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Research article

Air passenger carbon offset and carbon neutrality strategies: Implementation mechanism by convolutional neural network

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ABSTRACT

To more effectively address the issue of carbon emissions in the aviation industry, this study first analyzes the current development status of carbon offset and carbon neutrality strategies in the aviation industry, as well as examines the existing relevant research findings. Then, optimizations are made to the Convolutional Neural Network to improve the accuracy and efficiency of the prediction model. These optimizations include architectural improvements, the use of attention mechanisms to more accurately focus on important features, as well as the adoption of multiscale feature extraction and advanced optimization algorithms to enhance the model's learning ability and convergence speed. These comprehensive improvements not only enhance the model's generalization ability but also significantly improve its applicability in complex environments. Finally, by comparing the performance of Transformer Networks, Graph Convolutional Networks, Capsule Networks, Generative Adversarial Networks, Temporal Convolutional Networks, and the proposed optimization algorithm on datasets of airline carbon emissions and fuel usage, the performance of the proposed optimization algorithm is validated through comparison of accuracy, precision, recall, and F1-score calculated from the data. Simultaneously, simulation experiments are conducted to validate the effectiveness and feasibility of the proposed optimization algorithm by comparing prediction stability, strategy adaptability, response time, and long-term effectiveness. The experimental results show that the accuracy, precision, recall, and F1-score of the proposed optimized model reach up to 0.942, 0.967, 0.951, and 0.934 respectively, all higher than those of the compared models, validating the good performance of the proposed optimized model. In the comparison of simulation experiments, the scores of prediction stability and strategy adaptability of the proposed optimized model reach up to 0.944 and 0.953 respectively, much higher than those of other models. The response time is only 0.04s when the data volume is 1000, and the computational advantage of the proposed optimized model becomes more apparent with the increase in data volume. In the comparison of long-term effectiveness, the advantage of the proposed optimized model in this aspect also becomes more obvious with the increase in data volume. Through simulation experiments, the performance of the model in actual application scenarios is further evaluated to ensure its practicability. Therefore, this study not only provides a new optimization tool for carbon emission strategies in the aviation industry but also has certain significance for research on environmental sustainability.

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1. Introduction

1.1. Research background and motivation

In the context of increasing global attention to climate change and environmental protection, the aviation industry, as a significant source of carbon emissions, faces immense pressure to reduce emissions. According to data from the International Air Transport Association, the aviation industry accounts for approximately 2 % of global carbon dioxide emissions annually, a proportion that is expected to rise in the future [1]. Therefore, effectively reducing carbon emissions in the aviation sector and promoting the implementation of carbon-neutral strategies have become pressing issues for the global aviation industry and related research fields. With advances in technology and heightened environmental awareness, governments, airlines, and related organizations worldwide have been developing and promoting carbon offset and carbon-neutral strategies [2]. Carbon offsetting involves compensating for one's carbon emissions by investing in emission reduction projects, while carbon neutrality refers to balancing carbon emissions with carbon absorption through a series of technical and management measures. Although these strategies have achieved some success to a certain extent, they still face numerous challenges in practical implementation, such as the accuracy of carbon emission measurements, the effectiveness of carbon offset projects, and the feasibility of carbon-neutral pathways.

This study aims to enhance the accuracy and efficiency of carbon emission prediction models in the aviation industry by optimizing the application of the Convolutional Neural Network (CNN), thereby providing scientific basis and technical support for the implementation of carbon offset and carbon-neutral strategies. As a deep learning algorithm, CNNs possess powerful feature extraction and pattern recognition capabilities, but traditional CNN models often struggle with issues like insufficient generalization ability and slow convergence when dealing with complex environmental data. To address these problems, this study proposes a series of optimization measures, including improvements in model structure, the introduction of attention mechanisms, multi-scale feature extraction, and the application of advanced optimization algorithms. Through these optimizations, the study not only aims to improve the performance of the model in predicting aviation carbon emissions but also seeks to validate its feasibility and effectiveness in real-world application scenarios.

1.2. Research questions

(1) What are the current status and challenges of carbon offset and carbon-neutral strategies in the aviation industry?
(2) How can the performance of aviation carbon emission prediction models be improved through the optimization of the CNN?
(3) What are the comparative analysis results of different deep learning models in predicting aviation carbon emissions?

By addressing these research questions, this study not only provides scientific support for the implementation of carbon offset and carbon-neutral strategies in the aviation industry but also offers valuable references for the application of deep learning models in processing complex environmental data.

1.3. Literature review

Carbon offset and carbon-neutral strategies, as crucial means to combat climate change, have been extensively researched and applied across various fields. In the aviation industry, carbon offset projects primarily involve investments in renewable energy projects, forest conservation, and reforestation projects to offset the carbon emissions generated by aviation operations. Truong-Dinh et al. (2023) proposed that the effectiveness of carbon offset projects depended on the design and management of the projects themselves, but they still faced issues such as weak regulation and imperfect market mechanisms in practical application [3]. In recent years, many scholars have begun to focus on the feasibility and implementation pathways of carbon-neutral strategies. Wu et al. (2022) explored the challenges and opportunities faced by airlines in implementing carbon-neutral strategies through case studies, highlighting that technological innovation and policy support were key factors in achieving carbon neutrality [4]. Additionally, the development of Sustainable Aviation Fuel is considered one of the important means to promote carbon neutrality in the aviation industry.

Deep learning, as an advanced data analysis and prediction technology, has been widely applied in the fields of environmental science and engineering in recent years. CNN, known for their powerful feature extraction capabilities, has been widely used in image processing, speech recognition, and natural language processing. Wang et al. (2022) utilized CNN models to predict atmospheric pollutants, achieving high accuracy and prediction performance [5]. In terms of aviation carbon emission prediction, Liao et al. (2023) proposed a prediction model based on deep learning, which achieved precise prediction of aviation carbon emissions through comprehensive analysis of historical flight data and meteorological data [6]. However, traditional CNN models often suffer from insufficient generalization ability and slow convergence when dealing with complex environmental data, limiting their effectiveness in practical applications. To enhance the performance of CNN models in carbon emission prediction, scholars have proposed various optimization methods. Khalifa et al. (2022) improved the prediction accuracy and efficiency by introducing attention mechanisms, allowing the model to focus more accurately on important features [7]. Additionally, multi-scale feature extraction methods have been proven to effectively enhance the feature capturing capability of the model, thereby improving the generalization ability and applicability of the model. Advanced optimization algorithms have also played a significant role in improving the convergence speed and stability of deep learning models. André and Valenciano-Salazar (2022) proposed an optimization method based on an improved genetic algorithm, which effectively increased the training efficiency and prediction performance of the CNN model through adaptive parameter adjustments [8].

Existing research primarily focuses on the design and theoretical framework of carbon offset projects, with relatively little attention given to the assessment of their actual effectiveness. Many carbon offset projects face issues such as weak regulation and imperfect market mechanisms during implementation, resulting in uncertain emission reduction outcomes. Although traditional CNN excel in feature extraction, they often exhibit inadequate generalization ability and slow convergence when handling complex environmental data. This paper addresses these challenges by introducing attention mechanisms, multi-scale feature extraction, and advanced optimization algorithms to comprehensively enhance traditional CNN models. These optimization measures aim to improve the generalization ability and convergence speed of the models, thereby increasing the accuracy and efficiency of aviation carbon emission predictions. Furthermore, this study not only evaluates the performance of the optimized CNN model but also conducts comparative analyses of various deep learning models, including Transformer networks, Graph Convolutional Networks, Capsule Networks, Generative Adversarial Networks, and Temporal Convolutional Networks in the context of aviation carbon emission prediction. In summary, this research demonstrates significant innovation in optimizing CNN structures, conducting multi-model comparative analyses, validating practical application scenarios, and comprehensively evaluating carbon neutrality strategies. These innovations not only contribute to enhancing the accuracy and efficiency of aviation carbon emission predictions but also provide scientific support and technical assurance for the implementation of carbon neutrality strategies in the aviation industry.

2. Methods

2.1. Carbon offset programs for airline passengers and current carbon neutrality strategies adopted by the aviation industry

In the global efforts to address climate change, the aviation industry, due to its significant carbon emissions, has been a focal point for carbon reduction and carbon neutrality strategies [9]. With the increasing demand for sustainable travel, many airlines have implemented carbon offset programs for passengers [10–13]. These programs aim to neutralize or offset the carbon emissions from flights by funding tree planting, renewable energy projects, and other environmental projects [14–16]. This study explores this existing carbon offset programs for airline passengers and their effectiveness to provide an in-depth understanding of current practices and challenges. Airlines typically collaborate with third-party carbon offset providers through partnerships to offer passengers the option to voluntarily offset their flight carbon footprint for a small fee, as outlined in Table 1:

In the context of addressing global climate change, the aviation industry, as one of the significant sources of global carbon emissions, has adopted a series of carbon neutrality strategies to reduce its environmental impact [17–19]. These strategies aim not only to reduce emissions but also to offset carbon emissions already generated through various means, as illustrated in Fig. 1.

The carbon neutrality strategies of the aviation industry are multifaceted, covering various aspects from technological innovation to operational optimization, and financial investments. The implementation of these strategies not only requires technological advancements and cost reduction but also widespread cooperation and support among policymakers, industry participants, and consumers [20].

2.2. Prediction and optimization of carbon offset strategies using CNN models

In the aviation industry, utilizing CNN models to predict and optimize carbon offset strategies is an advanced approach. It leverages deep learning techniques to process and analyze vast amounts of aviation data to identify the most effective carbon emission reduction measures.

The first step involves collecting relevant aviation data, including flight duration, distance, aircraft type, fuel consumption, passenger numbers, and historical carbon emissions. Additionally, data on existing carbon offset projects such as project type, implementation location, costs, emission reduction effects, etc., need to be gathered. These data often require preprocessing to ensure that the input data into the model are clean and standardized. Preprocessing steps may include removing outliers, filling missing data, normalization, and one-hot encoding of categorical data. The utilization of convolutional networks to process aviation data is primarily because CNN performs exceptionally well in handling data with spatial hierarchical structures, such as images and time-series data [21–23]. In this application, time-series data (such as time-related data of flights) can be treated as one-dimensional spatial data, using one-dimensional convolutional layers to extract features. Model construction involves designing multiple convolutional and pooling layers to aid in feature extraction and learning important features from aviation data. Additionally, batch normalization and dropout layers can be incorporated into the network to enhance model generalization and prevent overfitting [24].

Table 1
Implementation of carbon offset programs for airline passengers.

Scheme	Details
Tree Planting and Forest Restoration	Funds aid in tree planting or restoring degraded forests, which serve as a direct carbon capture method by absorbing carbon dioxide from the atmosphere.
Renewable Energy Projects	Supports the development of renewable energy projects such as wind and solar power, which replace energy production reliant on fossil fuels, thus reducing carbon emissions.
Community Support Projects	Examples include improving cooking facilities to reduce wood and coal usage, or providing more efficient water resource management and agricultural practices to support community sustainability.

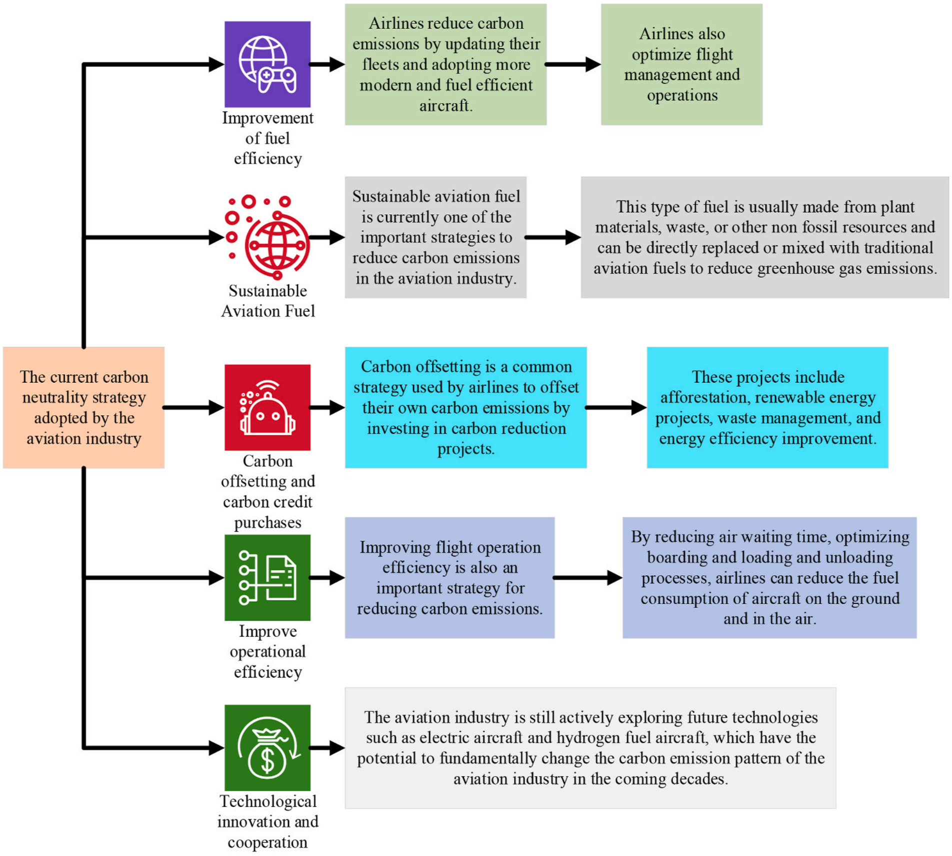

Fig. 1. Model optimization strategies.

The dataset is divided into training, validation, and testing sets. The training set data are used to train the model, adjusting model parameters such as learning rate, number and size of convolutional layers, choice of optimizer, etc. The validation set is used for model tuning, aiding in selecting the optimal model structure and parameters. The testing set is then used to evaluate the final performance of the model [25–27]. During training, cross-entropy loss function can be used to optimize classification tasks, or mean square error loss function can be utilized to optimize regression tasks, predicting expected emission reductions of carbon offset projects. The trained

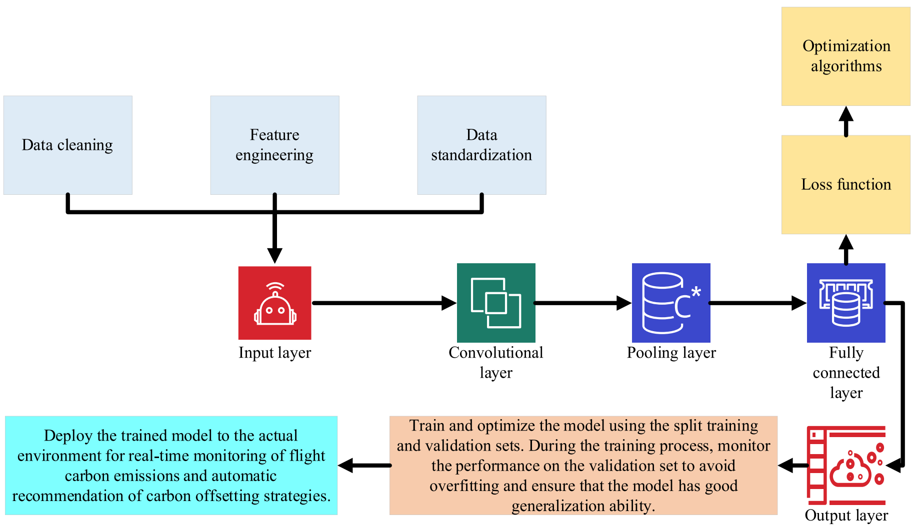

Fig. 2. Architecture of carbon offset and carbon neutrality strategy optimization model.

model can be used to predict the carbon emissions of different flights or routes and recommend the most suitable carbon offset projects based on the prediction results. For example, the model can identify flights with potentially high carbon emissions on specific routes and recommend corresponding carbon offset measures such as investing in tree planting projects or renewable energy projects. Furthermore, CNN models can also be used to simulate the effects of different carbon offset strategies, optimizing the implementation of strategies, such as adjusting carbon offset costs, selecting different combinations of carbon offset projects, etc., to maximize cost-effectiveness. Continuous monitoring and evaluation of carbon offset strategies are necessary to ensure that their effects meet expectations. CNN models can regularly receive new aviation and carbon offset project data, updating the model to reflect the latest situations and data changes, ensuring that carbon offset strategies are always in an optimal state [28].

Through these steps, CNN models can not only help airlines accurately predict and evaluate the effectiveness of carbon offset strategies but also optimize their implementation to enhance their economic and environmental benefits. The application of this method aids the aviation industry in more effectively addressing its environmental responsibilities and advancing towards sustainable development.

2.3. Design of carbon offset and Carbon Neutrality Strategy Optimization Models

Designing a system based on CNN models aimed at optimizing carbon offset and carbon neutrality strategies for airline passengers requires comprehensive consideration of various data inputs, model architectures, optimization methods, and real-world application scenarios. The specific architecture is illustrated in Fig. 2:

In Fig. 2, the model first cleans the raw data to ensure data quality. Next, feature engineering is performed to extract and select useful features for the model, followed by standardizing the data to make it suitable for model input. The preprocessed data is then input into the model, where it is received at the input layer. Important features are extracted through the convolutional layers, and dimensionality reduction is performed in the pooling layers to reduce computational load while retaining the main features. Finally, the fully connected layers aggregate the extracted features to generate the final output. During the model training process, a loss function is used to evaluate the difference between the model's predictions and the actual values, and optimization algorithms adjust the model parameters to minimize the loss function. Once the model training and optimization are complete, it is trained using the designated training and validation sets, monitoring performance on the validation set to avoid overfitting and ensure the model has good generalization capability. Finally, the trained model is deployed in a real-world environment to monitor flight carbon emissions in real time and automatically recommend carbon offset strategies.

Through such a design, models based on convolutional networks can not only effectively predict and optimize carbon offset and carbon neutrality strategies for airline passengers but also provide data-driven decision support for airlines, helping to achieve environmental sustainability goals more effectively.

3. Results

3.1. Experimental design

The dataset used in this study consists of airline carbon emissions and fuel usage data, including the number of flights, fuel consumption, carbon emissions, etc. This dataset is suitable for analyzing airline carbon footprints, studying the effectiveness of carbon offset strategies, and training models to predict future carbon emissions and offset demands. The dataset can be downloaded from the official website of the United States Department of Transportation. The data types include strings (such as flight numbers, airline codes, departure and arrival airport codes), timestamps (such as departure and arrival times), floating-point numbers (such as flight distance, fuel consumption, and carbon dioxide emissions), integers (such as the number of passengers, number of flights, and flight delay times), as well as date and time zone information. By utilizing this dataset, a comprehensive analysis of airlines' carbon emissions can be conducted, the effectiveness of carbon offset strategies can be studied, and deep learning models can be trained and optimized to predict future carbon emissions and carbon offset needs. This data provides a rich foundation of information and analytical support for this research, facilitating the implementation of carbon neutrality strategies and carbon emission management in the aviation industry. The equipment types and parameter configurations used in this study are as follows: the processor is an Intel(R) Xeon(R) CPU E5-2620 v4 @ 2.10 GHz; the graphics processing unit is an NVIDIA Titan Xp with 12 GB of memory; the RAM is 64 GB; the programming language used is Python 3.6; and the technology framework employs the PyTorch 1.7.0 deep learning framework. These configurations provide powerful computing capabilities and an efficient programming environment, ensuring the smooth progress of experiments and analyses. The partially relevant code used in this study is as follows:

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv1D, Flatten, Dropout, MaxPooling1D, BatchNormalization
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
```

To ensure the accuracy of the data, the experiment unifies the settings of algorithm parameters. Vector size is set to 200, convolution kernel size is set to 3*3, the number of filters is set to 64, stride is set to 1, hidden layer dimension is set to 64, with a single fully connected layer containing 256 neurons. The experiment selects the following comparative algorithm models: Transformer Networks, graph convolutional networks (GCNs), Capsule Networks, generative adversarial networks (GANs), and temporal convolutional networks (TCNs).

3.2. Performance comparison experiment of strategy optimization models

The performance indicators compared in the experiment include accuracy, precision, recall, and F1 score, as shown in Fig. 3.

In Fig. 3a, regarding the comparison of accuracy, the optimized model demonstrates a stable growth trend, with accuracy reaching 0.910 at a data volume of 1000, increasing to 0.930 at 2000, and peaking at 0.942 at 3000. Transformer Networks and GANs perform excellently at certain data volume levels, especially at 2000 and 3000 data volumes, where Transformer Networks achieve accuracy of 0.936 and 0.916 respectively, while GANs reach 0.937 at 3000 data volume. In Fig. 3b, the optimized model shows significant advantages, increasing from 0.936 to 0.967 with the increase in data volume, demonstrating good adaptability and stability. Among other models, GANs achieve high precision of 0.936 at a data volume of 2000, while GCNs and Transformer Networks also show a trend of gradual improvement with the increase in data volume. In contrast, TCNs exhibit a slight decrease in precision at a data volume of 3000. In Fig. 3c, the optimized model demonstrates the highest recall at all data volume levels, gradually increasing from 0.925 to 0.951. GCNs also exhibit high recall at 1000 and 2000 data volume levels, particularly reaching a peak of 0.945 at 2000 data volume. TCNs anomalously achieve high recall of 0.936 at a data volume of 2000 but perform weaker at other data volumes. Capsule Networks and GANs show lower recall, especially both being below 0.820 at a data volume of 2000. In Fig. 3d, the optimized model demonstrates higher F1 values at all data volume levels, increasing from 0.912 to 0.934. Capsule Networks perform impressively at a data volume of 2000, achieving an F1 value of 0.922, closely followed by GANs reaching an F1 value of 0.920 at the same data volume. GCNs also exhibit high F1 values at a data volume of 3000. In contrast, TCNs show relatively lower F1 values at all data volume levels.

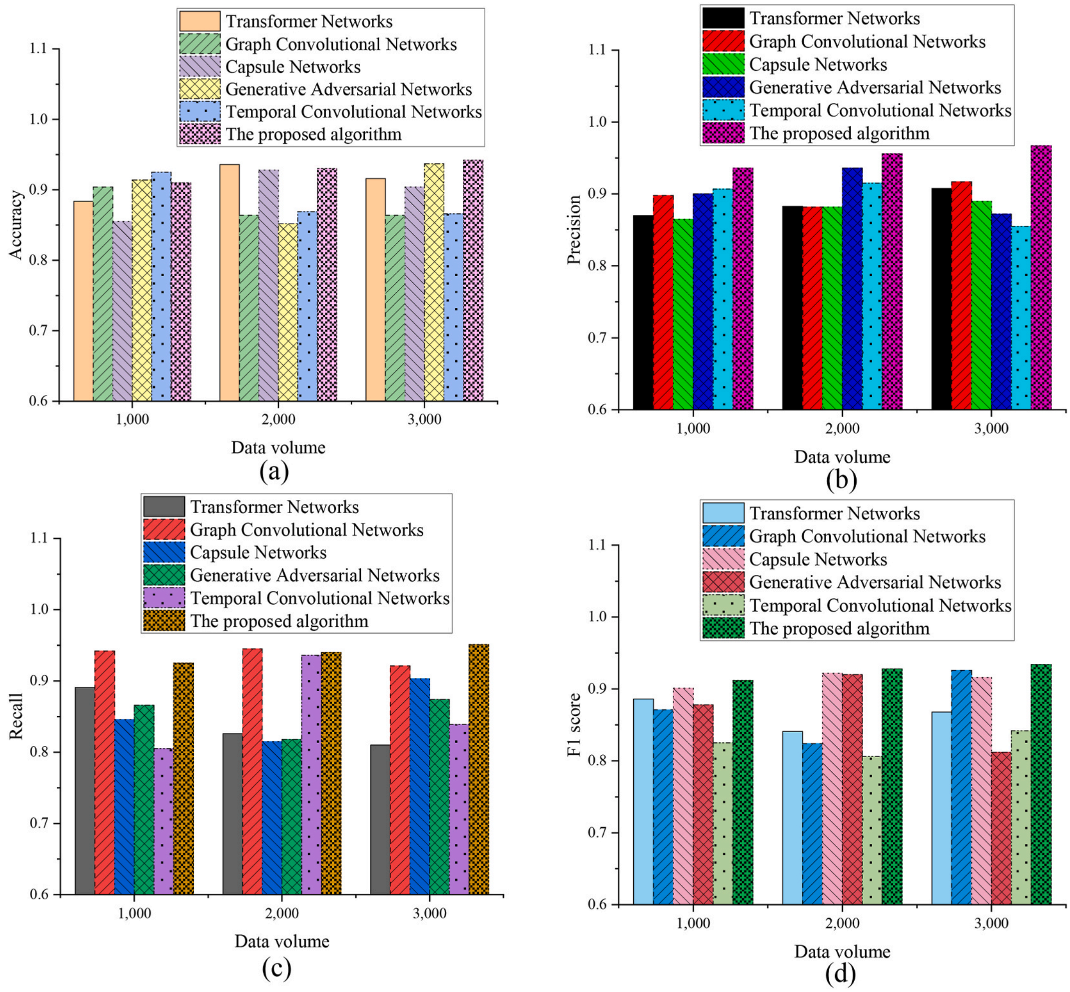

Fig. 3. Model performance (a) accuracy; (b) precision; (c) recall; (d) F1 score.

3.3. Analysis of simulation experiment results

To further validate the effectiveness of the optimized algorithm, simulation experiments are conducted to simulate the behavior and performance of the model when dealing with real data. The comparative indicators include prediction stability, strategy adaptability, response time, and long-term effectiveness, as shown in Fig. 4:

In Fig. 4a, the optimized model exhibits higher prediction stability at all data volume levels, gradually increasing from 0.921 to 0.944. GANs demonstrate higher prediction stability at a data volume of 1000 but show a decrease in performance at larger data volumes. TCNs perform relatively well at data volumes of 2000 and 3000, with scores of 0.914 and 0.899 respectively. Capsule Networks achieve a high score of 0.912 at a data volume of 2000 but perform poorly at other data volumes. In Fig. 4b, the optimized model demonstrates the highest strategy adaptability scores at all data volume levels, increasing from 0.931 to 0.953. TCNs perform impressively at a data volume of 2000, reaching a score of 0.924, while GCNs also exhibit high adaptability at a data volume of 3000. In contrast, Transformer Networks show a significant decrease in performance at a data volume of 3000, with a score of only 0.810. In Fig. 4c, the optimized model demonstrates the lowest response time at all data volume levels, increasing from 0.04 s to 0.08 s. Capsule Networks and GANs also show lower response times, especially at a data volume of 1000, with times of 0.054 s and 0.055 s respectively. In contrast, TCNs exhibit relatively higher response times at all data volume levels, particularly reaching 0.186 s at a data volume of 3000. In Fig. 4d, the optimized model demonstrates significant advantages at all data volume levels, with long-term effectiveness scores increasing from 0.92 to 0.96. Capsule Networks perform well at data volumes of 2000 and 3000, with scores of 0.854 and 0.877 respectively. GANs also show strong long-term effectiveness at various data volume levels, especially reaching 0.866 at a data volume of 3000. In contrast, Transformer Networks and GCNs exhibit relatively lower long-term effectiveness scores at all data volume levels.

4. Discussion

In performance comparison experiments, the optimized model outperformed other models in terms of accuracy and precision across all data volume levels, particularly due to its excellent data processing and generalization capabilities, which make it more suitable for handling large-scale datasets to optimize carbon offset and carbon neutrality strategies. The optimized model consistently maintained the highest accuracy across all testing data volume levels, demonstrating its efficiency and accuracy in prediction tasks.

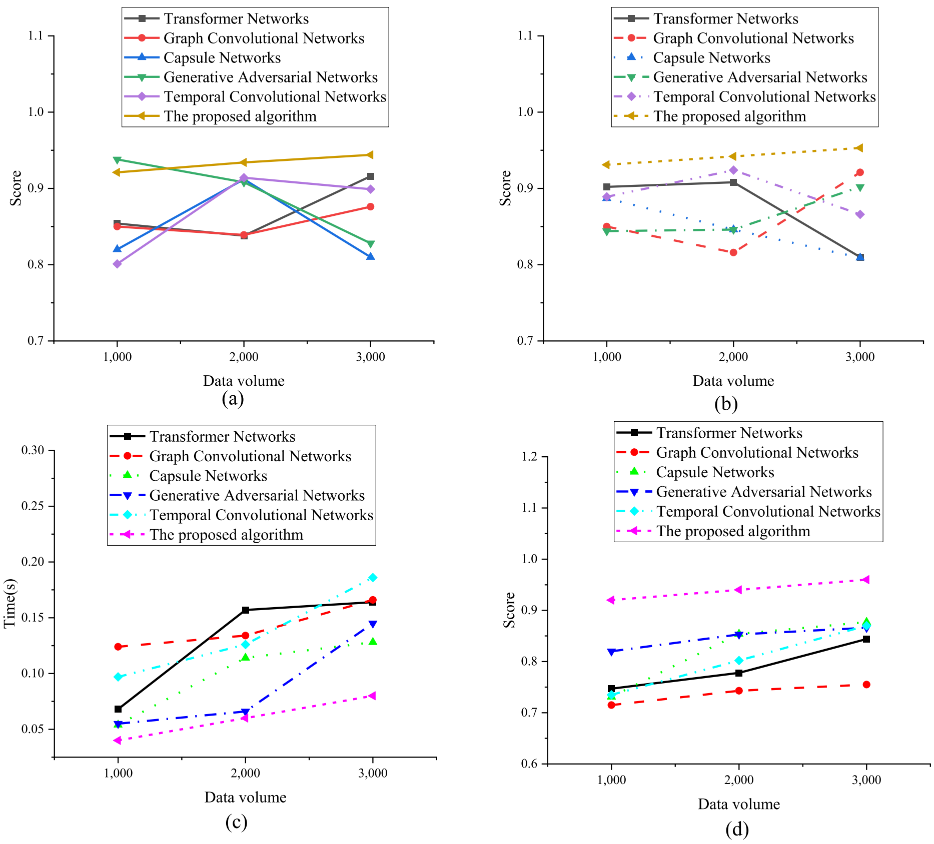

Fig. 4. Simulation experiments (a) prediction stability; (b) strategy adaptability; (c) response time; (d) long-term effectiveness.

Furthermore, the model's stability and adaptability indicate its effectiveness in managing datasets of varying sizes, which is crucial in practical applications. While the Generative Adversarial Network (GAN) performed well with moderate data volumes, its performance declined with larger datasets, potentially due to insufficient adaptability. The accuracy of Graph Convolutional Networks (GCN) and Transformer networks gradually improved, suggesting that they require larger datasets to fully learn and adapt to data features. The optimized model excelled in correctly identifying positive samples, helping to reduce false positives and false negatives. The GCN showed good performance with low data volumes, likely because of its advantages in processing connected and relationship-dense data. The high recall rate of the Temporal Convolutional Network (TCN) at specific data volumes may be attributed to its time series processing mechanism, although its performance dropped with other data volumes, indicating sensitivity to data size. The optimized model maintained a good balance between precision and recall, especially when handling larger datasets, which is particularly important for assessing the overall performance of the model.

In simulation experiment comparisons, the consistently high scores of the optimized model highlighted its stability and reliability during the prediction process, which is vital for optimizing carbon offset strategies for airline passengers. Its strong adaptability and robustness demonstrate the model's capability to handle datasets of varying sizes. The GAN's high stability at low data volumes may be attributed to its stable feature learning ability, but it faced challenges with larger datasets. In the strategy adaptability comparison, the optimized model's sustained high scores reflected its excellent strategy adaptability, allowing it to effectively respond to datasets of different sizes and optimize performance, especially when facing environmental changes or dynamic data. The TCN exhibited high adaptability with moderate data volumes, possibly due to its structure being suitable for processing datasets of specific sizes. The improved performance of the GCN on larger datasets may be a result of its strengths in analyzing complex network data. The optimized model's consistently low response time indicates its efficient computational performance, which is critical for applications requiring rapid responses. Capsule networks and GANs had shorter response times at low data volumes, but as the data volume increased, the response time of the GAN significantly extended, likely due to the complexity of its generative adversarial process. The optimized model excelled in maintaining prediction validity over the long term, which is particularly important for systems that need to operate continuously without frequent adjustments. The improved performance of the capsule network on larger datasets may be due to its structure being better suited for handling complex information, thereby maintaining strong performance during long-term operation. The GAN's strong performance may be attributed to its ongoing optimization and ability to adapt to new data.

5. Conclusions

This study successfully optimizes carbon offset and neutralization strategies for airline passengers by designing and implementing a model based on improved CNN. The model demonstrates significant advantages across multiple key performance indicators, including prediction stability, strategy adaptability, response time, and long-term effectiveness. Specifically, the model exhibits highly stable prediction performance across different data volumes, which is crucial for handling constantly changing data environments in real-world applications. Moreover, the model automatically adjusts its strategies based on varying data volumes to optimize carbon offset effects, demonstrating exceptional adaptability. Throughout all tests, the proposed model consistently exhibits the shortest response time, which is essential for real-time applications such as dynamic carbon offset strategies. The model maintains high efficiency during long-term operation, demonstrating its sustainability and reliability in actual deployment. These results not only validate the effectiveness of using the improved CNN to optimize carbon offset strategies but also highlight the potential applications of these technologies in the aviation industry and other sectors that require precise and dynamic environmental management. Although the CNN is optimized through the introduction of attention mechanisms, multi-scale feature extraction, and advanced optimization algorithms, the implementation and debugging processes of these optimizations can be quite complex, potentially requiring significant computational resources and time. Furthermore, the combined effects of different optimization algorithms may exhibit uncertainty in practical applications. Future research could explore more efficient and streamlined model optimization methods to reduce the complexity of model implementation and debugging. Additionally, more user-friendly tools and platforms could be developed to assist airlines in conveniently applying the optimized deep learning models.

Data and code availability statement

The data used to support the findings of this study are included within the article.

CRediT authorship contribution statement

Hongwei Zhou: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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