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Carbon Emissions Prediction for Sustainable Regional Transportation Based on a Hybrid Deep Learning Model

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Abstract

As passenger travel and freight transport demand continue to rise, transportation remains a major source of global carbon emissions. Predicting transportation carbon emissions helps support sustainable transportation planning and the development of scientifically sound emission reduction policies. However, there are currently no unified standards for accounting for transportation carbon emissions, and different approaches yield widely varying predictions, creating challenges for formulating carbon emission policies. In this study, a top-down approach based on China's energy statistical data is adopted to calculate regional transportation carbon emissions (TCE). Twenty factors influencing carbon emissions are selected, and Spearman correlation analysis is used to examine the correlations among these factors. Lasso regression and the STIRPAT model are employed to quantitatively analyze the influence of each factor. Subsequently, an improved hybrid deep learning model, GA-CNN-LSTM-Attention, is proposed to predict carbon emissions under baseline, restriction, and control scenarios. Finally, an empirical analysis is grounded in a case study of Fujian Province, China. The quantitative analysis results show that, of all the factors, the urbanization rate has the greatest impact on transportation carbon emissions in the region, and the GA-CNN-LSTM-Attention prediction model achieves higher forecasting accuracy. Under the first two scenarios, carbon emissions in the region show a year-by-year increasing trend from 2022 to 2035, with no emissions peak observed. Under the controlled scenario, carbon emissions are projected to peak in 2030, reaching approximately 70.28 million tons of CO₂. The prediction results provide a scientific basis for sustainable transportation development and government policymaking on carbon reduction.

Keywords: transportation carbon emissions; sustainable transportation development; influencing factors; STIRPAT model; hybrid deep learning model



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1. Introduction

The 2024 Global Carbon Budget report indicates that global CO₂ emissions from human activities reached a record high of 41.6 billion tons in 2024 [1,2]. Despite the accelerating global transition to clean energy, CO₂ emissions from fossil fuels continue to rise. To achieve the goal set in the 2015 Paris Climate Agreement [3], concerted efforts from all countries around the world will be required to limit the rise in global temperature to within 1.5 °C. The Chinese government has undertaken a series of actions to reduce carbon emissions, including the expansion of wind and solar power and the promotion of low-carbon transformation in industry and transportation, thereby making significant

contributions to tackling global climate change. The transportation sector plays a vital role in China's economy, but it also produces severe environmental pollution [4]. In 2021, carbon emissions originating from the transportation sector constituted approximately 9.1% of the nation's total carbon emissions [5]. Therefore, reducing transportation carbon emissions is an effective pathway to alleviating resource shortages and environmental issues in the country [6], while also promoting sustainable transportation development and long-term sustainability goals.

Following its commitment to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, the Chinese government has identified the transportation sector as a key area for carbon emission control under the dual-carbon policy [7,8]. Analyzing and controlling carbon emissions in the transportation sector are essential for meeting energy conservation and emission reduction targets [9,10].

Fujian Province, located on China's southeastern coast, is a core area of the Maritime Silk Road and an important part of the southeastern coastal economic belt [11]. According to the Fujian Statistical Yearbook 2023 [12], by the end of 2022, passenger and freight turnover in Fujian Province had reached record highs of 119 billion person-kilometers and 11,344 billion ton-kilometers, respectively [13]. The rapid development of transportation has led to negative impacts, including environmental degradation. Therefore, developing reliable methods for carbon emissions prediction and evaluation for transportation planning is essential for promoting low-carbon and sustainable transportation development.

With respect to the influencing factors of carbon emissions, most existing studies [14–16] select variables based on experience or use a single method for screening, which makes them susceptible to subjective factors. Moreover, some studies fail to account for multicollinearity among variables, thereby affecting the explanatory power and predictive accuracy of prediction models. In terms of carbon emissions prediction, traditional statistical and machine learning methods often struggle to capture the complex nonlinear relationships among multiple influencing factors.

Although deep learning models such as LSTM and CNN–LSTM–Attention have achieved relatively high prediction accuracy in recent studies, several limitations remain. First, many existing studies adopt fixed hyperparameter settings without further optimization, which may limit model adaptability and prediction performance. Second, conventional deep learning models often focus only on temporal dependency learning or local feature extraction, making it difficult to fully capture the complex nonlinear characteristics of transportation carbon emission data. In addition, the cross-regional generalization capability of existing prediction models remains relatively weak, especially under small-sample conditions.

To address these limitations, this study proposes a GA–CNN–LSTM–Attention hybrid deep learning model for regional transportation carbon emissions prediction. In the proposed framework, the CNN module is employed to extract local nonlinear features from the input data, while the LSTM module captures long-term temporal dependencies in carbon emission sequences. Subsequently, the Attention mechanism is introduced to assign adaptive weights to different hidden-state features, thereby improving the model's ability to identify important temporal information. Furthermore, a genetic algorithm (GA) is applied to optimize key hyperparameters of the deep learning model, including the learning rate, mini-batch size, number of LSTM units, and dropout rate, thereby enhancing model adaptability, prediction accuracy, and robustness.

Compared with conventional prediction methods, the proposed model demonstrates stronger nonlinear feature extraction capability, improved temporal sequence learning ability, and enhanced adaptive optimization performance. Therefore, this study makes improvements in both the screening of influencing factors and the prediction accuracy

of transportation carbon emissions, thereby providing scientific support for sustainable regional transportation planning and low-carbon transition. The main contributions of this study are outlined as follows.

- (1) Spearman correlation analysis is used to analyze the correlations among the influencing factors of carbon emissions. The key influencing factors are screened, and the extent of their impact is quantified using Lasso regression and the STIRPAT model.
- (2) A GA–CNN–LSTM–Attention deep learning prediction model is constructed. Feature extraction is performed through a convolutional neural network (CNN), temporal dependencies are captured by a long short-term memory (LSTM) network, and the Attention mechanism together with the genetic algorithm (GA) is employed to optimize model parameters. Compared with conventional deep learning models, the proposed model achieves higher prediction accuracy and stronger adaptability under limited sample conditions.

The remainder of this paper is structured as outlined below. Section 2 presents a literature review. Section 3 describes the selection of influencing factors and the carbon emissions prediction model. Section 4 provides a case-study-based empirical analysis along with comparative evaluations. Section 5 presents a discussion, and the conclusions are drawn in Section 6.

2. Literature Review

2.1. Research on Influencing Factors on TCE

The analysis of influencing factors not only identifies the main sources of carbon emissions [17], facilitating the formulation of effective emission reduction policies and reducing greenhouse gas emissions, but also contributes to the optimization of transportation planning and infrastructure construction, improvement of transportation efficiency, and reduction in congestion and energy waste.

Factor decomposition models are currently the most widely used methods for analyzing factors affecting transportation. The idea behind these models is to decompose carbon emissions into a set of different contributing factors, thereby deriving the contribution rates of each factor. This helps better understand the extent to which each factor influences changes in carbon emissions [18,19]. Ehrlich and Holden proposed the classic IPAT model in the early 1970s [20]. Utilizing the IPAT model, Shaari et al. [21] investigated the relationship between the expansion of the automobile industry and carbon dioxide emissions in ASEAN countries. Building upon the IPAT model, Liu et al. [13] incorporated structural adjustment factors to develop the IPAT–S model, and they found that structural adjustments help alleviate emission reduction pressures. In the analysis of factors influencing TCE, the Kaya identity and its extensions are also commonly used methods [22]. Scholars have utilized the Kaya identity and LMDI decomposition model to break down carbon emissions into economic factors, energy factors, and other relevant determinants, analyzing the factors that affect TCE in several countries and cities. The results indicate that economic factors and the level of transportation development significantly impact the rise in TCE [23–27].

Although the IPAT model and Kaya identity are widely applied, they also have notable drawbacks: both models simplify the complex relationships between the economy and the environment to some extent [28], potentially neglecting other important factors, such as policy changes and social behavior. In reality, the relationships among different factors may be complex and nonlinear. To overcome these shortcomings, Dietz T. and Rosa proposed the STIRPAT model [29]. Serving as an extension of the IPAT model, STIRPAT integrates more influencing factors, employs nonlinear relationships for decomposition, and can be expanded according to different research needs, offering greater flexibility. Li et al. [30]

used the STIRPAT model to decompose carbon emissions into five influencing factors. Their results indicated that population was the most significant determinant of carbon emissions. The extended STIRPAT model was employed to decompose the carbon emission factors within the transportation sector into several indicators, namely population size, per capita GDP, transportation energy efficiency, and transportation energy structure [31–33]. The results indicated that population and energy composition exert the most substantial influence on carbon emissions. Moreover, the level of urbanization also constitutes a key factor affecting TCE [34].

Various methods can be employed to analyze the factors influencing carbon emissions. As research has progressed, scholars have continuously optimized these research methods. However, the selection of influencing factors by scholars tends to be somewhat subjective, and when establishing models, potential multicollinearity issues among factors are often overlooked. Redundant factors may lead to overfitting in carbon emission models, resulting in significant deviations in future predictions. To ensure that models accurately capture the relationships among different influencing factors and to avoid overfitting, the screening and analysis of selected factors are particularly important.

2.2. Prediction of TCE

The main objective of predicting transportation carbon emissions is to analyze future trends in carbon emission changes, which is significant for understanding and recognizing the future state of carbon emissions. By accurately predicting carbon emissions, relevant agencies can formulate and evaluate transportation policies, promote innovation and development in transportation technologies, and enhance the overall sustainability of society.

The carbon emissions prediction models in the transportation sector mainly include time-series models, regression models, and system dynamics models [18]. Among these, the gray prediction method within time-series models is particularly effective for predicting time series that contain uncertain factors. Therefore, the gray forecast method has become a commonly used approach among scholars in predicting carbon emissions. Kazancoglu et al. [35] applied the gray prediction method to predict greenhouse gas emissions from general road transport, cars, light trucks, and heavy trucks in the EU, UK, France, Germany, and Italy for the years 2017 to 2025, examining the primary contributors to road traffic carbon emissions across various regions. Chen et al. [36] and Zhang [37] used the GM (1,1) model to predict TCE in Jiangsu and Gansu Provinces, with their research conclusions indicating that strong emission reduction measures are necessary to achieve peak emission targets in these provinces. Mao [38] employed the LMDI decomposition method to analyze carbon emissions arising from transportation in Henan Province. Using input–output data from 12 provinces in China, Zhang et al. [39] conducted a DEA–Malmquist model to assess the carbon emission reduction performance of the transportation sector in provinces along the Silk Road.

Although the gray prediction method is simple and direct, it relies on limited data and cannot explain the contributions of multiple influencing factors. In this context, many scholars have also used factor decomposition methods based on changes in transportation demand or scenario analysis to predict carbon emissions. The models frequently employed in the transportation sector are the Long-range Energy Alternatives Planning System (LEAP) model and Market Allocation of Technologies Model (MARKAL) [40]. Gu [41] used the LEAP model to divide road traffic into a four-layer structure and then combined predictions of traffic operation data to study CO₂ and air pollutant emissions in single and combined scenarios from 2021 to 2035. Liu et al. [42] created the PECE–LIU2017 model through the LEAP framework and analyzed carbon emission trends and the periods of peak activity

within China's transportation sector in different scenarios. Huang et al. [43] employed the LEAP model to predict TCE in Guangzhou and found that the peak time in the policy scenario is 2035, significantly later than the target year for carbon emission peak. Studies on urban TCE prediction have indicated that the enhancement of clean energy utilization constitutes a central priority for reducing emissions in urban transportation [44–46].

Regression prediction models based on factor decomposition provide trends in carbon emissions under various conditions, enhancing adaptability to future changes. However, scenario construction and demand prediction are often subjective and lack consideration of the intricate interdependencies among numerous variables, potentially leading to significant prediction deviations. Machine learning and neural network algorithms excel in handling complex data, demonstrating high accuracy and adaptability. Gao et al. [47] used the Lasso–SVM method to predict the TCE of the eight major economic zones of China over the period from 2021 to 2060. Traditional fossil fuels are the main contributors to TCE, and notable regional disparities are observed. Liu and Hu [48] studied TCE in 30 provinces of China using random forest, XGBoost, and KNN (K-nearest neighbor) algorithms and compared their prediction performance. XGBoost and random forest achieved superior predictive performance, with R^2 values above 0.97, while KNN performed poorly. Song et al. [49] used support vector machine (SVM), extreme gradient boosting (XGBoost), random forest (RF), and backpropagation (BP), in combination with Lasso regression and principal component analysis, to predict carbon emissions in the transportation sectors of 30 provinces in China. The model combining Lasso and SVM had the best prediction performance, and empirical analysis showed that the earliest peak times for TCE in Guangdong, Shanghai, Shandong, and Sichuan were 2029, 2028, 2030, and 2029, respectively. A deep learning model was employed by Wu et al. [6]. A convolutional neural network–gated recurrent unit–attention mechanism (CNN–GRU–Attention) was used to predict carbon emissions in Jiangsu's transportation industry. This model forecasted carbon emissions for Jiangsu's transportation sector from 2022 to 2035 under six different scenarios and proposed corresponding strategies for emission reduction.

Machine learning and neural network models in deep learning can effectively capture complex relationships among variables and perform well on high-dimensional data, achieving good performance for carbon emissions prediction problems involving many influencing factors. However, current research on carbon emissions prediction models combining heuristic algorithms and deep learning remains insufficient. In both machine learning studies and deep learning applications for carbon emissions prediction, the hyperparameters of the models are generally held constant. Heuristic algorithms can help prediction models find better hyperparameters, optimize model performance, improve convergence speed, and reduce overfitting. Therefore, the application of heuristic algorithms combined with deep learning carbon emissions prediction models is of great significance.

3. Methodology

3.1. Carbon Emission Calculation

According to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories [50], carbon emissions can be calculated using two approaches: the top–down approach and the bottom–up approach. The top–down approach estimates total carbon emissions by aggregating the energy consumption of an industry [51]. Compared with the bottom–up approach, this method is simpler, relies on more available data, and reduces the risk of calculation omissions. Therefore, a top–down approach was adopted in this study to calculate transportation carbon emissions. With reference to the methodology provided in

Volume 2 (Energy) of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, the calculation method of the top-down approach is defined as follows:

$$C = \sum_i E_i \cdot F_i \quad (1)$$

where C represents carbon emissions, E_i represents energy consumption, F_i represents the energy carbon emission factor, and i denotes energy type.

To simplify calculations in the following calculation process, the usage of different fuels can be converted into equivalent standard coal consumption. The conversion coefficients for translating transportation energy consumption into standard coal consumption are presented in Table 1.

Table 1. Standard coal conversion coefficients for transportation energy.

Energy Type	Raw Coal	Gasoline	Kerosene	Diesel	Fuel Oil	LPG	Natural Gas	Electricity
Standard coal conversion coefficient	0.714 ^a	1.471 ^a	1.471 ^a	1.457 ^a	1.429 ^a	1.714 ^a	1.10~1.33 ^b	0.123 ^c

Note: 1. The units are (kg standard coal/kg) for a, (kg standard coal/m³) for b, and (kg standard coal/kW·h) for c. 2. The coefficient data are sourced from the China Energy Statistical Yearbook.

If the standard coal conversion coefficient is denoted by μ , then Equation (1) can be transformed into Equation (2), which will be employed to determine the carbon emissions in the subsequent calculations.

$$C = \sum_i E_i \cdot \mu_i \cdot F_{SC} \quad (2)$$

where E_i represents energy consumption, μ_i represents the standard coal conversion coefficient, and F_{SC} represents the carbon emission factor of standard coal.

3.2. Analysis of Influencing Factors

3.2.1. Spearman Rank Correlation Coefficient

The Spearman rank correlation coefficient is used to evaluate the monotonic association between two variables [52]. This method examines the ordinal positions of the variables instead of their raw magnitudes and employs a correlation coefficient to indicate the strength of the association among the variables. The Spearman rank correlation coefficient does not depend on the data distribution type, making it suitable for complex or nonlinear data environments, and it has certain advantages in analyzing outliers. The formula used to compute the Spearman correlation coefficient between factors is defined as follows:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (3)$$

where ρ denotes the Spearman rank correlation coefficient, d_i is the rank difference between the two variables in each group of observations, and n is the sample size.

The correlation coefficient ρ takes values in the interval from -1 to $+1$. When the absolute value $|\rho|$ is closer to 0, this signifies a weaker correlation between the two variables [53].

3.2.2. Lasso Regression

Lasso regression can simplify the model, reduce its complexity, and alleviate potential multicollinearity issues among certain factors, thus reducing the risk of overfitting [54]. The objective function is defined as follows:

$$\text{loss} = \min \sum_{i=1}^n (f(x_i) - y_i)^2 + \lambda \|\omega\|_1 \quad (4)$$

where $f(x_i)$ represents the predictive value, y_i is the actual value, λ represents the regularization parameter, and ω denotes the regression coefficients of the variables.

3.2.3. STIRPAT Model

In order to assess the overall influence of population, economic, and technological factors on the environment, Ehrlich and Holdren introduced the IPAT model, commonly referred to as the Environmental Pressure Model [55]. The formula for the IPAT model is

$$I = PAT \quad (5)$$

In Equation (5), I represents the environmental factor; P denotes the population size; A represents the degree of wealth or economic standing; and T stands for the level of technology. The term “technology level” does not refer to a single specific indicator, but rather represents the actual values of a group of technology-related indicators.

The IPAT model assumes a linear relationship between these factors and environmental impacts, whereas, in reality, the relationship is often very complex and cannot be represented by a simple linear relationship. To overcome this limitation, York and others introduced the STIRPAT model [56], as shown in Equation (6). Applying the logarithmic transformation to both sides, Equation (6) may be rewritten as Equation (7).

$$I = aP^b A^c T^d e \quad (6)$$

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + e \quad (7)$$

where a , b , c , and d are model parameters, and e represents the error term of the model.

As a nonlinear model, STIRPAT can capture the non-proportional effects of changes in different factors on the environment. Additionally, it allows for the expansion of influencing factors based on research needs. Therefore, it is extensively used in analyzing the factors that influence transportation.

3.3. Carbon Emissions Prediction

3.3.1. Convolutional Neural Networks

Convolutional neural networks (CNNs) have been widely applied in domains including time-series prediction. The internal structure of a CNN consists of five parts [57], and is illustrated in Figure 1.

After performing convolution extraction on the input data within the convolution layer, the Rectified Linear Unit (ReLU) is commonly employed as an activation transform. The mathematical expression of the ReLU function is presented as follows:

$$\text{Relu}(x) = \max(0, x) \quad (8)$$

where $\text{Relu}(x)$ represents the output of the ReLU activation function, and x is the feature variable extracted from the convolutional layer.

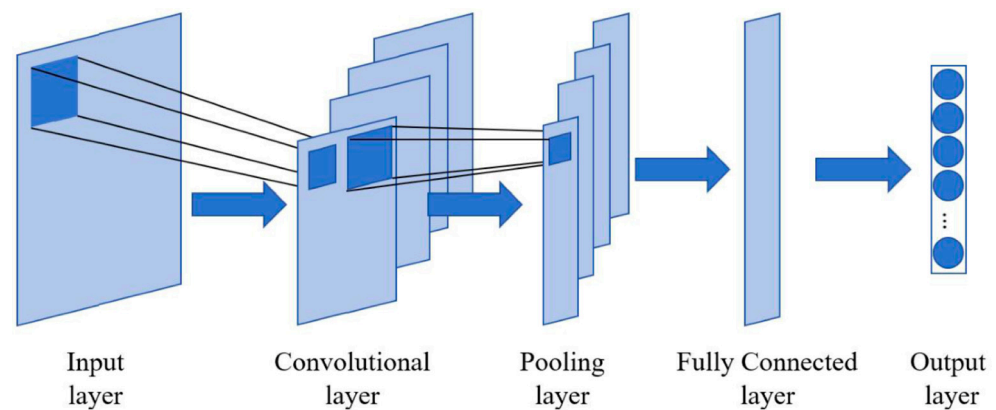


Figure 1. The specific structure of a CNN.

3.3.2. Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) networks were originally introduced by Hochreiter and Schmidhuber [58]. The structure is illustrated in Figure 2, and the definitions of the gating mechanism formulas are given by Equations (9)–(14).

$$f^t = \sigma(W_f \cdot [h^{(t-1)}, x^t] + b_f) \quad (9)$$

$$i^t = \sigma(W_i \cdot [h^{(t-1)}, x^t] + b_i) \quad (10)$$

$$\tilde{C}^t = \tanh(W_c \cdot [h^{(t-1)}, x^t] + b_c) \quad (11)$$

$$o^t = \sigma(W_o \cdot [h^{(t-1)}, x^t] + b_o) \quad (12)$$

$$C^t = f^t \otimes C^{(t-1)} + i^t \otimes \tilde{C}^t \quad (13)$$

$$h^t = o^t \otimes \tanh C^t \quad (14)$$

where t represents the time step; x^t and h^t represent the input and output vectors at time step t , respectively; C^t refers to the memory vector at time step t ; W_f , W_i , W_c , and W_o are the weight matrices; b_f , b_i , b_c , and b_o constitute the bias vectors; σ denotes the sigmoid activation function; $\tanh$ is the hyperbolic tangent function; f^t corresponds to the output of the forget gate; i^t is the output of the input gate; and $\tilde{C}^t$ is a temporary memory vector. The last two variables are combined to generate a new C^t with the long-term memory chain. $\otimes$ denotes the Hadamard product.

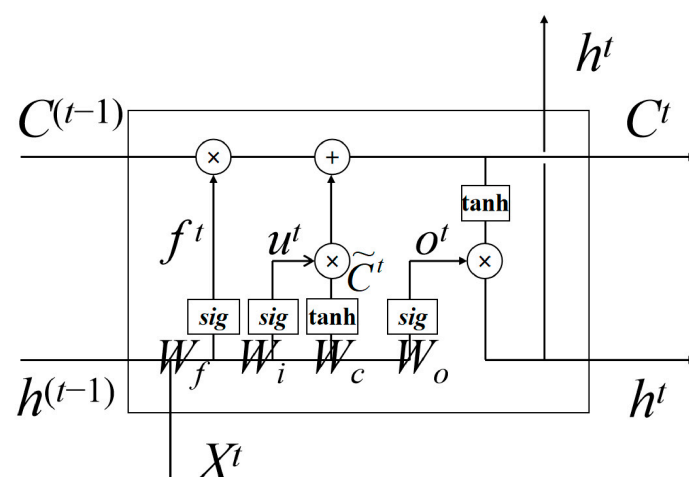


Figure 2. The structure of the LSTM unit.

3.3.3. Self-Attention Mechanism

The attention mechanism is a signal processing method that emulates the process by which the human brain handles information [59]. The self-attention mechanism can selectively focus on various segments while processing the input data, effectively capturing long-range dependencies [60]. The computational flow is as follows:

- (1) For the LSTM output sequence $H = (h^{t-n}, h^{t-n+1}, \dots, h^{t-1}, h^t)$, we calculate its similarity score matrix S .

$$S = H \cdot H^T \quad (15)$$

- (2) Through the application of the Softmax function, the similarity scores are transformed into a probability distribution [61]. This ensures that the total of the weights sums to 1.

$$a_j = \frac{e^{s_j}}{\sum_{t=n}^t e^{s_j}} \quad (16)$$

- (3) Ultimately, the computed weights are employed to calculate a weighted sum of all vectors, resulting in the self-attention sequence $A = (A^{t-n}, A^{t-n+1}, \dots, A^{t-1}, A^t)$, where the self-attention sequence A_j is defined as follows:

$$A_j = a_j \cdot h^j \quad (17)$$

where j represents the computation time step.

3.3.4. Genetic Algorithm

First proposed by John Holland in the 1970s, the genetic algorithm is a heuristic approach [62]. The algorithm is based on the theory of biological selection and evolution in nature and is widely used to solve and optimize various models. The genetic algorithm consists of several steps: initialization of the population, evaluation, selection, crossover, mutation, and iteration. The principles are illustrated in Figure 3.

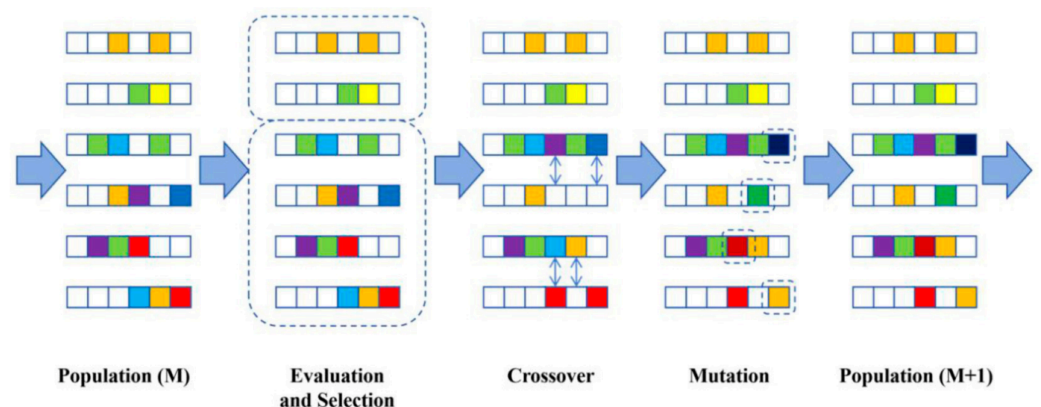


Figure 3. Principles of the genetic algorithm.

Through a genetic optimization algorithm, the hyperparameters can be tuned to obtain the most suitable hyperparameters for the model, thereby increasing the prediction accuracy and accelerating the convergence of the loss function.

3.3.5. Structure of the GA–CNN–LSTM–Self-Attention Prediction Model

In this study, the GA–CNN–LSTM–Self-Attention prediction model is utilized to predict transportation carbon emissions. In the proposed hybrid framework, the CNN module is first employed to extract local nonlinear features from the influencing factor data through convolution and pooling operations, thereby reducing redundant information and improving feature representation capability. The extracted feature sequences are then input into the LSTM network, which is responsible for capturing long-term temporal dependencies, historical variation patterns, and dynamic temporal information in transportation carbon emissions. Since transportation carbon emissions exhibit strong temporal continuity and long-term trends, the carbon emissions of previous years may significantly influence those of subsequent years, which cannot be effectively captured by the CNN module alone. Therefore, the CNN module mainly focuses on local feature extraction, while the LSTM module is responsible for learning temporal dependency characteristics.

Subsequently, the self-attention mechanism is introduced after the LSTM layer. The LSTM network outputs hidden state sequences representing temporal information at different time steps. However, the contributions of different temporal features to carbon emissions prediction may vary. Therefore, the self-attention mechanism assigns adaptive weights to the hidden state sequences generated by the LSTM network, enabling the model to focus more effectively on key temporal information and further improving the prediction accuracy of complex nonlinear time-series data. The prediction process can be seen in Figure 4.

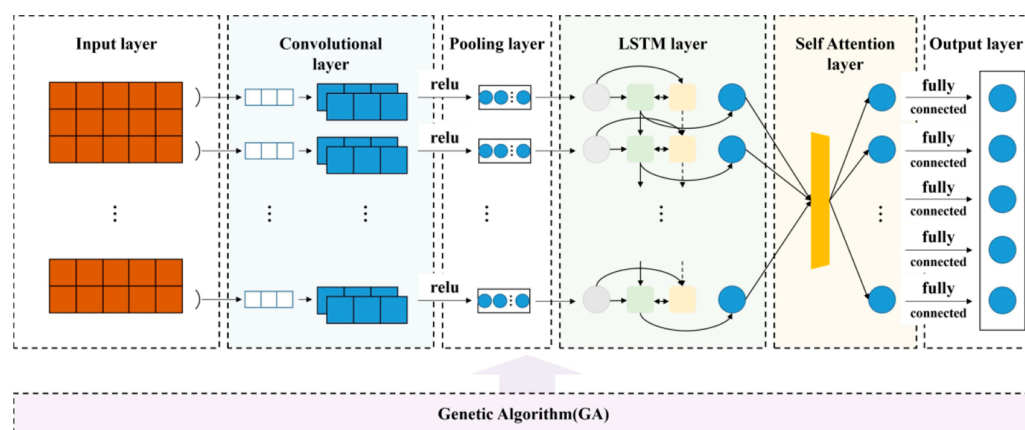


Figure 4. GA–CNN–LSTM–Self-Attention prediction model.

The procedure for predicting carbon emissions through the GA–CNN–LSTM–Self-Attention model is as follows:

1. Establish a CNN–LSTM–Self-Attention prediction model. A CNN is utilized to capture features from the input, and the dimensionality of the input features is compressed and reduced through convolution and pooling operations.
2. The processed information sequence is fed into the LSTM network to capture historical dependency data and produce the hidden layer information sequence H [60]. Subsequently, the self-attention mechanism is employed to allocate weights to the information sequence, thereby generating a new output sequence A .
3. The predicted results for carbon emissions are output through a fully connected layer and a regression layer.
4. Based upon the input results, a genetic algorithm is employed to iteratively optimize four hyperparameters of the model: Initial Learn Rate, Mini Batch Size, number of LSTM units, and dropout rate. The optimized hyperparameters are then re-input

into the prediction model, and the above process is repeated to obtain the prediction results optimized by the genetic algorithm.

3.3.6. Error Analysis

Three model evaluation indices were used in this study: R^2 (Coefficient of Determination), MAE (Mean Absolute Error), and RMSE (Root Mean Square Error). Their calculation methods are defined as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y_{pre})^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (18)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - y_{pre}| \quad (19)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y_{pre})^2} \quad (20)$$

where n denotes the sample size, y_i represents the actual value, and y_{pre} denotes the predicted value. $\bar{y}$ is the mean of the actual values.

The absolute and relative errors are also introduced to assess the discrepancies between the actual values and the predicted values. The methods for calculating these errors are as follows:

$$abs = |y_{pre} - y_i| \quad (21)$$

$$rel = \frac{|y_{pre} - y_i|}{|y_i|} \times 100 \% \quad (22)$$

where abs denotes the absolute error and rel denotes the relative error.

3.4. Selection of Influencing Factors

Identifying the factors which influence transportation carbon emissions is crucial for subsequent research. When selecting these factors, it is important to consider their relevance to carbon emissions, scientific validity, and data availability comprehensively.

Drawing upon a synthesis of prior studies [63–65] and an assessment of the significance of factors associated with carbon emissions, the following 20 influencing factors were initially selected for further analysis. The specific factors, symbols, and explanations are presented in Table 2.

Table 2. Details of the preliminary selection of influencing factors.

Influencing Factors	Symbol	Indicator Explanation and Calculation Method
Population	PO	Total permanent resident population
GDP	G	Gross regional product
Transportation GDP	TG	Gross output of the transportation industry
Urbanization Rate	UR	Ratio of urban population to total permanent resident population
Consumption Level	CL	Total retail sales of consumer goods
Vehicle Ownership	NOV	Total number of civilian vehicles

Table 2. Cont.

Influencing Factors	Symbol	Indicator Explanation and Calculation Method
Passenger Turnover	PT	Sum of passenger transport turnover after conversion for various modes
Freight Turnover	FT	Sum of freight transport turnover after conversion for various modes
Average Passenger Transport Distance	PTD	Average distance of passenger transport
Average Freight Transport Distance	FTD	Average distance of freight transport
Public Transport Volume	PV	The sum of public bus and rail transport passenger volume
Carbon Emission Intensity	CEI	Ratio of transportation carbon emissions to transportation GDP
Transportation Infrastructure Level	TIL	Ratio of usable road length to urban area
Transportation Structure	TS	Ratio of road passenger and freight turnover to total turnover
Industrial Structure	IS	Ratio of tertiary industry GDP to regional GDP
Proportion of Oil Energy	POE	Share of oil energy consumption converted to standard coal
Proportion of Railway Electrification	ERR	Ratio of electrified railway mileage to operational length
Proportion of Highway Greening	GRH	Ratio of green highway mileage to total operational mileage
Proportion of Highways	PH	Ratio of highway mileage to total operational mileage
Proportion of Electricity Energy	PEE	Proportion of electricity consumption converted to standard coal

4. Empirical Analysis

4.1. Carbon Emission Calculation Results

Located on the southeastern coast of China, Fujian Province possesses one of the most advanced comprehensive transportation systems in the country. Therefore, Fujian Province was selected as the case study region in this paper. Based on the transportation energy consumption data of Fujian Province published in the China Energy Statistical Yearbook, transportation carbon emissions and their compositional changes were calculated using Equation (2). The conversion coefficients of various energy sources into standard coal are listed in Table 1, while the F_{SC} of standard coal was calculated as 2.752 tons of CO₂ per ton of standard coal based on relevant references and statistical data. The detailed calculation results are presented in Figure 5.

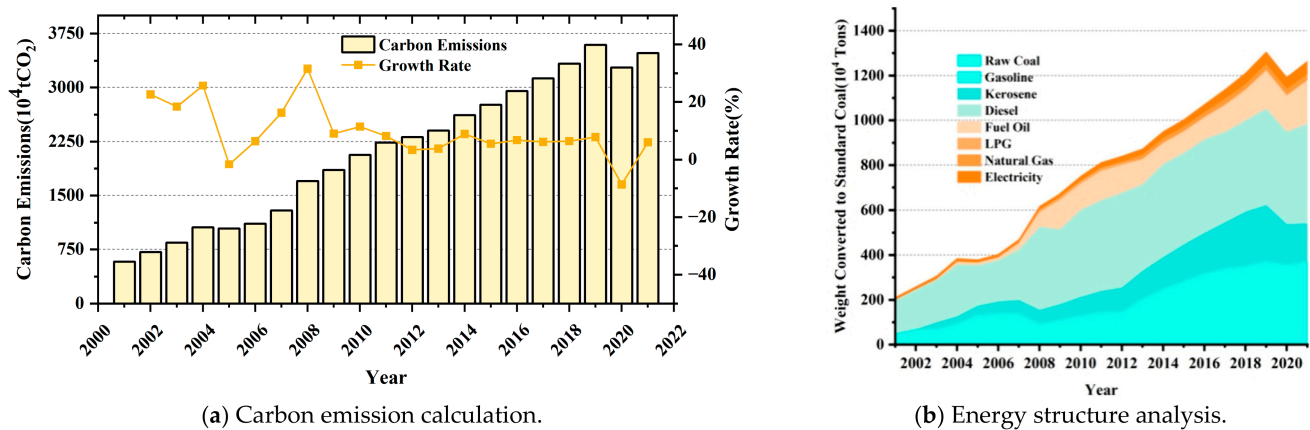


Figure 5. Results of carbon emission calculation and energy structural analysis.

As shown in Figure 5a, the y-axis represents the total carbon emissions of the transportation sector and the annual growth rate, respectively. From 2001 to 2021, transportation carbon emissions in Fujian Province exhibited an overall upward trend, with the growth rate remaining positive in most years. In 2020, due to the impact of the COVID-19 pandemic, transportation demand declined significantly, resulting in a noticeable reduction in carbon emissions.

Based on the standard coal conversion coefficients, Figure 5b analyzes the energy composition structure of carbon emissions, where the y-axis represents the amount of each energy type converted into standard coal equivalent. The principal energy sources contributing to carbon emissions are gasoline, kerosene, and diesel. The share of electricity in the total energy consumption of Fujian Province's transportation sector remains relatively small, which may be related to the difficulty in accurately accounting for electric vehicle energy consumption, as many vehicle owners charge their vehicles at home.

4.2. Selection of Carbon-Emissions-Influencing Factors

4.2.1. Data Preprocessing

When aiming to analyze the influencing factors and predict carbon emissions, it is necessary to standardize these factors to eliminate the impact of differing data dimensions on carbon emissions. The Z-score standardization method is detailed in Equation (23).

$$Z_i = \frac{X_i - \bar{X}}{\sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - \bar{X})^2}} \quad (23)$$

where Z_i indicates the standardized value, X_i denotes the original observation, and $\bar{X}$ represents the mean of the original observations.

4.2.2. Spearman Correlation Analysis Results

Based on the Fujian Statistical Yearbook, the specific values of the 20 initially selected influencing factors from 2001 to 2021 were obtained. Spearman rank correlation analysis was then conducted to calculate the correlation coefficients between carbon emissions and the influencing factors, and the results are presented in Figure 6.

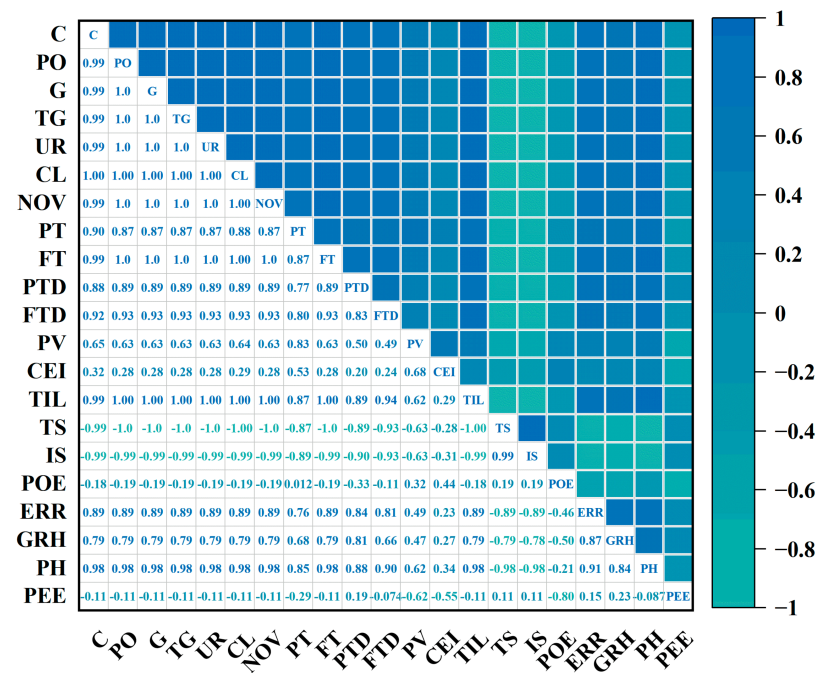


Figure 6. Results of Spearman correlation analysis.

In the heatmap, many factors exhibit Spearman rank correlation coefficients with carbon emissions close to 1 or -1 . This indicates strong positive or negative monotonic relationships with carbon emissions. The transportation structure and industrial structure are strongly negatively correlated with the monotonic changes in carbon emissions, meaning that, when carbon emissions change, the respective proportions of road passenger turnover and road freight turnover exhibit variation in the opposite direction, and the same applies to the industrial structure. Additionally, the proportions of oil energy and electricity energy also show a negative correlation, but the coefficients are close to 0, indicating that the relationship is not as significant as the aforementioned factors.

4.2.3. Final Selection of Influencing Factors

Using the Lasso regression method, carbon emissions served as the dependent variable, while the 20 influencing factors were treated as independent variables for the selection process. The selection was conducted using RStudio Version 2024.09.0+375. The results are illustrated in Figure 7.

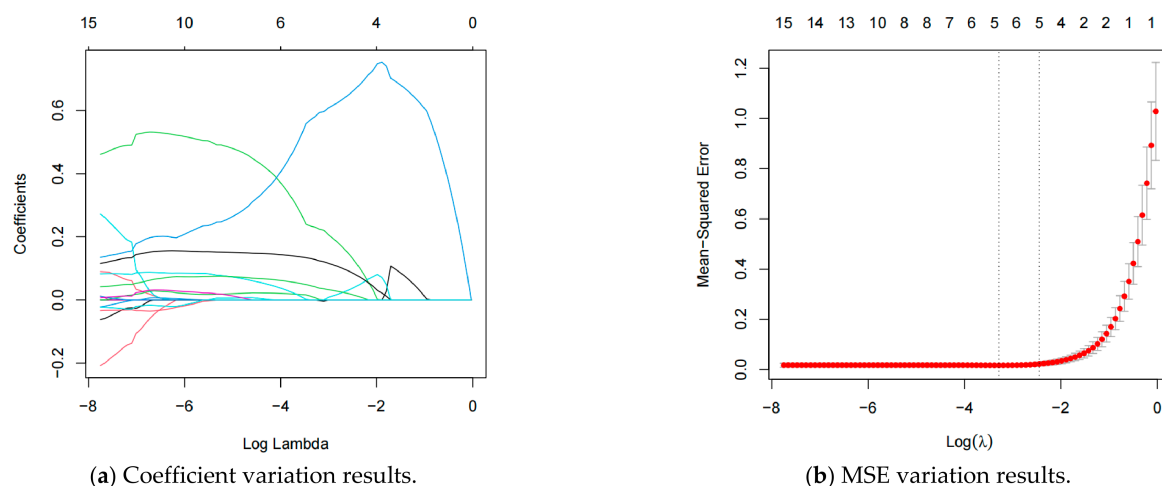


Figure 7. Lasso regression model results.

Figure 7a illustrates the variation in the coefficients of each influencing factor as the regularization parameter changes. The different curves in Figure 7a represent the coefficient trajectories of the influencing factors during the Lasso regression process. Figure 7b shows the variation in the number of retained influencing factors and the mean squared error (MSE) with changes in the regularization parameter. According to the results of the Lasso regression analysis, when the MSE reaches its minimum value, five influencing factors are retained. The selected influencing factors are: (1) transportation GDP (TG), (2) urbanization rate (UR), (3) passenger turnover (PT), (4) average freight transport distance (FTD), and (5) proportion of railway electrification (ERR). These five factors were identified as having the strongest relationship with carbon emission variations. Therefore, they were subsequently used as independent variables in the carbon emissions prediction model.

4.2.4. Results of the STIRPAT Model

The five selected influencing factors are categorized into three main classes, population (A), economy (P), and technology (T), as presented in Table 3.

Table 3. Classification results.

	Population (A)	Economy (P)	Technology (T)
Influencing Factor	UR PT	TG	FTD ERR

Based on the classification shown in Table 3 and the principles of the STIRPAT model, the STIRPAT model is appropriately expanded to the following STIRPAT model formula.

$$\ln I = \ln a + b \ln P_{UR} + c \ln P_{PT} + d \ln A_{TG} + f \ln T_{FTD} + g \ln T_{ERR} + e \quad (24)$$

To mitigate potential multicollinearity issues among the influencing factors, ridge regression analysis was utilized to estimate the model parameters. The ridge trace is shown in Figure 8.

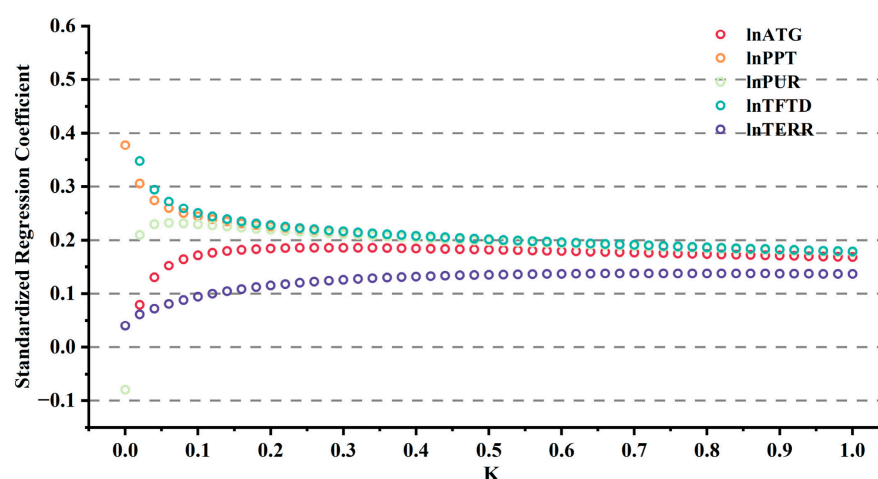


Figure 8. Ridge trace.

As seen in Figure 8, when the ridge parameter K is approximately 0.16, the values of the coefficients stabilize; therefore, $K = 0.16$ was selected. The model parameters when $K = 0.16$ are presented in Table 4, and Table 5 presents the values of the STIRPAT coefficients derived via ridge regression.

Table 4. Ridge regression metric results.

Indicator Name	Value	Indicator Name	Value
Mult R	0.989	SE	0.096
RSquare	0.978	F value	133.973
Adj RSqu	0.971	Sig F	0.000

Table 5. Ridge regression parameter results.

	Regression Coefficient	Standard Error of the Regression Coefficient	Standardized Regression Coefficient
$\ln A_{TG}$	0.274	0.036	0.247
$\ln P_{PT}$	0.318	0.067	0.203
$\ln P_{UR}$	0.925	0.085	0.247
$\ln T_{FTD}$	0.469	0.094	0.200
$\ln T_{ERR}$	0.322	0.120	0.111
Constant	1.412	0.601	0.000

Thus, the STIRPAT model of transportation carbon emissions in Fujian Province is derived as presented below:

$$\ln I = 1.412 + 0.925 \ln P_{UR} + 0.318 \ln P_{PT} + 0.274 \ln A_{TG} + 0.469 \ln T_{FTD} + 0.322 \ln T_{ERR} \quad (25)$$

The model coefficients represent the elasticity of transportation carbon emissions with respect to changes in the influencing factors. For example, the coefficient of the urbanization rate (UR) is 0.925, indicating that a 1% increase in the urbanization rate leads to a 0.925% increase in transportation carbon emissions, suggesting a positive relationship between urbanization and carbon emissions. This may be attributed to the fact that the urbanization process leads to population concentration, increased travel demand, and growth in vehicle ownership, thereby promoting transportation energy consumption. The same interpretation applies to the other influencing factors.

From the model, the ranking of the influencing factors based on their impact, from highest to lowest, is as follows: urbanization rate (UR), average freight transport distance (FTD), proportion of railway electrification (ERR), passenger turnover (PT), and transportation GDP (TG).

4.3. Comparison of Carbon Emissions Prediction Models

The values of the five influencing factors from 2001 to 2021, comprising a total of 21 samples, were used as independent input variables for the model, while the actual carbon emission values of the corresponding years were taken as the benchmark outputs. Due to the limited number of annual samples, the dataset was randomly divided into training and testing sets at a ratio of 80% to 20%. However, this approach may introduce potential temporal leakage because the chronological order of the time-series data was not strictly preserved.

The genetic algorithm was configured with a population size of 30, a maximum of 50 generations, single-point crossover, and a mutation probability of 10%, with the root mean square error (RMSE) on the testing set adopted as the fitness function. Based on this framework, the GA–CNN–LSTM–Self-Attention prediction model was trained and tested, and its prediction performance was compared with those of the SVR (support vector regression), LSTM, and CNN–LSTM–Self-Attention models. The comparison results are

shown in Figure 9, while the fitness curve of the GA–CNN–LSTM–Self-Attention model is presented in Figure 10.

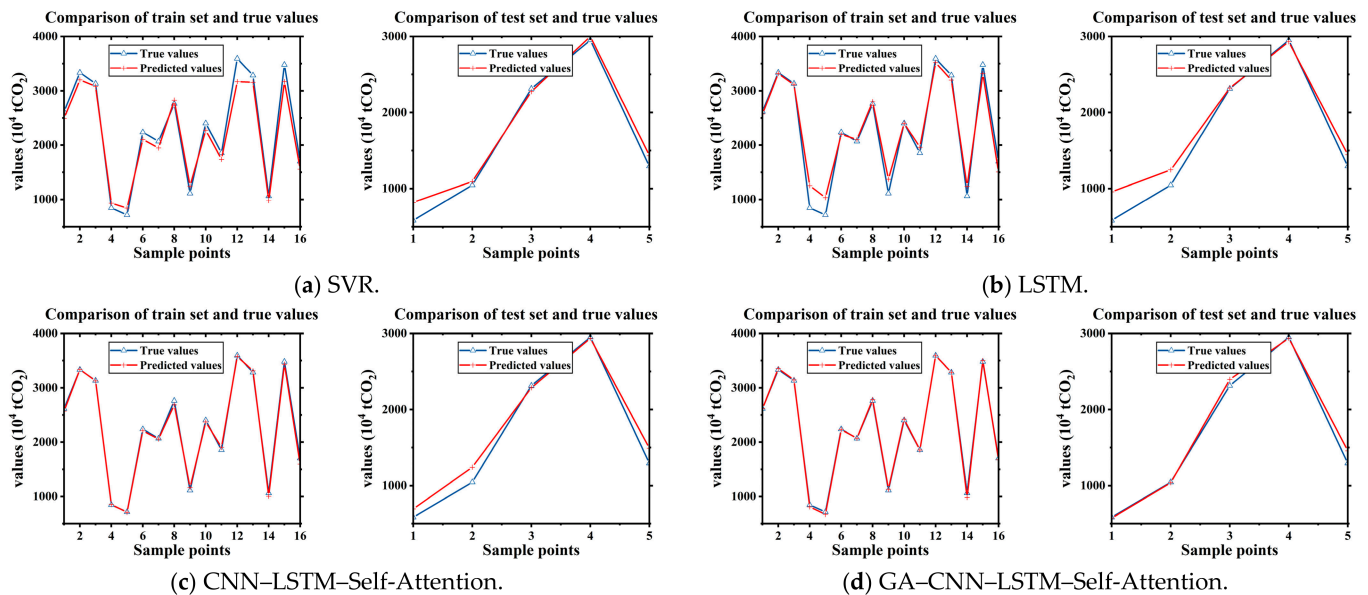


Figure 9. Train and test set fitting performance of the four models.

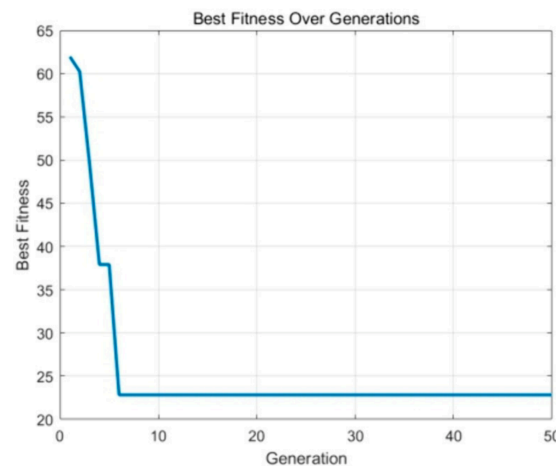


Figure 10. Fitness curve of the GA–CNN–LSTM–Self-Attention model.

Among the four models, the GA–CNN–LSTM–Self-Attention prediction model demonstrated good results in both training and testing. The fitting degree of the training and testing sets to the actual values was highest among the tested models. As shown by the fitness curve, the genetic algorithm also achieved a good convergence speed, successfully identifying the optimal hyperparameter values for the model by the sixth iteration.

The calculation results of R^2 , MAE, and RMSE for the four models are shown in Table 6.

Table 6. Evaluation indices of the four models.

Prediction Model	R^2	MAE	RMSE
SVR	0.978	102	128
LSTM	0.945	153	456
CNN–LSTM–Self-Attention	0.977	97	295
GA–CNN–LSTM–Self-Attention	0.994	57	152

Note: The units for MAE and RMSE are (10^4 tCO₂).

The GA–CNN–LSTM–Self-Attention prediction model achieves the best performance, with an R^2 of 0.994 and MSE and RMSE values of 57 and 152, respectively, both significantly lower than those of the other comparison models. Overall, genetic algorithm optimization can enhance the predictive performance of the model.

It should be noted that the COVID-19 pandemic in 2020 caused a significant decline in transportation demand, resulting in an unusual reduction in transportation carbon emissions during that year. In this study, the 2020 sample was retained in the model training process because the pandemic represented an actual external shock rather than a data error. However, this unusual fluctuation may still affect the model's learning of long-term emission trends and introduce uncertainty into future prediction results to some extent. Therefore, the prediction results should be interpreted with caution when considering the influence of unexpected external events. Future studies may further improve prediction robustness by incorporating external shock variables or adopting more robust time-series prediction methods.

5. Discussion

5.1. Scenario Setting

Scenario analysis is an effective approach for assessing the impacts of future uncertainties on decision-making and its potential outcomes. Constructing various possible future scenarios helps researchers and decision-makers understand the potential results under different conditions. Three scenarios were analyzed in this study: (a) baseline, (b) restriction, and (c) control, where the growth rates of influencing factors were adjusted according to different levels of policy intervention. Detailed descriptions of the three scenarios are provided below.

- (a) **Baseline Scenario:** This scenario does not adopt additional carbon emission restriction measures to lower carbon dioxide emission levels while ensuring policy objectives. The variation rates of the factors are primarily based on historical growth rates and socioeconomic development.
- (b) **Restriction Scenario:** This scenario considers the impacts of moderate low-carbon policy interventions on transportation development. Specifically, policies promoting public transportation construction, green travel, transportation structure optimization, railway electrification, and clean energy utilization are taken into account. Under these measures, the pace of urbanization is expected to accelerate, the efficiency of passenger and freight transportation will improve, clean energy utilization will increase, and the level of electrification will continue to rise. These assumptions are mainly based on relevant transportation and low-carbon development plans issued by the Chinese government and Fujian Province.
- (c) **Control Scenario:** Building on the restriction scenario, this scenario further strengthens policy implementation, further optimizing efficiency in passenger and freight transportation, reducing and constraining the utilization of fossil fuels, and increasing the proportion of clean energy. Under this influence, the growth rate of transportation GDP is expected to temporarily slow down.

Trends in influencing factors serve as the foundation for carbon emission scenario predictions, making the precise settings of these factors extremely important. The specific basis for the settings is provided below.

Urbanization rate: Fujian provincial government projections suggest that the urbanization rate will reach 71.5% by 2025. With continued progress expected by 2035, urbanization is projected to enter a mature stage, with the urbanization rate reaching 78% and the urban population peaking, achieving the basic realization of new urbanization. Based on this

target, different growth rates for the urbanization rate in Fujian Province from 2022 to 2035 were set.

Passenger Turnover Volume: The relevant document issued by the authorities in Fujian Province emphasizes the need to “actively guide low-carbon travel, accelerate the construction of large-capacity public transportation infrastructure such as urban rail transit, bus exclusive lanes, and rapid bus systems, and actively encourage the public to choose green and low-carbon transportation methods.” Based on these policy objectives, the growth rates for passenger turnover volume were determined.

Proportion of Electrified Railway Mileage: Based on the strategic documents regarding the development of a modern transportation network and low-carbon development in the railway sector, China aims to achieve an electrification rate of at least 78% for railways by 2030. By 2021, Fujian Province had already achieved an electrified railway mileage of 84.3%, exceeding the set target ahead of time. Over the past five years, the annual growth rate of the proportion of electrified railway mileage in Fujian has been 0.8%. Based on this, growth rates for the proportion of electrified railway mileage were set.

Average Freight Distance: The relevant plan for the development of a modern comprehensive transportation system proposed by the State Council of China aims to establish an efficient freight service system. The Fujian Provincial Transportation Department’s “Implementation Plan for Further Optimizing and Adjusting the Transportation Structure” describes plans to significantly improve the level of multimodal transport in Fujian by the end of 2027, striving to form a development pattern where the long-distance transportation of bulk goods and containers is primarily carried out via rail and water. In the future, due to improvements in the freight structure, the average freight distance in Fujian Province is expected to decline.

Transportation GDP: The report from the relevant authorities in Fujian Province indicates that the main expected goals for economic and social development in 2025 are as follows: “Strive to promote high-quality development, focusing on economic system reform to further deepen reforms comprehensively and expand high-level opening-up. The expected growth rate of the province’s GDP is 5.0% to 5.5%, aiming for better results based on actual conditions.” The average growth rate of transportation GDP in Fujian Province over the past decade has been 7%, and based on this, growth rates for transportation GDP were established.

In summary, the parameters for the urbanization rate, passenger turnover volume, proportion of electrified railway mileage, average freight transport distance, and transportation GDP growth rate as transportation influencing factors in Fujian Province are detailed in Table 7.

Table 7. Scenario parameter settings.

Variable Name	Scenario Type	Growth Rate Parameter Settings (%)		
		2022–2025	2026–2030	2031–2035
Urbanization Rate	Baseline	0.9	0.8	0.75
	Restriction	1.5	0.7	0.4
	Control	2	0.5	0.2
Transportation GDP	Baseline	7	8	10
	Restriction	6.5	8	9
	Control	6.5	5	4
Passenger Turnover	Baseline	5	7	9
	Restriction	4.5	5	6
	Control	4.5	3	1

Table 7. Cont.

Variable Name	Scenario Type	Growth Rate Parameter Settings (%)		
		2022–2025	2026–2030	2031–2035
Average Freight Transport Distance	Baseline	1.5	2.5	3.5
	Restriction	1.5	0.5	−0.5
	Control	1	−0.5	−2
Proportion of Railway Electrification	Baseline	0.6	0.4	0.2
	Restriction	0.7	0.45	0.2
	Control	0.8	0.5	0.2

5.2. Results of Different Scenarios

Using the GA–CNN–LSTM–Self-Attention prediction model and the scenario parameter settings, the predicted carbon emission values were calculated from 2022 to 2035. The results are illustrated in Figure 11, and the corresponding growth rate predictions are presented in Figure 12, with detailed values provided in Table 8.

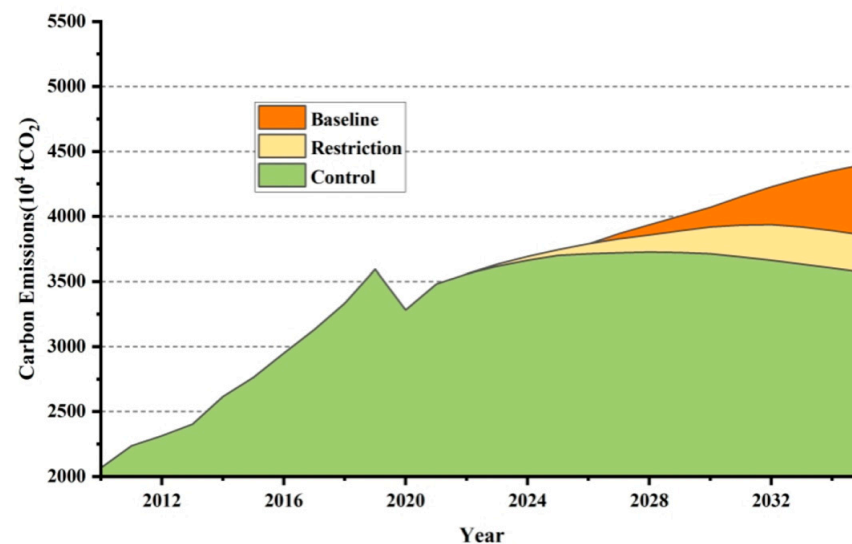


Figure 11. Scenario prediction results of carbon emissions.

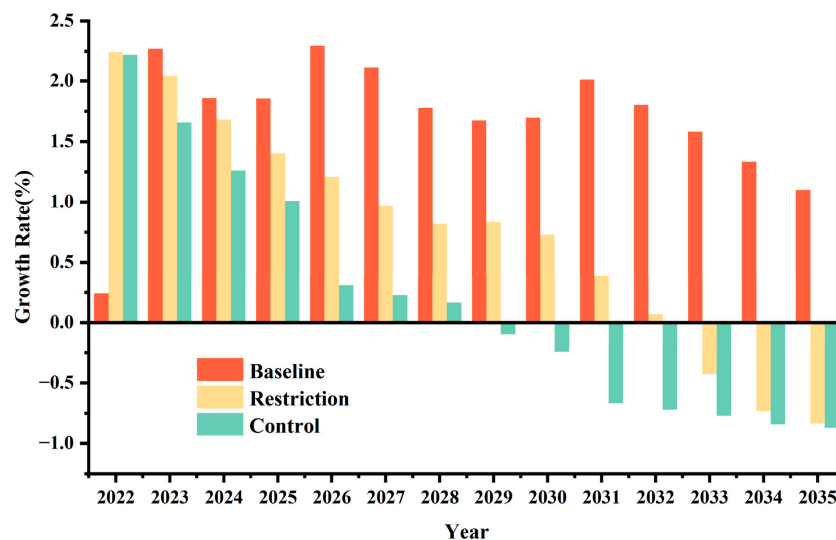


Figure 12. Scenario prediction results of the carbon emission growth rate.

Table 8. Specific values of carbon emissions predictions in different scenarios.

Year	Baseline (Million Tons)	Growth Rate (%)	Restriction (Million Tons)	Growth Rate (%)	Control (Million Tons)	Growth Rate (%)
2022	34.89	0.24	35.59	2.24	35.58	2.22
2023	35.68	2.27	36.31	2.04	36.17	1.66
2024	36.34	1.86	36.92	1.68	36.62	1.26
2025	37.02	1.85	37.44	1.40	36.99	1.01
2026	37.87	2.29	37.89	1.21	37.11	0.31
2027	38.67	2.11	38.26	0.97	37.19	0.23
2028	39.35	1.78	38.57	0.82	37.25	0.16
2029	40.01	1.67	38.90	0.83	37.22	−0.09
2030	40.69	1.70	39.18	0.73	37.13	−0.24
2031	41.51	2.01	39.33	0.39	36.88	−0.67
2032	42.26	1.80	39.36	0.07	36.61	−0.72
2033	42.93	1.58	39.19	−0.43	36.33	−0.78
2034	43.50	1.33	38.90	−0.73	36.02	−0.85
2035	43.98	1.10	38.58	−0.84	35.71	−0.87

Carbon emissions in Fujian Province are projected to increase continuously from 2022 to 2035 under the baseline scenario, with no identifiable carbon emission peak during the study period. The annual growth rate of carbon emissions ranges from approximately 1.0% to 2.3%. Under the restriction scenario, carbon emissions are projected to peak in 2032 at approximately 39.36 million tons of CO₂, indicating that the target of carbon peaking before 2030 would not be achieved. Under the control scenario, carbon emissions are expected to peak in 2028 at approximately 37.25 million tons of CO₂, successfully achieving the carbon peaking target before 2030. Compared with the baseline scenario, cumulative carbon emissions in Fujian Province from 2022 to 2035 under the restriction and control scenarios are projected to decrease by approximately 20.28 million tons and 41.89 million tons of CO₂, respectively.

Based on the empirical results, several policy implications can be proposed. First, since the urbanization rate was identified as the most influential factor affecting transportation carbon emissions, future urban development should emphasize low-carbon urbanization strategies, including optimizing urban spatial layouts, promoting transit-oriented development, and improving public transportation systems. Second, as road transportation remains the dominant source of transportation carbon emissions, greater efforts should be made to optimize the transportation structure by encouraging the transfer of bulk freight transportation from road transport to railways and waterways. Third, the improvement of railway electrification and clean energy utilization should continue to be promoted to reduce dependence on fossil fuels and improve transportation energy efficiency. In addition, accelerating the electrification of road transportation, including the promotion of electric vehicles and charging infrastructure construction, may further contribute to carbon emission reduction. Finally, the scenario analysis indicates that carbon emissions can only peak under the control scenario, suggesting that stronger low-carbon policy interventions are necessary to achieve regional carbon reduction targets.

6. Conclusions

This study investigates the influencing factors of transportation carbon emissions in Fujian Province and explores sustainable transportation development pathways through carbon emissions prediction from 2022 to 2035. A top-down approach was employed to compute the carbon emissions from 2001 to 2021. Based on prior research and scholarly judgments, 20 potential influencing factors associated with TCE were selected. The

Spearman–Lasso–STIRPAT method was used to analyze these factors. In the final phase of the study, the predictive performance of the GA–CNN–LSTM–Self-Attention model was compared with that of the SVR, LSTM, and CNN–LSTM–Self-Attention models. The GA–CNN–LSTM–Self-Attention model, combined with scenario analysis, was then applied to forecast carbon emissions in Fujian for the years 2022 to 2035. From this research, the main findings are summarized as follows.

1. Over the past two decades, energy consumption in Fujian’s transportation sector has typically demonstrated a rising trend, with carbon emissions peaking in 2019 at approximately 35.94 million tons of CO₂. Carbon emissions decreased in 2020 because of the COVID-19 pandemic, but they are currently undergoing a gradual recovery. The primary energy sources contributing to carbon emissions in Fujian’s transportation sector are gasoline, kerosene, and diesel, while the use of electric energy in transportation has not yet been widely adopted.
2. The analysis of influencing factors revealed that the urbanization rate (UR), average freight transport distance (FTD), proportion of railway electrification (ERR), passenger turnover (PT), and transportation GDP (TG) constitute the five most significant determinants of carbon emissions in Fujian, with respective STIRPAT model coefficients of 0.925, 0.469, 0.322, 0.318, and 0.274.
3. In comparison to the SVR, LSTM, and CNN–LSTM–Self-Attention models, the GA–CNN–LSTM–Self-Attention prediction model demonstrated better predictive accuracy, confirming its effectiveness. As indicated by the predictions, neither the baseline scenario nor the restriction scenario succeeds in achieving the objective of attaining carbon peaking before 2030. In the control scenario, carbon emissions are expected to reach their peak in 2028, amounting to approximately 37.25 million tons of CO₂. The transportation sector in Fujian Province has significant potential for emission reduction. These findings indicate that promoting low-carbon transportation transition is essential for achieving sustainable regional development.

Although this study has demonstrated good prediction performance in transportation carbon emission forecasting, several methodological limitations still exist. Due to the limited number of annual samples, potential overfitting risks may exist in the proposed hybrid deep learning model. In addition, the random train–test splitting strategy may introduce temporal leakage because the chronological order of the time-series data was not strictly preserved. Therefore, the prediction results should be interpreted with caution regarding long-term generalization capability.

Furthermore, more heuristic optimization algorithms can be introduced to optimize the hyperparameters of deep learning models. The indicator system for transportation carbon emissions can also be further expanded, and more comprehensive influencing factor screening mechanisms can be established to improve the interpretability, prediction accuracy, and robustness of the model.

The findings of this study also have important implications for sustainable transportation development and regional low-carbon transition. By improving the prediction accuracy of transportation carbon emissions and identifying key influencing factors, this study can provide scientific support for sustainable transportation planning, energy structure optimization, and long-term carbon reduction policy formulation. In particular, the proposed prediction framework may contribute to promoting sustainable urbanization, improving transportation energy efficiency, and supporting the achievement of carbon peaking and carbon neutrality goals.

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