated strong performance in predicting CO₂ emissions across different sectors. Its effectiveness stems from its ability to utilize lagged information from historical observations to forecast future values, making it particularly suitable for datasets where past patterns influence future trends. The model consists of three key parameters (p , d , q), which are identified using the Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Augmented Dickey-Fuller (ADF) tests to ensure stationarity. Although ARIMA has limitations in handling non-linear and highly seasonal data, numerous studies have reported its superior performance compared to traditional grey models [6] and other forecasting techniques in carbon emission prediction. For example, ARIMA outperformed Prophet and Holt-Winters Exponential Smoothing (HWES) in forecasting carbon emissions from coal-fired power plants [17]. Moreover, ARIMA (1,0,1) was identified as the most effective model for short-term prediction of CO₂ emissions in HGL, petroleum-excluded biofuels, and natural gas industrial sectors in the United States [7]. Other studies have also shown that ARIMA surpassed Support Vector Machine (SVM) and Prophet models in predicting methane emissions from livestock using annual data from 1961 to 2019 [18], as well as carbon emissions measured in a strawberry greenhouse using sensor data collected at intervals ranging from 1 to 60 minutes over four months [8]. The optimal ARIMA configuration is selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which evaluate the trade-off between model complexity and goodness of fit.

Prophet, developed by Facebook's data science team, is another forecasting model designed to handle time series data with irregularities and seasonal patterns. The model decomposes a time series into trend, seasonality, and holiday components, enabling it to capture complex behavioural patterns such as weekly and yearly cycles as well as the effects of special events. This capability makes Prophet particularly suitable for applications in sectors such as agriculture and industry, where seasonal variations significantly influence the observed data. In addition, Prophet can effectively manage missing values and automatically detect seasonal patterns, reducing the amount of preprocessing and manual parameter tuning required. Its simplicity and robustness make it a practical forecasting tool in real-world scenarios. Namboori compared ARIMA, SVM, Support Vector Regression–Particle Swarm Optimisation (SVR-PSO), and Prophet models for forecasting CO₂ emissions from the electric power sector and found that Prophet achieved the best overall performance [19]. Similarly, Vineet Sawant reported that Prophet was the most suitable model for forecasting emissions in industrial sectors involving distillate fuel oil, petroleum coke, and other petroleum products [7].

BiLSTM networks are advanced deep learning models that excel in sequence and time series analysis. Unlike traditional LSTM networks, which process information only in the forward direction, BiLSTM models analyse data in both past-to-future and future-to-past directions. This bidirectional architecture enables the model to capture contextual information from both ends of a sequence, improving its ability to model complex temporal dependencies. BiLSTMs are particularly effective at retaining information over long periods, making them well-suited for CO₂ emission forecasting, where both historical trends and temporal relationships play significant roles. Their capability to learn long-term dependencies is especially beneficial when working with large datasets or datasets containing

intricate temporal patterns. Previous studies have demonstrated the effectiveness of BiLSTM in forecasting applications, where it has outperformed alternative deep learning models in predicting future trends across various domains. For instance, Aamir et al. implemented LSTM, Gated Recurrent Unit (GRU), and BiLSTM models to forecast carbon dioxide emissions in South Asia through 2030 using World Bank data from 1971 to 2020. Their findings showed that BiLSTM achieved superior predictive performance compared to both LSTM and GRU models [16]. These results highlight the potential of BiLSTM as a powerful tool for carbon emission forecasting and predictive analytics involving sequential and time series data.

3.2.5 Evaluation

The evaluation metrics that will be used to evaluate the forecasting accuracy of the models are MAE and RMSE. They are used because they are popular if compared to other evaluation metrics. This statement is justified by the literature reviews conducted above, 14 out of 19 papers used MAE and RMSE to evaluate their forecasting models in predicting the CO₂ emissions in various sectors. The lower the value of the MAE and RMSE, indicating the lower the error performed by the models and the higher the forecasting accuracy.

3.2.6 Deployment

The deployment phase involves the practical application of the best model to set up a real-time forecasting system for carbon emissions. This system is integrated into an existing dashboard used by stakeholders to monitor and manage carbon emissions effectively. An automated alert system through email will also be integrated into the system to alert the stakeholders when the carbon emissions exceed the predefined threshold. A presentation, configuration manual, and a comprehensive document will be presented for deployment.

4. RESULTS AND DISCUSSIONS

This section presents the findings from the systematic methodology, CRISP-DM. The flow of the implementation of the study and the email alert systems is illustrated in Figure 3 and Figure 4, respectively. The flow of implementation aids in achieving the research objectives.

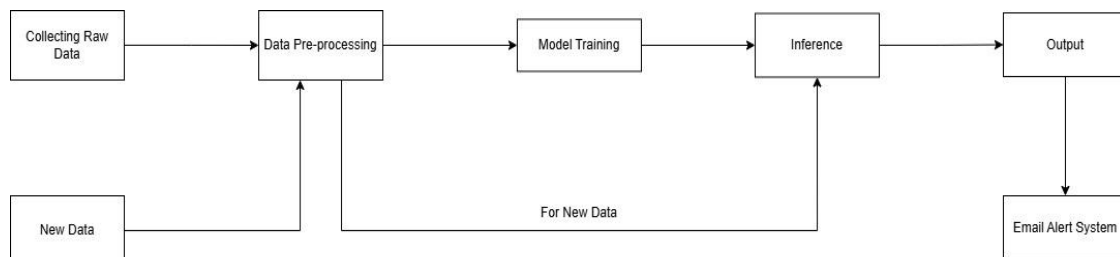


Figure 3. Implementation Flow of the Dashboard

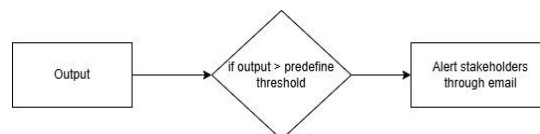


Figure 4. Implementation Flow of the Email Alert System

4.1 Acquiring Data

The dataset used for this study is publicly available and obtained from CAISO. The dataset contains 5-minute-resolution carbon emission data for electricity consumption from thousands of industrial, agricultural, residential, and commercial building profiles in the U.S., measured in metric tons per megawatt-hour from 12 April 2018 to 12 April 2020 with a temporal resolution of 5 minutes. The raw dataset contains 33 columns and 210550 rows with NA values. The raw dataset is shown in Figure 5. The description of the dataset is shown in Figure 6.

4.2 Exploratory Data Analysis

The EDA on the dataset is performed in Jupyter Notebook environment. From Figure 7, it summarises key data quality aspects including missing values and duplicated rows in the dataset. The dataset contains minimal missing values and no duplicated entries, indicating good data integrity for further analysis. There are only two data types in the dataset, which are datetime64 and float, as shown in

Figure 8. For the outliers' analysis, a modified z-score that is greater than 3.5 is considered an outlier. In Figure 9, the outliers for the CO2 features are visualised in box plots, providing a clearer comparative view across features. From

Figure 10, we can observe that the power production of resources like coal are highly correlated to their corresponding CO2 emissions. Moreover, data segmentation is performed by plotting the total CO2 emissions for every hour from Monday to Sunday with dates ranged from 13 May 2018 to 8 June 2018 using heatmap as shown in Figure 11. This visualisation justifies that CO2 emissions are higher during weekdays' nighttime period, whereas CO2 emissions are lower during weekends' brunch period.

date	month	day	weekday	hour	interval	5min_ending	demand_DayAF	demand_HourAF	demand_actual	demand_net	wind_curtail_MW	solar_curtail_MW	solar_MW	wind_MW	geothermal_MW	biomass_MW	biogas_M
4/12/2018	4	12	4	0	1	0:00	22555	21942	21825	17634	0	0	0	4228	706	242	
4/12/2018	4	12	4	0	2	0:05	20916	21661	21694	17555	0	0	0	4196	716	238	
4/12/2018	4	12	4	0	3	0:10	20916	21661	21619	17430	0	0	0	4214	725	240	
4/12/2018	4	12	4	0	4	0:15	20916	21661	21556	17331	0	0	0	4268	724	241	
4/12/2018	4	12	4	0	5	0:20	20916	21494	21459	17197	0	0	0	4291	724	246	
4/12/2018	4	12	4	0	6	0:25	20916	21494	21415	17092	0	0	0	4344	683	257	
4/12/2018	4	12	4	0	7	0:30	20916	21494	21348	16974	0	0	0	4419	663	251	
4/12/2018	4	12	4	0	8	0:35	20916	21232	21255	16839	0	0	0	4449	663	246	
4/12/2018	4	12	4	0	9	0:40	20916	21232	21177	16796	0	0	0	4413	664	245	
4/12/2018	4	12	4	0	10	0:45	20916	21232	21138	16742	0	0	0	4427	663	238	
4/12/2018	4	12	4	0	11	0:50	20916	21024	21034	16665	0	0	0	4417	664	237	
4/12/2018	4	12	4	0	12	0:55	20916	21024	20959	16625	0	0	0	4353	664	237	
4/12/2018	4	12	4	1	1	1:00	20916	21024	20856	16645	0	0	0	4258	665	238	
4/12/2018	4	12	4	1	2	1:05	20087	20767	20787	16634	0	0	0	4189	664	239	
4/12/2018	4	12	4	1	3	1:10	20087	20767	20724	16558	0	0	0	4167	665	237	
4/12/2018	4	12	4	1	4	1:15	20087	20767	20631	16533	0	0	0	4130	665	237	
4/12/2018	4	12	4	1	5	1:20	20087	20564	20587	16451	0	0	0	4154	665	238	
4/12/2018	4	12	4	1	6	1:25	20087	20564	20533	16383	0	0	0	4169	665	237	
4/12/2018	4	12	4	1	7	1:30	20087	20564	20525	16306	0	0	0	4235	664	235	
4/12/2018	4	12	4	1	8	1:35	20087	20414	20449	16214	0	0	0	4259	656	238	
4/12/2018	4	12	4	1	9	1:40	20087	20414	20357	16178	0	0	0	4237	637	236	
4/12/2018	4	12	4	1	10	1:45	20087	20414	20303	16108	0	0	0	4210	637	236	
4/12/2018	4	12	4	1	11	1:50	20087	20255	20270	16086	0	0	0	4203	636	236	
4/12/2018	4	12	4	1	12	1:55	20087	20255	20217	16081	0	0	0	4153	638	236	
4/12/2018	4	12	4	2	1	2:00	20087	20255	20209	16088	0	0	0	4132	639	235	
4/12/2018	4	12	4	2	2	2:05	19556	20147	20172	15972	0	0	0	4196	643	238	
4/12/2018	4	12	4	2	3	2:10	19556	20147	20234	15977	0	0	0	4274	645	238	
4/12/2018	4	12	4	2	4	2:15	19556	20147	20219	15935	0	0	0	4296	644	239	
4/12/2018	4	12	4	2	5	2:20	19556	20099	20153	15894	0	0	0	4285	643	241	
4/12/2018	4	12	4	2	6	2:25	19556	20099	20130	15842	0	0	0	4305	644	239	
4/12/2018	4	12	4	2	7	2:30	19556	20099	20103	15759	0	0	0	4330	644	238	
4/12/2018	4	12	4	2	8	2:35	19556	20022	20022	15762	0	0	0	4296	645	240	
4/12/2018	4	12	4	2	9	2:40	19556	20022	19967	15719	0	0	0	4261	645	238	

Figure 5: Raw Dataset

[source: raw.githubusercontent.com/grgmiller/CAISO_data/master/CAISOdata.csv.]

No.	Column Name	Column Description
1	date	Date
2	month	Specific month
3	day	Day of the month
4	weekday	Specific day
5	hour	Specific hour
6	interval	Time interval
7	5min_ending	Specific 5-minute period ending time
8	demand_DayAF	Demand day-ahead forecast
9	demand_HourAF	Demand hour-ahead forecast
10	demand_actual	Actual demand
11	demand_net	Net demand
12	wind_curtail_MW	Amount of potential wind energy production that was curtailed, measured in megawatts
13	solar_curtail_MW	Amount of potential solar energy production that was curtailed, measured in megawatts
14	solar_MW	Actual amount of solar energy production, measured in megawatts
15	wind_MW	Actual amount of wind energy production, measured in megawatts
16	geothermal_MW	Actual amount of geothermal production, measured in megawatts
17	biomass_MW	Actual amount of biomass production, measured in megawatts
18	biogas_MW	Actual amount of biogas production, measured in megawatts
19	sm_hydro_MW	Actual amount of small hydroelectric power production, measured in megawatts
20	battery_MW	Actual amount of power output of battery storage, measured in megawatts
21	renewable_MW	Actual amount of renewable energy production, measured in megawatts
22	natgas_MW	Actual amount of natural gas production, measured in megawatts
23	lg_hydro_MW	Actual amount of large hydroelectric plants production, measured in megawatts
24	imports_MW	Actual amount of power production through imports from other regions or countries, measured in megawatts
25	nuclear_MW	Actual amount of nuclear energy production, measured in megawatts
26	coal_MW	Actual amount of coal production, measured in megawatts
27	other_MW	Actual amount of others production, measured in megawatts
28	imports_co2	Amount of CO2 emissions from imports
29	natgas_co2	Amount of CO2 emissions from natural gas
30	biogas_co2	Amount of CO2 emissions from biogas
31	biomass_co2	Amount of CO2 emissions from biomass
32	geothermal_co2	Amount of CO2 emissions from geothermal
33	coal_co2	Amount of CO2 emissions from coal

Figure 6: Description of Column Names in the Dataset

	Metric	Value
0	Missing Values	7909
1	Duplicate Rows	0

Figure 7. Missing Values and Duplicate Rows in the Dataset

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210549 entries, 0 to 210548
Data columns (total 32 columns):
#   Column                Non-Null Count  Dtype
---  -
0   datetime_local         210549 non-null  datetime64[ns]
1   month                  210549 non-null  float64
2   day                    210549 non-null  float64
3   weekday                210549 non-null  float64
4   hour                   210549 non-null  float64
5   interval                210549 non-null  float64
6   demand_DayAF           210537 non-null  float64
7   demand_HourAF          210537 non-null  float64
8   demand_actual          210537 non-null  float64
9   demand_net             210404 non-null  float64
10  wind_curtail_MW         207093 non-null  float64
11  solar_curtail_MW        207093 non-null  float64
12  solar_MW                210537 non-null  float64
13  wind_MW                 210537 non-null  float64
14  geothermal_MW           210249 non-null  float64
15  biomass_MW              210537 non-null  float64
16  biogas_MW               210537 non-null  float64
17  sm_hydro_MW             210537 non-null  float64
18  battery_MW              210537 non-null  float64
19  renewable_MW            210249 non-null  float64
20  natgas_MW               210537 non-null  float64
21  lg_hydro_MW             210537 non-null  float64
22  imports_MW              210537 non-null  float64
23  nuclear_MW              210537 non-null  float64
24  coal_MW                 210537 non-null  float64
25  other_MW                210537 non-null  float64
26  imports_co2             210537 non-null  float64
27  natgas_co2              210537 non-null  float64
28  biogas_co2              210537 non-null  float64
29  biomass_co2             210537 non-null  float64
30  geothermal_co2          210537 non-null  float64
31  coal_co2                210537 non-null  float64
dtypes: datetime64[ns](1), float64(31)
memory usage: 51.4 MB

```

Figure 8. Data Types of All Features

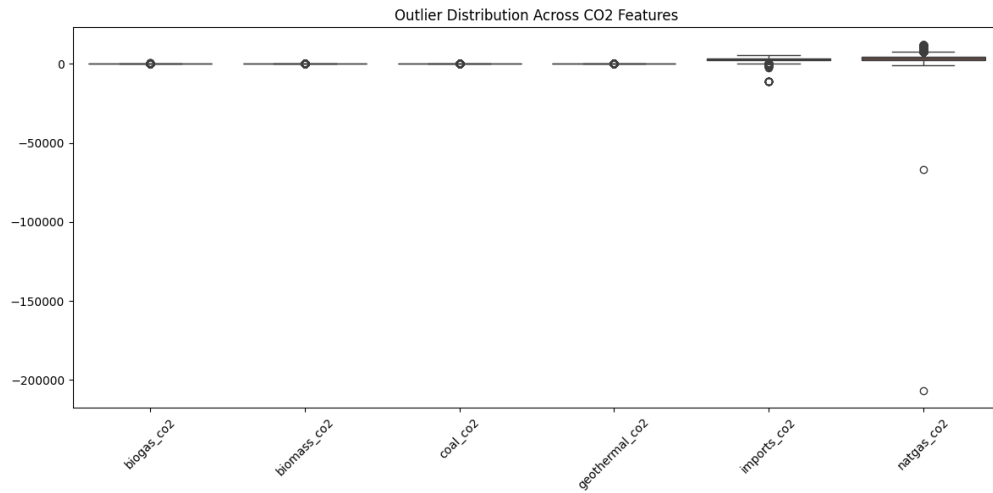


Figure 9. Outlier Distribution Across CO2 Features

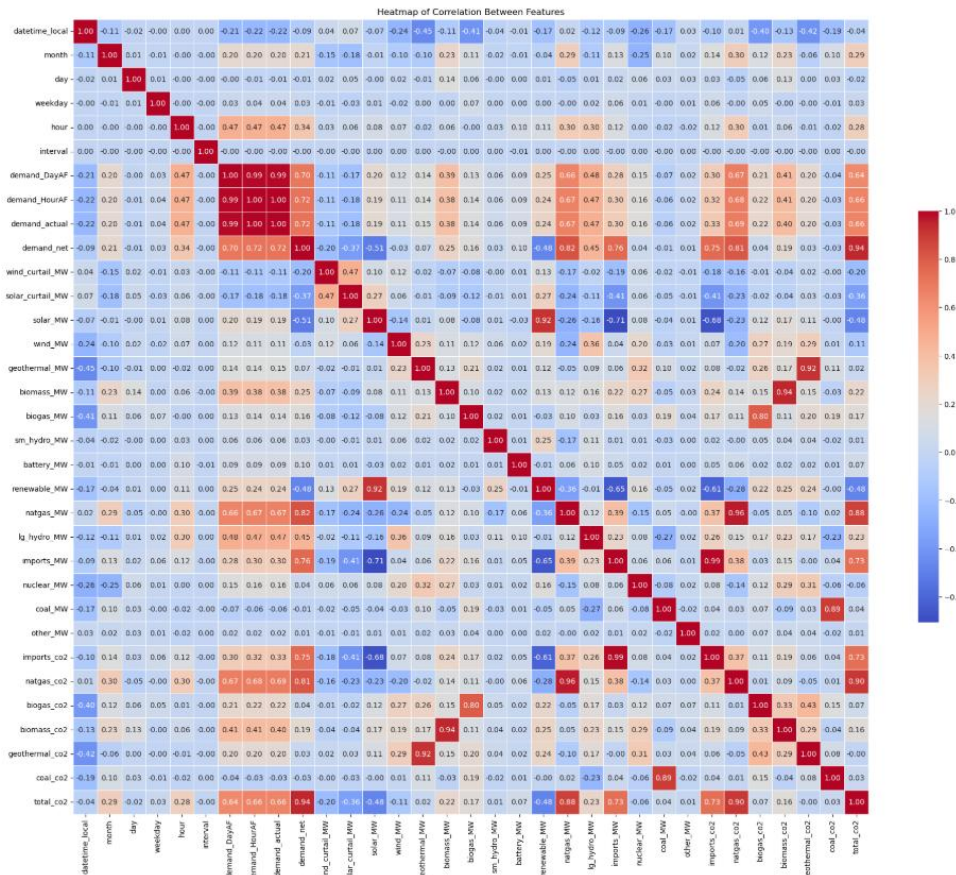


Figure 10. Heatmap of Correlation Matrix of the Numeric Features

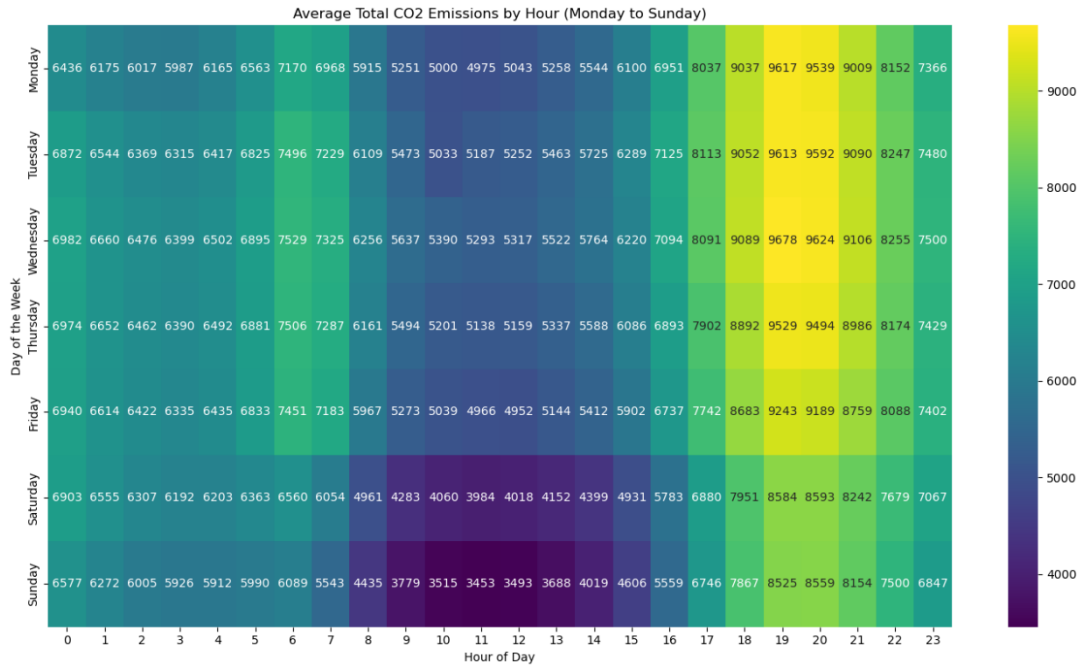


Figure 11. Heatmap of Total CO2 Emissions by Hour from Monday to Sunday

4.3 Data Preprocessing

Data preprocessing is important to promote the efficiency of training and testing processes for forecasting models. Data preprocessing is performed in the Jupyter Notebook environment. After loading the CAISO dataset, the columns with names "date" and "5min_ending" are combined to form an identifier named "datetime_local" as shown in Figure 12. The missing values of the features are imputed with the median value. Feature selection is also performed to select only significant features that will affect the target features, reducing the dimensionality of the dataset to improve the efficiency of training and testing the forecasting models. The feature selection process is guided by the correlation heatmap, and the features selected are shown in Figure 13. Outliers detected in the CO2 features and "total_co2" feature using the modified z-score are removed. The outliers only occupy approximately 2.5% of total records in the dataset, hence, they are removed with the least information loss. Lastly, split the dataset without outliers into training, testing, and unknown sets in 80%, 19%, and 1%, respectively, ensuring robust model evaluation.

	datetime_local	month	day	weekday	hour	interval	demand_DayAF	demand_HourAF	demand_actual	demand_net	...	imports_MW	nuclear_MW	coal_MW	oth
0	2018-04-12 00:00:00	4.0	12.0	4.0	0.0	1.0	22555.0	21942.0	21825.0	17634.0	...	5263.0	1616.0	2.0	
1	2018-04-12 00:05:00	4.0	12.0	4.0	0.0	2.0	20916.0	21661.0	21694.0	17555.0	...	5117.0	1616.0	3.0	
2	2018-04-12 00:10:00	4.0	12.0	4.0	0.0	3.0	20916.0	21661.0	21619.0	17430.0	...	5281.0	1617.0	3.0	
3	2018-04-12 00:15:00	4.0	12.0	4.0	0.0	4.0	20916.0	21661.0	21556.0	17331.0	...	5296.0	1618.0	4.0	
4	2018-04-12 00:20:00	4.0	12.0	4.0	0.0	5.0	20916.0	21494.0	21459.0	17197.0	...	5439.0	1617.0	4.0	

Figure 12. Head of Dataset After Creating Identifier datetime_local

```

      datetime_local month day hour geothermal_MW biomass_MW \
0      2018-04-12 00:00:00 4.0 12.0 0.0      706.0      242.0
1      2018-04-12 00:05:00 4.0 12.0 0.0      716.0      238.0
2      2018-04-12 00:10:00 4.0 12.0 0.0      725.0      240.0
3      2018-04-12 00:15:00 4.0 12.0 0.0      724.0      241.0
4      2018-04-12 00:20:00 4.0 12.0 0.0      724.0      246.0
...
210544 2020-04-12 23:35:00 4.0 12.0 23.0      903.0      279.0
210545 2020-04-12 23:40:00 4.0 12.0 23.0      903.0      276.0
210546 2020-04-12 23:45:00 4.0 12.0 23.0      903.0      277.0
210547 2020-04-12 23:50:00 4.0 12.0 23.0      903.0      258.0
210548 2020-04-12 23:55:00 4.0 12.0 23.0      903.0      279.0

      biogas_MW battery_MW renewable_MW natgas_MW imports_MW coal_MW \
0      242.0      -40.0      5813.0      5853.0      5263.0      2.0
1      242.0      -45.0      5779.0      6011.0      5117.0      3.0
2      241.0      -33.0      5827.0      6286.0      5281.0      3.0
3      241.0      -31.0      5884.0      6317.0      5296.0      4.0
4      241.0      -9.0      5934.0      6019.0      5439.0      4.0
...
210544 226.0      -12.0      4169.0      6286.0      4863.0      17.0
210545 225.0      19.0      4111.0      6276.0      4789.0      17.0
210546 225.0      13.0      4086.0      6258.0      4732.0      17.0
210547 225.0      13.0      4065.0      6224.0      4658.0      16.0
210548 225.0      7.0      4088.0      6256.0      4598.0      16.0

      imports_co2 biogas_co2 geothermal_co2 biomass_co2 natgas_co2 \
0      2714.0      146.0      8.0      123.0      3007.0
1      2666.0      147.0      8.0      123.0      2992.0
2      2586.0      146.0      8.0      121.0      3070.0
3      2658.0      144.0      8.0      121.0      3164.0
4      2629.0      142.0      8.0      119.0      3097.0
...
210544 2183.0      119.0      8.0      124.0      2756.0
210545 2137.0      119.0      8.0      123.0      2784.0
210546 2115.0      118.0      8.0      122.0      2767.0
210547 2075.0      118.0      8.0      122.0      2761.0
210548 2048.0      118.0      8.0      117.0      2754.0

      coal_co2
0      2.0
1      2.0
2      3.0
3      3.0
4      3.0
...
210544 13.0
210545 13.0
210546 13.0
210547 13.0
210548 13.0

[210549 rows x 18 columns]

```

Figure 13. Selected Features

4.4 Model Construction

4.4.1 ARIMA

After pre-processing the dataset, the manual selection of the hyperparameters of the ARIMA model is performed. A stationarity test for the time-series data is performed using the ADF test as shown in **Figure 14**, and it is stationary because the p-value is less than 0.05. Hence, no differencing is needed, and the value of parameter d is 0 for all the CO₂ features. From **Figure 15**, it can be observed that the ACF plots tail off gradually, indicating the value of the hyperparameter q is 0 for all the CO₂ features, whereas for PACF plots, they all cut off sharply after the first lag, indicating the value of the hyperparameter p is 1 for all the CO₂ features. Hence, the ARIMA (1, 0, 0) is selected to train and test the dataset. The ARIMA model is imported from the statsmodels library in Python. The `arima_model_selection` function takes the parameters: training and testing sets, the features that will be predicted, and the hyperparameters' values. Seven CO₂ features will be predicted, which are `imports_co2`, `natgas_co2`, `biogas_co2`, `biomass_co2`, `geothermal_co2`, `coal_co2`, and `total_co2`. However, Table 3 only displays the primary target, `total_co2`. The model will be trained based on the training set in the `train_data.csv` file and tested based on the testing set in the `test_data.csv` file. Then, the ARIMA (1, 0, 0) model for corresponding CO₂ features will be printed together with their corresponding evaluation metrics: MAE and RMSE that evaluate their forecasting accuracy. The model is saved into files with the Pkl extension using the pickle module, enabling future reuse of the models. Lastly, the training and testing time taken by the model is displayed for comparison purposes afterwards.

```

Results of Dickey-Fuller Test:
Test Statistic      -22.934242
p-value             0.000000
#Lags Used          76.000000
Number of Observations Used  164059.000000
Critical Value (1%)   -3.430390
Critical Value (5%)  -2.861558
Critical Value (10%) -2.566779
dtype: float64

```

Figure 14. Stationarity (ADF) Test Results

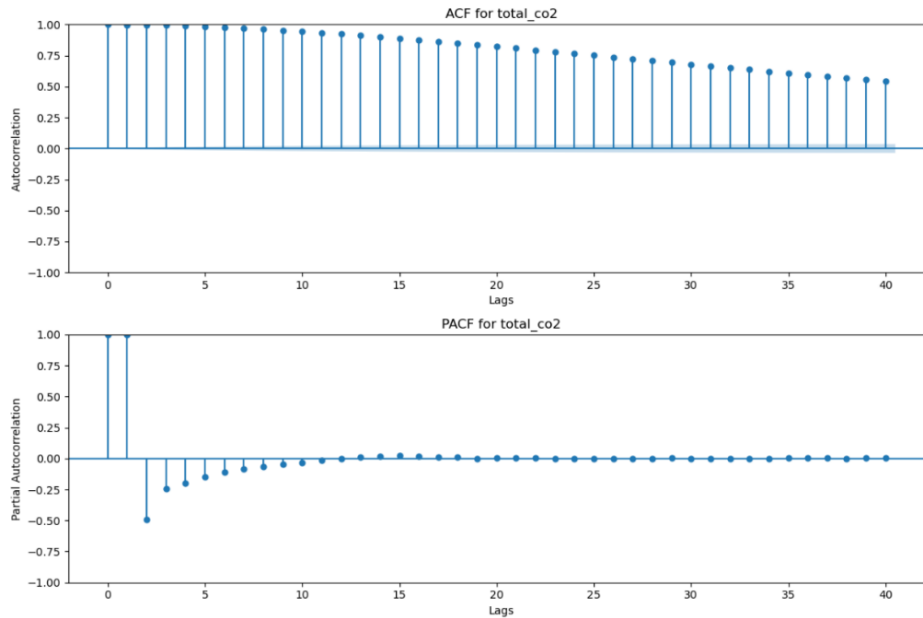


Figure 15. ACF and PACF Plots for total_co2

4.4.2 Prophet

The Prophet model is imported from the Prophet library in Python. The `predict_with_prophet` function takes the parameters: training and testing sets, and the feature that will be predicted, which helps in prediction by Prophet. A data frame is created to reshape the training set based on the requirement of the Prophet model, and the columns "datetime_local" and "y" must be included. The column "y" refers to all the CO2 features same as the ARIMA models. The trained model is saved into a Pkl file using the pickle module. Then, the model is used to predict the testing set and evaluated using the MAE and RMSE metrics. Lastly, the results and time taken by the model to train and test are displayed. The Prophet model is constructed based on the research paper by [20] with the parameter as shown in

Table 2. The Values of the Parameters of Time Series Forecasting Model

Model	Parameter	Value
Prophet	Seasonality mode	Additive
	Change point prior scale	0.5
	Change point	15
ARIMA	Autoregressive term (p)	1
	Difference term (d)	0
	Moving average term (q)	0
BiLSTM	Look back	1

	Number of neurons in LSTM	50
	Activation function	RELU
	Epochs	10
	Batch size	1
	Optimiser	Adam

4.4.3 BiLSTM

The BiLSTM model is constructed from the layers LSTM, Dense, and Bidirectional from the Keras library in Python. Before this, the neural network model was constructed using the Sequential and load_model classes from Keras. The predict_with_bilstm function takes parameters: training and testing sets, epochs, and batch size. 10 epochs and a batch size of 1 are initialised due to limited computational resources. Before training and testing the model with the dataset, a min-max scaler is utilised to standardise the range of the CO2 features because BiLSTM is sensitive to the scale of data. The create_dataset function is also used to prepare the training and testing sets for model training and testing after scaling the data. A bidirectional LSTM layer and a dense layer as the output layer are constructed in a sequential model with the Rectified Linear Unit (ReLU) activation function to form a BiLSTM. The model is then compiled using the Adam optimiser and mean squared error loss function. The constructed BiLSTM is fitted to the training set and saved into an h5 file. Then, it is also used to predict the testing set and using the inverse transform function in the scaler library, ensuring that the predicted CO2 emissions are not values ranging from 0 to 1. The forecasting accuracy is evaluated using the MAE and RMSE metrics. Lastly, the time taken for BiLSTM to train and test is also displayed.

4.5 Comparison of Models Results

After training and testing the models with pre-processed dataset, the models' results are compared in this section. For ARIMA (1, 0, 0) model, the total time taken used to train and test for all the CO2 features is 32.41 seconds. Computation time is fast due to predefined hyperparameters. From Figure 16, we can observe that the ARIMA (1, 0, 0) model is underfitting.

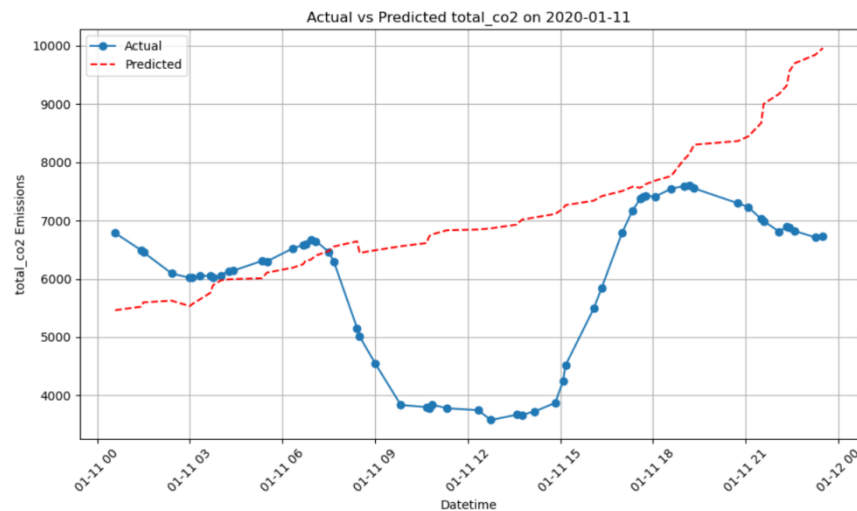


Figure 16. Line Chart of Actual vs Predicted total_co2 by ARIMA(1, 0, 0) on 2020-01-11

Besides, for Prophet model, the total time taken used to train and test for all the CO2 features is 986.94 seconds. The computation time is longer than the ARIMA (1, 0, 0) model because it takes time to learn the pattern of the dataset. The model generalizes well but slightly underfit to the dataset and the plot of actual and predicted values is shown in Figure 17.

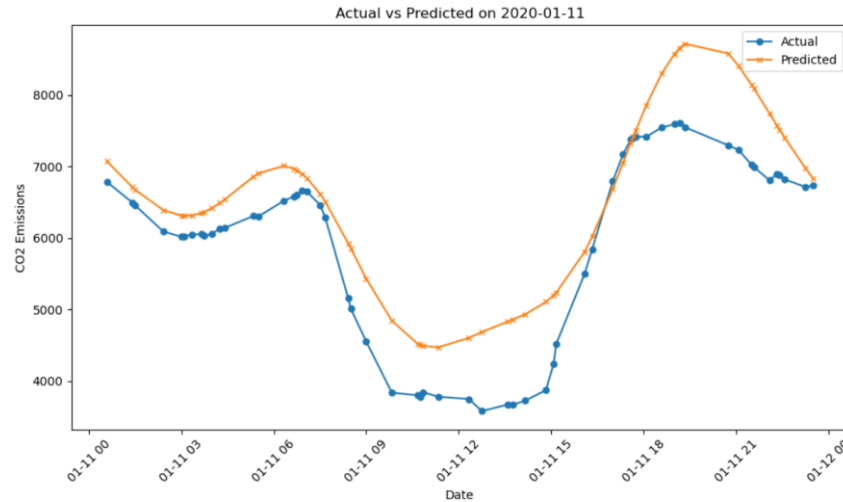


Figure 17. Line Chart of Actual vs Predicted total_co2 by Prophet on 2020-01-11

Moreover, for the BiLSTM model, the total time taken to train and test for all the CO2 features is 16329.47 seconds. The computation time is the longest if compared to the other two models, indicating of large computational load required by the BiLSTM model. From Figure 18, we can observe that the validation loss for total_co2 remains flat above the training loss, indicating the model generalises well to the dataset. From Figure 19, we can observe that the actual and predicted CO2 emissions do not differ significantly, indicating that the model overall generalises well to the dataset.

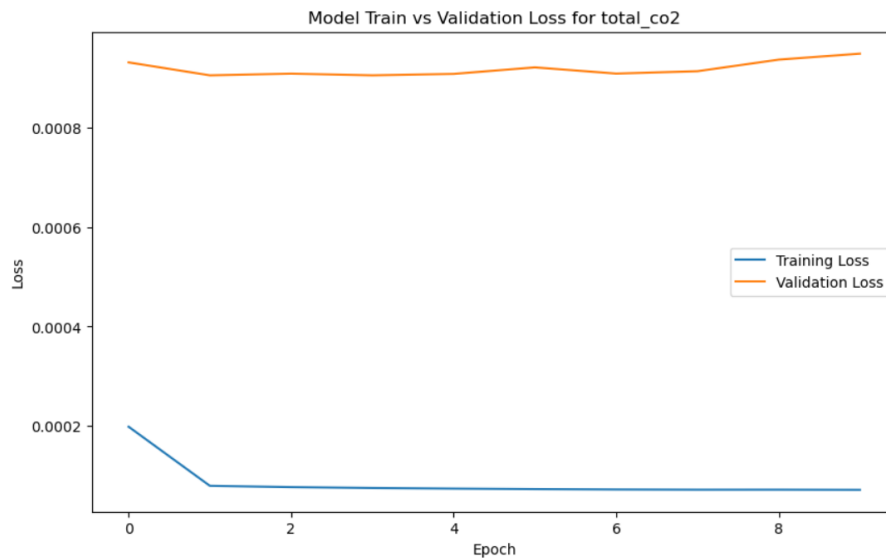


Figure 18. BiLSTM Model Train vs Validation Loss for total_co2

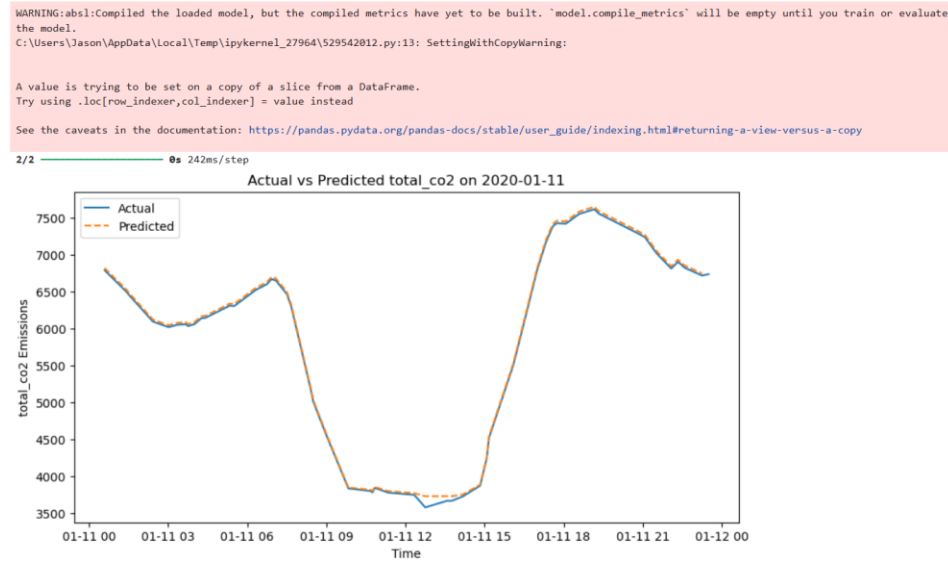


Figure 19. Line Chart of Actual vs Predicted total_co2 by BiLSTM on 2020-01-11

The results shown in Table 3 exhibits that BiLSTM is the best forecasting model in predicting carbon emission in different circumstances.

Table 3. MAE and RMSE Evaluation Results for ARIMA (1, 0, 0), Prophet and BiLSTM Models.

CO2 Features	ARIMA (1, 0, 0)		Prophet		BiLSTM	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
total_co2	1728.797	2203.464	831.346	1102.884	266.726	429.228

4.6 Dashboard and Email Alert System

The user interface of the dashboard is shown in Figure 20, including the actual and predicted CO2 emissions visualisation, a tree map that visualises the top ten days that contribute more CO2 emissions, a box plot of actual CO2 emissions that displays the outliers of the data and lastly actual CO2 emissions with corresponding threshold values visualisation.

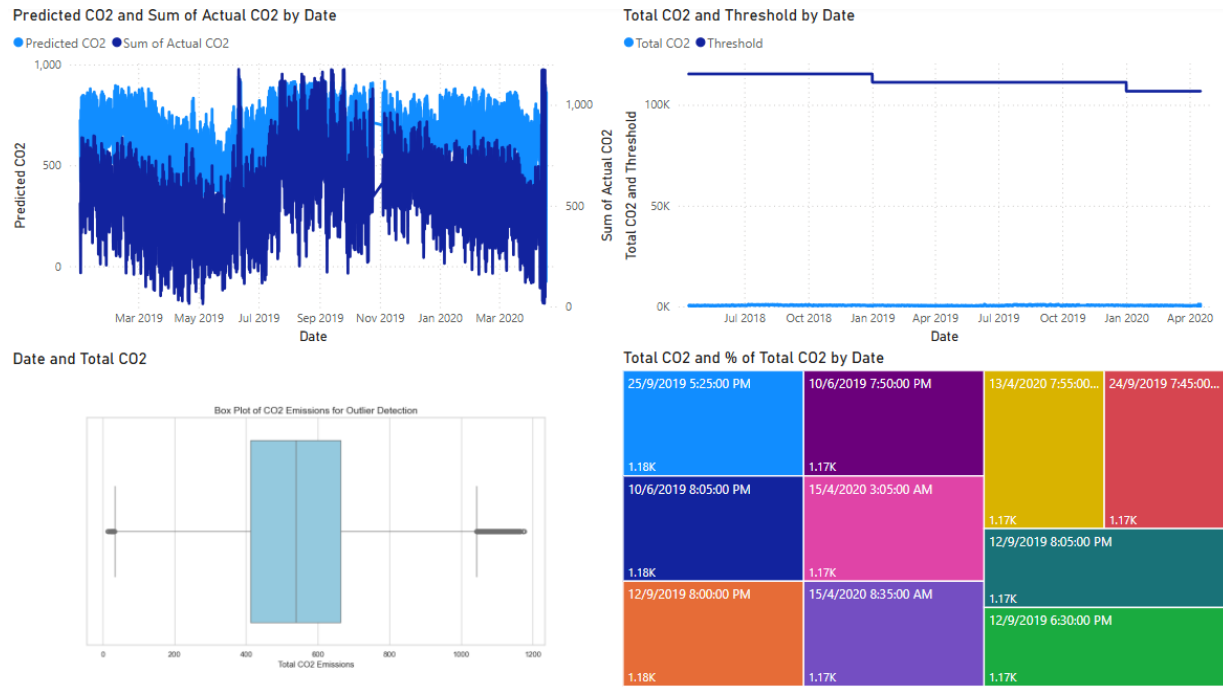


Figure 20: Dashboard Visualisation User Interface

The sample alert email sent to the stakeholder is shown in Figure 21. The email is automatically triggered and sent to the stakeholder when the actual CO₂ emissions exceed the predefined threshold value.

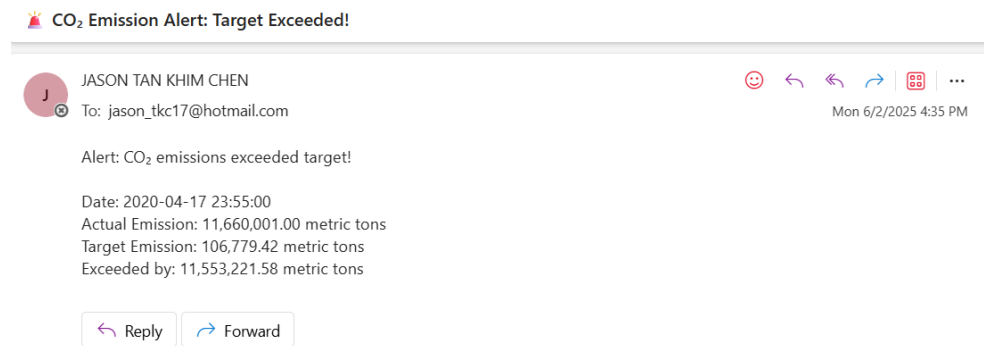


Figure 21: Sample Alert Email

4.7 Contributions

The study's comprehensive analysis provides valuable contributions to academia, industry practice, management strategy, and societal understanding of time series forecasting models in the electrical grid as shown in Figure 20.

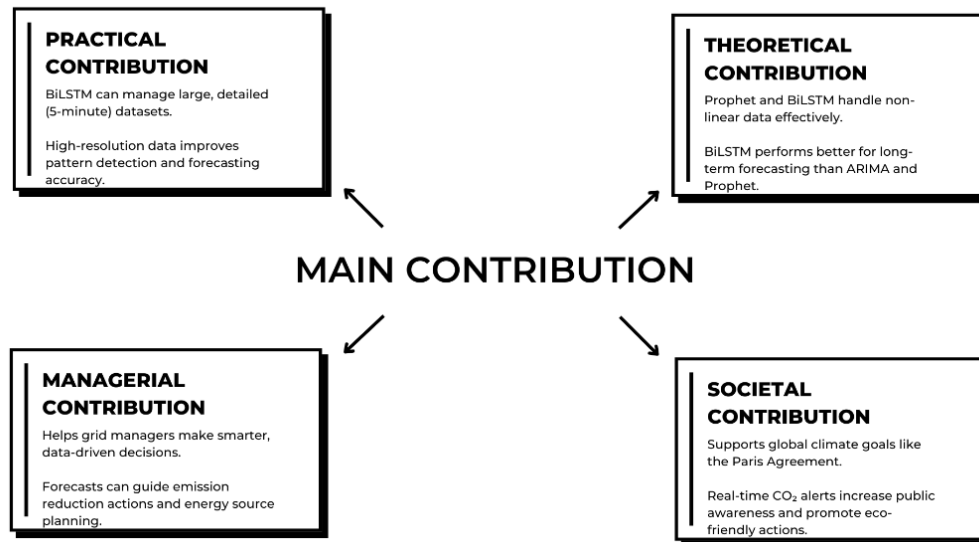


Figure 22. Main Contributions

4.7.1 Theoretical Contribution

This research contributes to the theoretical understanding of how different forecasting models handle complex CO₂ emission data. Specifically, to H1's validation suggests that both Prophet and BiLSTM models can effectively handle non-linear data. This is proved by the close match between predicted and actual CO₂ values in the visualisations. H2's validation suggests that BiLSTM can handle long-term forecasting. This is proved by comparing BiLSTM with other time series forecasting models like ARIMA and Prophet, and the MAE and RMSE values are way lower than theirs. For electrical grid managers and decision-makers, the results underscore the importance of time series forecasting models in promoting the efficiency and complex data handling capabilities that can be brought, rather than focusing solely on cost. This emphasises the adoption of technology that significantly enhances complex data handling and operational efficiency, aligning with the positive findings of H1 and H2.

4.7.2 Practical Contribution

This study offers practical insights into real-world use of time series forecasting models. For instance, H2: It shows that BiLSTM handles long-term and complex trends in CO₂ emissions better than traditional models. H3: The use of the high-resolution CAISO dataset with 5-minute temporal resolution is associated with improved model accuracy, as it preserves important short-term variations in emissions data. This hypothesis is partially supported by the study's own results, where the 5-minute resolution achieved lower MAE and RMSE than the hourly and daily resolutions. However, this comparison should be interpreted with caution, as the three resolutions also differed substantially in sample size, which may have independently contributed to the higher error observed. A scale-independent metric like MAPE was not computed to fully isolate the effect of resolution from sample size. External support for H3 is drawn from Figure 23, which, although based on a different BiLSTM implementation than the one used in this study, similarly shows improved BiLSTM performance when trained on higher-resolution data. These findings suggest that combining advanced models like BiLSTM with high-resolution data has the potential to improve forecasting performance, particularly for predicting CO₂ emissions in dynamic electricity grid environments, though further validation with normalized metrics is needed to confirm this within the present study's own experimental setup.

H3 VALIDATION: RESOLUTION COMPARISON			
5MIN	MAE=0.007488	RMSE=0.057326	Samples=205170
HOURLY	MAE=0.022863	RMSE=0.196463	Samples=17147
DAILY	MAE=1.061930	RMSE=1.311568	Samples=724

Figure 23. MAE and RMSE Evaluation Results for BiLSTM with 5-minute, Hourly and Daily Resolution.

4.7.3 Managerial Contribution

The findings of this research offer valuable insights for electrical grid managers and policymakers on managing the integration of time series forecasting models into electrical grid systems. The validation of hypotheses H1, H2, H3, and H4 suggests that modern forecasting tools can improve operational efficiency, handle complex data patterns, and provide early warning alerts. This suggests that electrical grid managers could focus on:

- Use these forecasts to plan emission reduction strategies more effectively.
- Decide when and how to switch to renewable energy sources based on predicted emission spikes.
- Monitor grid performance with real-time alerts to ensure compliance with climate regulations. These tools support long-term management goals, including achieving net-zero emissions by 2050, and align with smarter, data-driven decision-making strategies in the energy sector.

These management strategies can ensure that the integration of time series forecasting models is aligned with the goals of achieving net-zero carbon emissions by 2050, ultimately leading to a more environmentally friendly earth.

4.7.4 Societal Contribution

On a broader societal level, this study offers the social implications of adopting time series forecasting models in the electrical grid. This research supports H3 and H4 by showing how technology can make environmental data more accessible and useful. The real-time alert system enables quicker response to high emissions, while the dashboard visualization improves transparency. This encourages:

- Achieving sustainability goals, such as those stated in the Paris Agreement.
- Raised public awareness and engagement in promoting a clean and healthy environment through the data accessible and understandable.

In a nutshell, the acceptance of hypotheses H1 through H4 highlights the positive correlation between the benefits of time series forecasting models in improving the operational efficiency and complex data handling capabilities. The research found that time series forecasting is important in providing evidence-based strategy planning and decision-making for the electrical grid managers. This suggests that these technologies could improve the quality of the environment indirectly through cooperation from all parties.

5. CONCLUSION

The forecasting models used to predict CO2 emissions are ARIMA, Prophet and BiLSTM models based on the dataset in electricity grid, spanning from 2018 to 2020. Throughout this study, I observed that the models have their own advantages in handling the time-series data, the BiLSTM model performed well in predicting the CO2 emissions with the lowest MAE and RMSE values.

The BiLSTM could be further enhanced provided that large computational resources are available. Besides, the hyperparameters for ARIMA and Prophet models are poor, leading to underfitting issues. In the future, I would like to proceed with the operations of the email alert system and implement the Carbon Emission Prediction Dashboard in terms of backend and frontend. Other than that, I might consider integrating auto-ARIMA or other innovative solutions for the Prophet and ARIMA models to overcome the issue of underfitting.

Moreover, there is confusion in resolution comparison and sample size. The comparison of forecasting accuracy across 5-minute, hourly, and daily resolutions (H3) is potentially confused by differences in sample size, as lower resolutions

(particularly daily, with only 724 samples) produces fewer training and testing samples than higher resolutions. Although hourly and daily values were derived using mean aggregation to preserve a comparable unit scale, the possibility remains that the larger error observed at lower resolutions reflects reduced data availability rather than a genuine effect of temporal resolution. Additionally, this study did not compute scale-independent error metrics such as MAPE or normalized RMSE, which would allow a more direct comparison of relative forecasting accuracy across resolutions. Future work should incorporate normalized error metrics and control for sample size either through resampling or cross-validation, to more accurately validate the relationship between data resolution and forecasting accuracy.

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Jason Tan Khim Chen: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – Original Draft Preparation;

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CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. <https://publicationethics.org/>

DATA AVAILABILITY

The data in this study are available in raw.githubusercontent.com/grgmiller/CAISO_data/master/CAISOdata.csv.

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