Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-9
DOI: *10.15244/pjoes/210105* ONLINE PUBLICATION DATE: 2025-12-09

Original Research

Machine Learning Methods for Forecasting Flight Carbon Emissions

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Received: 6 April 2025
Accepted: 31 August 2025

Abstract

This paper seeks to develop an effective model for forecasting aviation carbon emissions by leveraging comprehensive flight-level data for the year 2019. To achieve this objective, we employed traditional time series models – Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR) – alongside machine learning approaches: Random Forest (RF), Multilayer Perceptron (MLP), and Long Short-Term Memory (LSTM) networks. These methodologies were utilized to predict carbon emissions for individual flights as point estimates. In addition, we applied the Variational Mode Decomposition (VMD) method to decompose the data into its constituent components, leading to the development of the models VMD RF, VMD MLP, and VMD LSTM for comparative analysis. The findings reveal several key insights: firstly, the VMD LSTM model demonstrated superior performance in prediction accuracy, closely followed by the VAR model; secondly, the prediction errors associated with VMD RF, VMD MLP, and VMD LSTM were consistently lower than those of their non-decomposed counterparts (RF, MLP, and LSTM), which highlights the effectiveness of data decomposition in enhancing predictive outcomes. This paper contributes innovative methodologies for forecasting aviation carbon emissions, providing critical insights to support initiatives aimed at reducing carbon emissions within the aviation sector.

Keywords: aviation carbon emission, forecast, machine learning models, variational mode decomposition

Introduction

While transportation activities facilitate the movement of people and goods, they also contribute significantly to environmental degradation, particularly through the deterioration of air quality [1]. Among these, the climate impacts, air pollution, and other environmental consequences associated with aviation activities have drawn growing concern [2-4]. According to the International Energy Agency, the aviation industry is projected to grow continuously at a rate of 4.3%, surpassing other transportation sectors. In 2022, global CO_2 emissions from the aviation industry accounted for 2% of the total energy-related CO_2 emissions. If global commercial aviation were treated as a country, its emissions would be sufficient to rank it sixth in the global CO_2 emissions list. Notably, the aviation sector has become a major and rapidly expanding contributor to global carbon emissions [5].

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Carbon emissions have drawn wide attention from the scientific and political fields. Many studies have underscored the critical role of environmental policy formulation in addressing ecological challenges [6, 7]. For the aviation industry, international industry organizations have successively set a series of emission targets, including the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) and the resolution to reach net-zero carbon emissions by 2050. Faced with a series of emission reduction targets, developing accurate CO_2 emission prediction methods is essential [8] as it can assist policymakers to assess emission patterns and formulate targeted mitigation strategies [9-11]. Moreover, such methods can support airlines in meeting carbon reduction targets while optimizing operational costs [12].

When it comes to aviation carbon emission prediction, the existing literature widely utilizes decomposition analysis to identify the driving factors behind aviation carbon emissions. By combining various potential influencing factors and establishing different scenarios, they simulate the future medium to long-term trends in aviation carbon emissions, providing robust support for the formulation of decarbonization policies. However, there are still some limitations. First, relevant research mainly focuses on specific countries or regions such as the United States, China [13-15], and Europe [16]. For instance, Cui et al. (2023) predicted carbon emissions in South American countries from 2023 to 2027 under three different scenarios, providing data support for carbon emission control in the South American aviation industry [17]. Additionally, while a few studies focus on the global aviation industry, they often only concentrate on the future emission trends of international aviation due to its high economic contribution and growth scale [18]. Furthermore, most studies currently rely on monthly or annual data [13, 19], and further research utilizing more granular flight-level micro-scale daily data is needed to gain a deeper understanding of aviation industry carbon emissions.

Some forecasting studies have utilized classical methods such as mathematical-statistical methods and econometric models [20, 21]. With the development of artificial intelligence and machine learning technology, an increasing number of studies have explored the use of artificial intelligence-based methods such as Artificial Neural Networks (ANN) [22, 23], Random Forest (RF) [10], Support Vector Machines [24], and various hybrid methods combining multiple computational intelligence models to enhance prediction accuracy [25, 26]. For instance, Li and Sun (2021) predicted CO_2 emissions at the city level in China using machine learning methods. They established a CO_2 prediction model with 18 predictor variables, demonstrating that the XGBoost model performed best in predicting CO_2 emissions [27]. Rao et al. (2023) developed a Ridge Regression-based STIRPAT extended model to forecast carbon emissions in Hubei Province, China [28]. It can be seen that machine learning methods are frequently utilized and exhibit good performance in many carbon emission prediction studies, including those in the transportation sector. For example, Wen et al. (2022) employed a Random Forest (RF) model to forecast air and CO_2 pollution in the road network of Chengdu, China [29]. The results demonstrated the model's excellent performance. Khajavi and Rastgoo (2023) proposed a hybrid model that optimizes Random Forest using multiple metaheuristic algorithms to predict CO_2 emissions from the road transport sector in China. They validated the accuracy of this method against a hybrid SVR model and an RSM model [10]. These studies highlight the superiority of machine learning algorithms in predicting carbon emissions in the transportation sector, particularly in road traffic emission forecasts. However, to the best of our knowledge, the application of machine learning methods for predicting carbon emissions in the aviation sector is not as extensive. A relevant study by Demir (2022) involved constructing a time series model combined with genetic algorithms to forecast the number of flights, passenger demand, and aviation-related carbon emissions in the UK up to 2029 [30].

In summary, existing literature research related to aviation carbon emission prediction often utilizes scenario analysis methods [13, 14, 31]. While this method can analyze emission trends in different scenarios based on the driving factors of aviation carbon emissions, there is still room for improvement in terms of prediction accuracy and flexibility. In addition, it is worth noting that due to the nonlinear characteristics of CO_2 emissions, traditional prediction methods often struggle to achieve the desired level of accuracy [25, 32]. Machine learning (ML) methods, as one of the fastest-growing areas in intelligent technology today, are considered an important means of meeting prediction demands through computer science and data statistics [33]. ML methods have shown promising performance in existing carbon emission prediction studies [9, 34], but their potential for precise prediction of aviation carbon emissions is yet to be fully explored. Furthermore, existing research often focuses solely on the carbon emissions of specific countries or regions, or only predicts the global international aviation market, lacking a global perspective that covers domestic and international aviation carbon emissions.

Therefore, to provide comprehensive data support for decarbonization and offer flexible and applicable forecasting methods, this study attempts to introduce advanced machine learning model forecasting methods. Given the huge impact of the COVID-19 pandemic on aviation in 2020 and 2021, and the incomplete recovery in 2022 and 2023 after the pandemic, in this study, 2019 is regarded as a representative year of stable aviation operations. Based on a total of about 43,800,000 flight-level data in 2019, this paper examines the predictive performance of traditional time series models and machine learning models for aviation carbon emissions, with a particular focus on comparing the effectiveness of single predictions versus decomposing the data into components for prediction. First, we conducted a comprehensive calculation of the daily carbon emissions from flight records in 2019, referencing the International Civil Aviation Organization (ICAO) carbon emissions calculator, and aggregated these into daily carbon emissions. Second, we used Variational Mode Decomposition (VMD) to decompose daily aviation carbon emissions into a finite number of complex-valued intrinsic mode functions (IMFs) components and a residual component. Third, we applied two traditional time series models, Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR), along with three machine learning models: Random Forest (RF), neural network methods such as Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM), for single-point value prediction. Then, we utilized the aforementioned machine learning models to forecast the Intrinsic Mode Functions (IMFs) obtained after VMD. Finally, the prediction results were compared to identify the optimal forecasting model.

This study contributes to previous research in multiple ways. First, in terms of research methodology, this paper seeks to introduce advanced machine learning methods into the field of aviation carbon emissions forecasting. Through simulated training on historical data, this paper validates the applicability of this method for predicting aviation carbon emissions in different future periods, thereby enriching predictive techniques. Second, in terms of the research scope, this paper considers both global international aviation and domestic aviation, aiding in understanding the overall situation of global aviation industry carbon emissions and providing policymakers with more comprehensive decision-making foundations. Third, in terms of research samples, this paper utilizes historical daily flight operation data, which is beneficial for constructing more accurate prediction models and enhancing the scientific rigor and reliability of the prediction results.

The remainder of this paper is organized as follows. Section 2 explains the machine learning models adopted. The detailed flight-level data source, carbon emission calculation method, predicted results, and further analysis will be conducted in Section 3, and the last section concludes this study, reveals the limitations of the research, and proposes possible future research directions.

Materials and Methods

In this paper, we not only forecast using our time series as a one-dimensional signal, but we also use Variational Mode Decomposition (VMD) to decompose our signal and apply different forecasting models to compare whether such a mode of decomposing raw data into components could help forecasting.

As for models, we focus on four types of different models to forecast carbon emission of flights in 2019, which are traditional time series model Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR), traditional machine learning method Random Forest (RF), neural network method Multilayer Perceptron network (MLP), and Long Short-Term Memory neural networks (LSTM). The potential advantages of the forecasting approach in this paper are as follows:

Various models of time series and machine learning were selected to help us better identify the model with the best predictive performance through comparison.

The combination of VMD decomposition and multiple machine learning prediction models can deeply explore the intrinsic structure of time series data. It can also make full use of the advantages of different models, effectively address the nonlinear characteristics of aviation carbon emissions, and achieve more accurate and stable predictions.

In summary, the predictive methods used in this study can more accurately capture the changing trends in data, potentially providing new insights and directions for research in flight carbon emission prediction and other relevant fields.

Variational Mode Decomposition (VMD)

Variational Mode Decomposition (VMD) is a widely used decomposition method that decomposes an input signal, in our case, carbon emission time series data, into a discrete number of intrinsic mode functions. Compared to another popular decomposition method, empirical mode decomposition (EMD), VMD would be much more robust to sampling and noise.

For each mode, the VMD process has the following steps: firstly, constructs the analytic signal by means of the Hilbert transform in order to obtain a unilateral frequency spectrum; secondly, the mode's spectrum is shifted to baseband according to the displacement property of the Fourier transform; thirdly, the bandwidth is estimated through the H1 Gaussian smoothness. We need to minimize the sum of the spectral widths of all the IMFs as follows:

$$\min_{\{u_k\},\{\omega_k\}} \{\textstyle\sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \} \tag{1}$$

$$s.t. \textstyle\sum_{k=1}^{K} u_k = f \tag{2}$$

where u_k are the different modes, ω_k are the center of frequencies, f is the raw signal, K is the mode number, $\delta(t)$ is the Dirac Delta. This minimization problem is solved through Lagrangian multipliers in a sequence of iterative sub-optimizations called the alternating direction method of multipliers (ADMM) [35].

Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR)

In the Autoregressive Integrated Moving Average (ARIMA) model, the future value of a time series

d-th order differenced value is assumed to be a linear function of p past observations and q random errors, which is

$$y_t^d = c + \varphi_1 y_{t-1}^d + \cdots + \varphi_p y_{t-p}^d + \theta_1 \varepsilon_1 + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{3}$$

And for Vector Autoregression (VAR), we have

$$Y_t = c + \varphi_1 Y_{t-1} + \cdots + \varphi_p Y_{t-p} \tag{4}$$

where Y_t and φ are vectors.

Random Forest

Random Forest is one of the integrated algorithms. It employs an ensemble of multiple decision classification trees, randomly selecting features from them before voting or averaging the results. As a traditional machine learning method, we imply Random Forest to forecast. A Random Forest is a collection of tree predictors, or weak learner, $Tr(X_t)$, 1 – 1, 2, ..., J where X_t represents the observed input, point value or vector (IMFs). The prediction result is the unweighted average over the collection:

$$\hat{Y}_t = \frac{1}{J}\sum_{j=1}^{J} Tr(X_t) \tag{5}$$

Multilayer Perceptron Network (MLP)

We also apply a Multilayer Perceptron network (MLP), a very popular ANN model for time series forecasting. MLP is probably one of the most widely used algorithms in artificial intelligence (AI), inspired by biological neural networks in the brain and simplified to mimic them. We can describe the relationship between the output Y_t and the input lag $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$, where p is the order of lag, as follows:

$$\hat{Y}_t = \hat{A}_0 + \sum_{i=1}^{q} A_t^i f\left(X_{t-1}, X_{t-2}, \cdots, X_{t-p}\right) \tag{6}$$

Here, X_{t-i} could be point value, which is Y_{t-i}, or vector (IMFs). $f(\cdot)$ is a linear function that depends on the model structure or hidden layer, and q is the number of nodes in the last hidden layer. The conjugate gradient error minimization is used to train the MLP network.

Long Short-Term Memory Neural Networks (LSTM)

Long Short-Term Memory (LSTM) is a special kind of recurrent neural network (RNN). LSTM is capable of learning long-term dependencies and dealing with the vanishing gradient problem present in traditional RNNs [36]. As a widely used forecasting neural network, in this paper, the input of LSTM is past data, point value, or sub-signal (IMFs), and the output data is the forecasting result.

Carbon Emission Calculation

The real-time data required for this paper is was obtained from the OAG database, which includes detailed information on each flight, such as origin and destination, aircraft type, great circle distance, and carrier name. Considering the abnormal samples of global civil aviation meltdowns during COVID-19 after 2020, we selected the flight information between January 1, 2019, and December 31, 2019, including about 43.800,000 flight data.

This study estimates flight-level carbon emissions using historical flight data and the ICAO Carbon Emissions Calculator (Version 11.1), a standardized methodology developed by the International Civil Aviation Organization (ICAO). Widely recognized as an industry benchmark, this approach has been empirically validated in numerous aviation emissions studies and is extensively adopted in academic research. The calculation formula for each passenger's aviation carbon emissions is as follows:

$$CE_i = \frac{3.16 \times (F \times PF)}{S \times PL} \tag{7}$$

In this Equation, CE_i denotes the estimated carbon emissions per passenger, where 3.16 is the fixed fuel coefficient, F represents the total fuel consumption, PF is the passenger-to-freight factor (pax), S indicates the number of economy-class seats, and PL stands for the passenger load factor (pax load factor). The ICAO's methodology enables individual passengers to quantify their carbon footprint accurately. Since this study focuses on the aggregate emissions of a single flight, the total carbon emissions per flight can be calculated using the following formula:

$$CE = 3.16 \times F \tag{8}$$

From this, the specific calculation process is outlined as follows:

Step 1: Referencing Appendices B and C of the ICAO carbon emissions calculator document, the "total fuel" for each flight was determined based on the aircraft type and the adjusted great circle distance for that flight.

Step 2: The individual flight carbon emissions data for all global flights daily were aggregated to obtain 365 data points representing the daily carbon emissions of the global aviation industry in 2019.

Results and Discussion

Decomposition Based on VMD

In Fig. 1, the "Signal" represents the changing trend of global aviation carbon emissions. From January

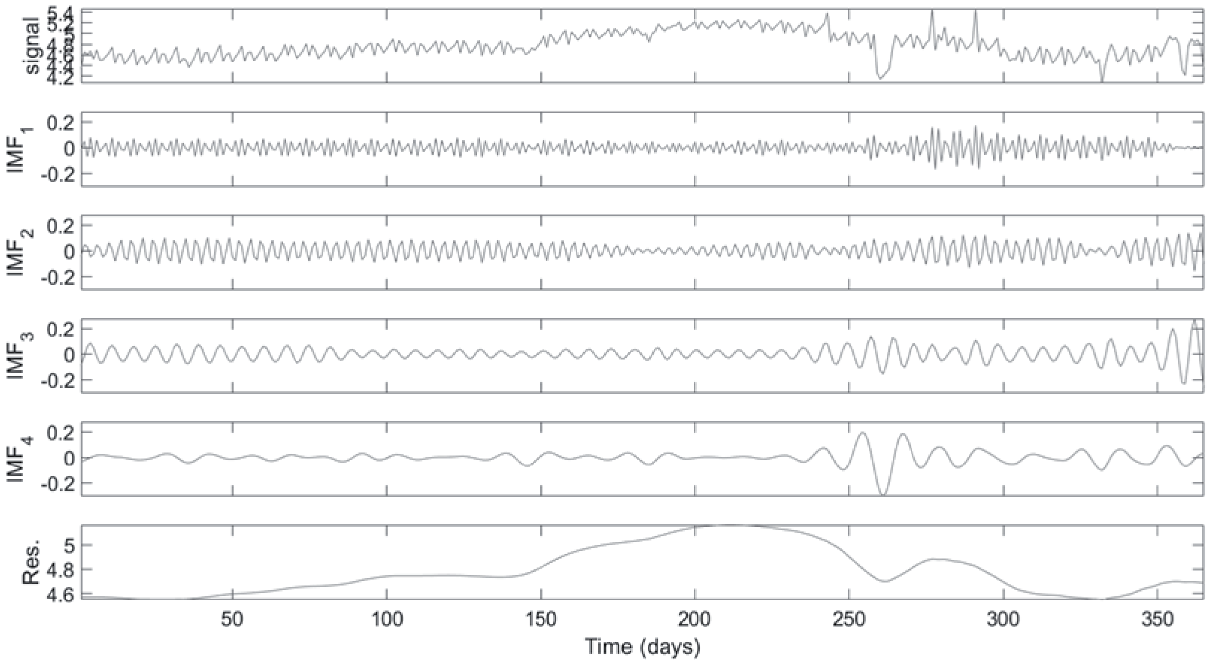

Fig. 1. Variational Mode Decomposition of aviation carbon emission.

to May 2019, the carbon emissions remained within a relatively stable fluctuation range. However, starting from June 2019, there was a noticeable oscillating upward trend in global aviation carbon emissions, reaching two peaks in September of the same year. Subsequently, the emissions underwent a period of oscillating decline, ultimately falling back to a level similar to that of early 2019. This variation may be attributed to the combined effects of various factors such as changes in international flights and fluctuations in aviation fuel prices, among others. Furthermore, we applied the Variational Mode Decomposition (VMD) method to decompose the global aviation carbon emissions into several complex-valued intrinsic mode functions (IMF) and a residual component. Based on the IMFs above, predictions were conducted using three machine learning algorithms.

Forecasting Results Comparison

To evaluate the performance of the forecasting models applied, this study employs root mean square error (RMSE) and mean absolute percentage error (MAPE) for quantitative assessment of forecasting results obtained from the machine learning algorithms, both of which are frequently used in relevant literature, where smaller RMSE and MAPE results are desirable [37, 38].

The calculation formulas are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \check{Y}_i)^2}{n}} \tag{9}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \check{Y}_i}{Y_i}\right| \tag{10}$$

where Y_i represents the true value, $\check{Y}_t$ represents the predicted value, and n is the number of predicted samples.

Table 1 presents the error metrics for all models utilized in this study. It can be seen that the RMSE value varies from 0.06765 to 0.22254 for aviation carbon emissions. As another evaluation index, the MAPE value varies from 0.010639 to 0.036326. Previous studies have suggested that if MAPE≤0.1, the forecast results can be classified as “high prediction accuracy”

Table 1. Comparison of the models with RMSE and MAPE results.

	RMSE	MAPE
ARIMA	0.18998	0.034857
VAR	0.1467	0.021655
RF	0.18263	0.030961
VMD RF	0.16853	0.029566
MLP	0.22254	0.036326
VMD MLP	0.16198	0.028189
LSTM	0.18829	0.030942
VMD LSTM	0.06765	0.010639

Note: VMD RF, VMD MLP, VMD LSTM refer to machine learning models that decompose data into components for prediction, while RF, MLP, and LSTM are for single-point value prediction.

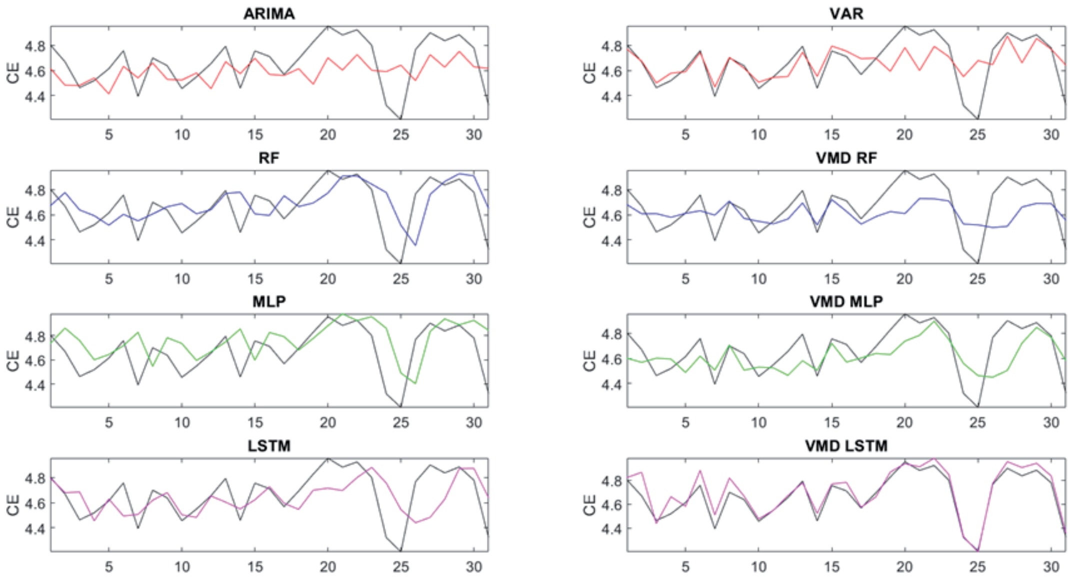

Fig. 2. Performance of models in test data.
Note: the black curves represent the actual trend of the original data, while the colored curves depict the predicted trend of aviation carbon emissions by the model used in this paper.

[39]. Therefore, it is possible to say that the forecasting results for each algorithm can be categorized as "high prediction accuracy".

It can be seen from Table 1 and Fig. 2:

First, based on the RMSE and MAPR results, the forecasting performance ranking from high to low of each model roughly emerged as follows: VMD LSTM, VAR, VMD MLP, VMD RF, RF, LSTM, ARIMA, and MLP. There is no doubt that the prediction errors of the VMD LSTM model exhibited a substantial gap when compared to the other models, with the RMSE result of 0.06765 and the MAPE result of 0.010639. This can also be proved in Fig. 2, which greatly underscores the superior predictive capability of the VMD LSTM model in forecasting aviation carbon emissions.

Second, compared to only using machine learning models for point value prediction, the utilization of VMD for data decomposition before forecasting generally demonstrated higher accuracy. It proves the importance of employing the VMD method for data decomposition, which can effectively enhance prediction accuracy.

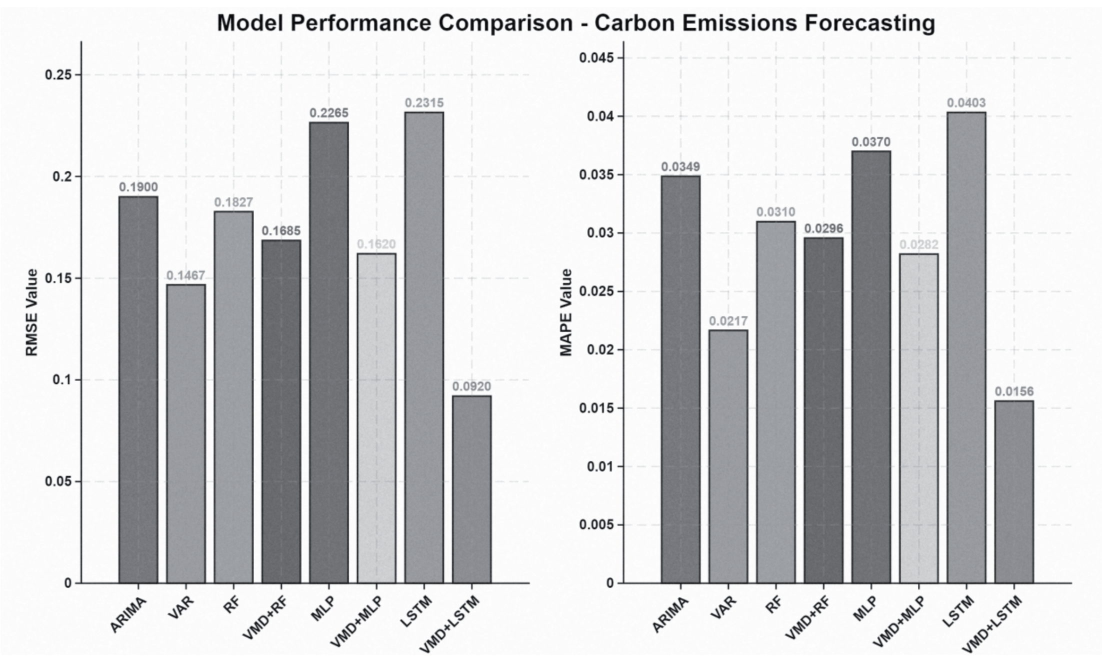

Fig. 3. DM test result.

Third, it can be observed that an increase in model complexity corresponded with improved prediction accuracy, indicating that elevating model complexity within an appropriate range can enhance the accuracy and robustness of predictions.

Diebold-Mariano Test

To statistically validate the performance superiority of the VMD-LSTM model in carbon emission forecasting, we employed the Diebold-Mariano (DM) test for rigorous significance analysis. The results, presented in Fig. 3, demonstrate that the VMD-LSTM hybrid model achieves statistically significant improvements over comparative models across both RMSE and MAPE evaluation metrics. These findings robustly confirm the methodological efficacy of integrating Variational Mode Decomposition with LSTM neural networks for enhanced carbon emission prediction accuracy.

Conclusions

Against the backdrop of global consensus on low-carbon development in aviation, this paper aims to explore practical carbon emission prediction tools for the aviation industry, thereby providing scientific data support for policymakers and relevant stakeholders worldwide.

To achieve this goal, this paper employs time series models and machine learning models, as well as two prediction paradigms: single point value prediction and data decomposition into component prediction. Based on the global daily flight data in 2019 from the OAG database, through the algorithm test and the comparison of carbon dioxide emissions forecasting results, the following conclusions are drawn:

(1) The mode decomposition of raw data into components can enhance prediction accuracy, as evidenced by the error values being lower for VMD RF (RMSE = 0.16853, MAPE = 0.029566), VMD MLP (RMSE = 0.16198, MAPE = 0.028189), and VMD LSTM (RMSE = 0.06765, MAPE = 0.010639) compared to RF (RMSE = 0.18263, MAPE = 0.030961), MLP (RMSE = 0.22254, MAPE = 0.036326), and LSTM (RMSE = 0.18829, MAPE = 0.030942) respectively.

(2) The predictive performance of the VMD LSTM model significantly outperforms all other models, followed by the VAR model. The RMSE value of VMD LSTM is 0.07905 lower than that of VAR, and the MAPE value is 0.011016 lower than that of VAR. The VMD LSTM model can be applied to medium to long-term forecasting of aviation carbon emissions.

This study demonstrates that the Variational Mode Decomposition (VMD) method combined with machine learning algorithms provides a robust framework for predicting CO_2 emissions in the aviation industry. The proposed VMD-LSTM hybrid model effectively captures periodic trends and temporal dependencies in emission patterns, achieving higher forecasting accuracy compared to conventional methods. These advancements hold critical implications for global decarbonization strategies, offering a data-driven approach to emission mitigation. From a practical standpoint, the proposed VMD-LSTM model enables policymakers to better assess and manage aviation emissions, providing actionable insights for designing effective mitigation strategies. Furthermore, the high-precision daily emission forecasts can assist airlines in optimizing carbon trading strategies while aiding airports and regulatory authorities in dynamically adjusting operational quotas and market-based policies.

In addition, the proposed method demonstrates high computational efficiency by optimizing VMD preprocessing and employing a lightweight LSTM architecture, reducing resource requirements for both training and inference. With its deployment-friendly characteristics, the approach can operate effectively on conventional hardware while meeting real-time processing demands, making it suitable for continuous monitoring applications in institutional or aviation settings.

There are also some limitations in this paper. Firstly, the larger the dataset, the better the training effectiveness of the model. However, due to data processing limitations, this study utilized only 365 data points from one year for training and testing. For enhanced applicability in emission management, future studies could extend the current framework to finer spatiotemporal resolutions, such as hourly-level or entity-specific (e.g., per-airline or per-airport) carbon emission predictions. Such granular modeling would empower stakeholders to optimize operational decisions, strengthen carbon accountability, and facilitate dynamic carbon trading. Secondly, external variables that may impact emissions were not considered in this study. Therefore, for future research on aviation carbon dioxide emissions, it would be interesting to expand the dataset, add some potential influencing factors, and explore the combination of diverse machine learning models to optimize the forecasting results. Thirdly, an increasing number of predictive studies have adopted hybrid modeling approaches to improve prediction accuracy, suggesting a promising direction for future research. Integrating VMD with advanced machine learning techniques, such as voting regressors, ensemble models, or transformer-based architectures, could further enhance the precision of aviation carbon emission predictions. Such methodological advancements would provide more reliable data for policymakers, industry stakeholders, and environmental researchers.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

The authors would like to thank Professor Yan from Beijing University of Posts and Telecommunications and Dr. Wang from Nankai University for their support of this study.

Conflict of Interest

The authors declare no conflict of interest.

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