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Forecasting Road Freight Demand and Estimating Carbon Emissions Using ConvLSTM: The Chengdu-Chongqing Urban Cluster Case

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Abstract: *In recent years, the emission problems associated with freight transportation in urban areas have become increasingly severe, significantly affecting residents' health and the environment. To address this, this study focuses on the Chengdu-Chongqing urban cluster as a typical example and proposes a pollutant measurement and prediction method based on forecasting highway freight transportation volume in the region. The study utilizes OD (Origin-Destination) data of road freight from the online freight exchange platform (OFEP) in the Chengdu-Chongqing area, collected between November 1, 2017, and March 7, 2018. Taking into account the time and spatial characteristics of freight data, a spatiotemporal prediction model of OD freight volume is developed using ConvLSTM. For comparison, an LSTM model is also established. The results indicate that the ConvLSTM model, which incorporates spatial characteristics, achieves higher prediction accuracy. Using the predicted freight demand data, carbon emissions are calculated using a top-down approach, revealing the distribution of carbon emissions across each OD pair in the Chengdu-Chongqing urban cluster. The analysis of short-term emission trends provides valuable insights into the precise regulation of carbon emissions from road freight.*

Keywords: *road freight prediction, carbon emission measurement, ConvLSTM, OD Freight Volume*

1. Introduction

Urban freight systems are increasingly strained by growing logistics demand and worsening congestion, driven by urbanization and e-commerce. Freight vehicles contribute nearly 30% to urban traffic congestion, which incurs global economic losses of $1 trillion annually[1]. Enhancing freight efficiency and reducing carbon emissions have become urgent under China's "dual carbon" goals. This study proposes a novel approach to freight flow prediction and carbon emission management, focusing on the spatiotemporal dynamics of road freight in urban clusters.

Urban road freight forecasting has advanced significantly. Traditional methods like the grey model, regression analysis, and time series approaches [3-4] handle stable freight demand well but struggle with dynamic urban systems. With the rise of big data and AI, methods like BP neural networks [5] and LSTM models [6-8] have improved short-term freight predictions. However, many models overlook freight demand's intrinsic spatial patterns, focusing instead on external features like economic indicators and weather. To address this, this study employs a ConvLSTM model, which captures spatiotemporal variations more effectively than LSTM. This approach enhances freight demand predictions, identifies carbon emission hotspots, and supports targeted mitigation strategies.

Despite advances in carbon emission measurement, freight transportation lacks a standardized approach. Current methods include top-down macro-level accounting, which relies on historical data but offers limited real-time insights, and bottom-up micro-level accounting, which provides precision but faces data collection challenges. This study addresses these issues by utilizing road freight volume predictions to generate timely, reliable data for carbon emission measurement, mitigating the latency of top-down methods.

We utilized freight OD data from the online freight exchange platform (OFEP), focusing on the freight volume between 16 cities in the Chengdu-Chongqing urban cluster from November 2017 to March 2018. Based on this dataset, we developed a ConvLSTM model to forecast intercity freight demand for the upcoming week and calculated the carbon emissions for the entire region during the same period. In total, over 800,000 records were processed. The ConvLSTM model demonstrated a 9% improvement in accuracy compared to traditional LSTM models, underscoring the critical role of spatial features in freight flow forecasting. This research bridges the gap in short-term freight demand and carbon emission predictions within urban clusters, effectively addressing the growing challenges of freight-related carbon emissions. This integrated framework lays the foundation for more precise and effective carbon emission management in the freight sector, aligning with broader sustainability goals and the urgent need for climate action.

2. Literature Review

2.1. Literature review about road freight volume forecasting

In terms of the selection of research objects, current road freight forecasting models mainly focus on predicting long-term time series of road freight volume, often considering only economic factors and temporal trends [4-6]. However, limited attention has been paid to the spatial characteristics of freight demand. Reference [10] emphasized that regional freight volume involves multiple origins and destinations, making it necessary to forecast freight volumes for multiple OD pairs simultaneously. This approach not only expands the scope of freight forecasting research but also better aligns with practical production and operational needs. Time series forecasting methods focus on analyzing temporal trends to make predictions. For example, ARMA has been used to quantitatively predict road freight volume, supporting market management decisions [4]. However, these methods face limitations in addressing nonlinear problems and environments characterized by significant changes or fluctuations.

Regarding research methods, prediction models based on statistical theory are relatively simple. For example, the gray model prediction method effectively handles situations with uncertain data systems and limited data availability [2]. Reference [3] analyzed the correlation between influencing factors and road freight volume using scatter plots. After eliminating weakly correlated factors, a multiple linear regression model was employed to predict road freight volume in 2018. However, such methods are constrained by their reliance on approximating each factor as a linear function. Machine learning methods have demonstrated strong potential in overcoming these limitations. Many studies have utilized LSTM and its variants to build models for forecasting freight volume, with substantial success in short-term predictions [6-9]. For instance, Reference [9] combined CNN and LSTM to simultaneously extract the temporal and spatial features of urban rail passenger flow, demonstrating CNN's potential for capturing the spatial characteristics of transportation volume. Similarly, Reference [11] utilized Markov and GM(1,1) models for predictions, showcasing the versatility of combining traditional statistical models with machine learning techniques.

2.2. Literature review about transportation carbon emission measurement

The transportation sector is the second-largest source of global carbon emissions, according to the IEA. Carbon emission measurement methods for freight lack a unified standard, with two main approaches used internationally: top-down and bottom-up. The top-down method calculates emissions by multiplying sector-wide fuel consumption data with emission coefficients, suitable for industry-level estimates. For example, Reference [12] analyzed direct and indirect transportation emissions, while Reference [13] applied the method to Gansu Province's emissions from 2000–2003 using IPCC guidelines. The bottom-up method uses detailed data, such as mileage, vehicle types, and fuel-specific emission factors, for higher precision[14]. Reference [15] applied this method to measure emissions in China’s urban clusters, incorporating travel activity, mode share, fuel intensity, and emission factors. While top-down is limited by delayed accuracy, bottom-up offers precision but requires extensive data, posing significant challenges.

3. Methodology

3.1. Multidimensional spatiotemporal freight flow data construction

The prediction and allocation of urban OD freight volume is a complex process that involves multidimensional spatiotemporal data. For this purpose, this study represents freight flow data, incorporating weather and distance information, as multidimensional spatiotemporal images. Freight OD data for a single day is typically recorded in an OD matrix. Assuming the dataset consists of M origin

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cities and N destination cities over a period of T days, the freight volumes for each city on a given day are treated as "pixel values." The daily OD matrix $X_d \in \mathbb{R}^{M\times N}$ represents the freight volume from each origin city to each destination city.

$$X_d = \begin{bmatrix} x_d[1,1] & x_d[1,2] & \cdots & \cdots & x_d[1,N] \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_d[a,1] & \cdots & x_d[a,b] & \cdots & x_d[a,N] \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_d[M,1] & x_d[M,2] & \cdots & \cdots & x_d[M,N] \end{bmatrix} \tag{1}$$

Each element $\mathrm{X}_d[i,j]$ in the matrix denotes the freight volume from origin city i to destination city j. If data is missing, it is filled with 0.

Similar to freight data, weather data also exhibits both spatial and temporal dimensions. Constructing a weather matrix allows for an effective representation of the impact of weather conditions on freight transportation. As a significant factor influencing the prediction of city group OD freight volume, weather conditions must be incorporated into the model for feature learning. Therefore, the daily weather data collected for each city requires further processing. By creating a matrix that includes multiple weather indicators, the potential impact of weather factors on freight transportation can be quantified, providing a solid foundation for subsequent analysis or model input.

Since drivers typically rely on the weather conditions of the departure city as the primary reference for their daily freight plans, this study focuses on the weather data of the departure city. Based on the collected weather data, a weather OD matrix $W_d \in \mathbb{R}^{N\times K}$ is generated, as follows:

$$W_d = \begin{bmatrix} w_d[1,1] & \cdots & w_d[1,K] \\ w_d[2,1] & \cdots & w_d[2,K] \\ \vdots & \ddots & \vdots \\ w_d[M,1] & \cdots & w_d[M,K] \end{bmatrix} \tag{2}$$

3.2. ConvLSTM Model

The road freight volume is influenced by factors such as the policy environment, regional industrial output, freight index, transportation capacity, and other indicators. It generally follows a two-dimensional spatiotemporal pattern, exhibiting nonlinearity and short-term random fluctuations. Therefore, forecasting regional road freight demand requires considering both temporal and spatial characteristics. Temporally, this is reflected in the historical demand patterns of regional road freight and the time evolution of external factors. Spatially, it manifests in the spatial distribution of freight volumes within the OD matrix and the varying distribution of regional economic indicators. Given the nonlinear relationships inherent in these characteristics, this study adopts a neural network approach for freight volume forecasting.

The Convolutional Long Short-Term Memory (ConvLSTM) network, proposed in 2015 [16], is a deep learning model variant that combines the spatial feature extraction capabilities of CNN with the time-series processing strength of LSTM. Its architecture is shown in *Figure 1*.

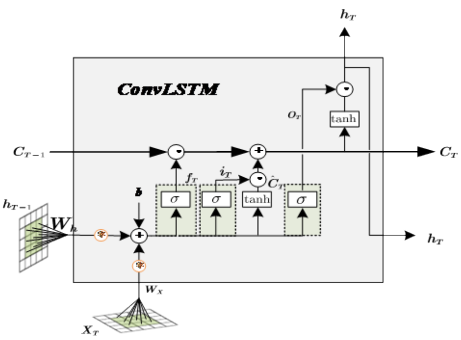

Figure 1: The structure of ConvLSTM.

ISSN 2616-5775 Vol. 8, Issue 1: 71-79, DOI: 10.25236/AJCIS.2025.080110

Considering the impact of the historical freight volume of the first d days immediately adjacent to date t, we took the OD data of the freight volume of the first d days as the input of the main network model, and the processed spatiotemporal information flow would be further screened and updated through the three gate units of ConvLSTM. The state information h_{d-1} of the previous period, the comprehensive state of the cell C_{d-1} and the current input variable X_d are fed to the "input gate" and "forgetting gate", the information passes through the "forgetting gate", resulting in the proportion f_d that C_{d-1} is retained, the "input gate" produces the remaining proportion i_d of the candidate state $\tilde{C}_d$, the "output gate" judges the state feature o_d of the current freight volume based on the state information h_{d-1} of the previous period and X_d, and generates the current state information h_d based on the above information. This process is repeated many times according to the set size of d and the number of samples, and finally we get the spatiotemporal state information of freight volume extracted by ConvLSTM. The specific calculation process is as follows:(*j*=1,2,…, *d*)

Forget gate:

$$f_d = \sigma(W_f * [h_{d-1}, X_d] + W_f \circ C_{d-1} + b_f) \tag{3}$$

Input gate:

$$i_d = \sigma(W_i * [h_{d-1}, X_d] + W_i \circ C_{d-1} + b_i) \tag{4}$$

Candidate Cell State:

$$\tilde{C}_d = \tanh(W_c * [h_{d-1}, X_d] + b_c) \tag{5}$$

Comprehensive state:

$$C_d = f_d \circ C_{d-1,} + i_d \circ \tilde{C}_d \tag{6}$$

Output gate:

$$o_d = \sigma(W_o * [h_{d-1}, X_d] + W_o \circ C_{d-1} + b_o) \tag{7}$$

Hidden State:

$$h_d = o_d \circ \tanh(C_d) \tag{8}$$

Here, * means convolution operation, $\circ$ means Hadamard product, W represents the convolution kernel weight coefficient matrix (for example, W_f is the weight coefficient matrix of the "forget gate" convolution kernel, W_i is the weight coefficient matrix of the "input gate" convolution kernel, and so on); b represents the bias vector (for example, b_f is the bias vector of the "forgetting gate", b_i is the bias vector of the "input gate", and so on); $\sigma(\cdot)$ represents that the activation function of ConvLSTM is sigmoid function; $g(\cdot)$ represents that the activation function of ConvLSTM is tanh function; C is the storage state of spatiotemporal characteristic information of freight volume in nerve cells.

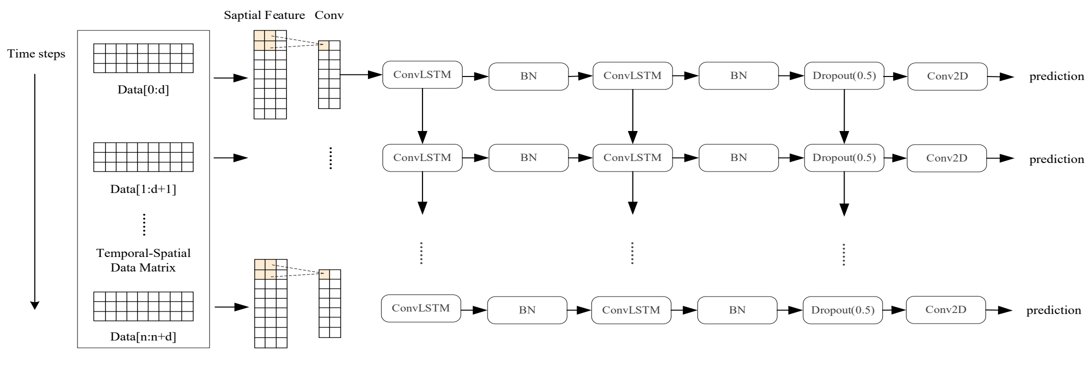

Figure 2: The overall structure of the model.

Finally, we used a Conv2D layer to filter and reduce the dimensionality of the spatiotemporal patterns output by the ConvLSTM layer. The spatiotemporal features were input into the convolutional layer with a stride of 1 for the convolution kernel and zero-padding applied. Through the Conv2D layer, the previously extracted feature information was fused, reducing the input data from multiple dimensions to a one-dimensional channel dimension. To enhance the model's generalization ability and running speed while preventing changes in data distribution across intermediate network layers, we added a Batch Normalization (BN) layer after each ConvLSTM laye. To avoid overfitting, we incorporated a dropout layer into the model. The Dropout layer reduces model complexity by randomly dropping some neurons during each training batch. The overall structure of the model is shown in Figure 2.

3.3. Calculation of Regional Future Carbon Emissions

Based on the forecasted road freight volume, the corresponding carbon dioxide emissions are then measured. This provides a reference for the freight platform to regulate freight activities in a timely manner according to carbon emission warnings, helping to prevent excessive concentration of carbon emissions in certain areas. Given the availability of data, this study used a top-down method to estimate the carbon emissions of the Chengdu-Chongqing urban cluster for the following week.

According to the methodology outlined in the IPCC (2023) [17], the carbon emissions of road freight are calculated using the *Formula (9)*.

$$E = \sum_j T_j \cdot EF_j \cdot C_j \tag{9}$$

Here, j represents the type of fuel, E represents the energy consumption of road freight, T_j represents the turnover of road freight with fuel j (100 million ton-kilometers), EF_j represents the energy consumption per unit turnover of road freight with fuel j, C_j represents j fuel carbon emission factor.

4. Experimental Design

4.1. Research Object and Data source

The freight OD data used in this study is sourced from a domestic online freight trading platform, This study specifically focuses on the departure and destination cities within the Chengdu-Chongqing urban agglomeration, in line with the Chengdu-Chongqing Twin-City Urban Cluster Development Plan. Sixteen cities were selected for analysis, including Chengdu, Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, Ziyang, and Chongqing. The study area is depicted in *Figure 3*.

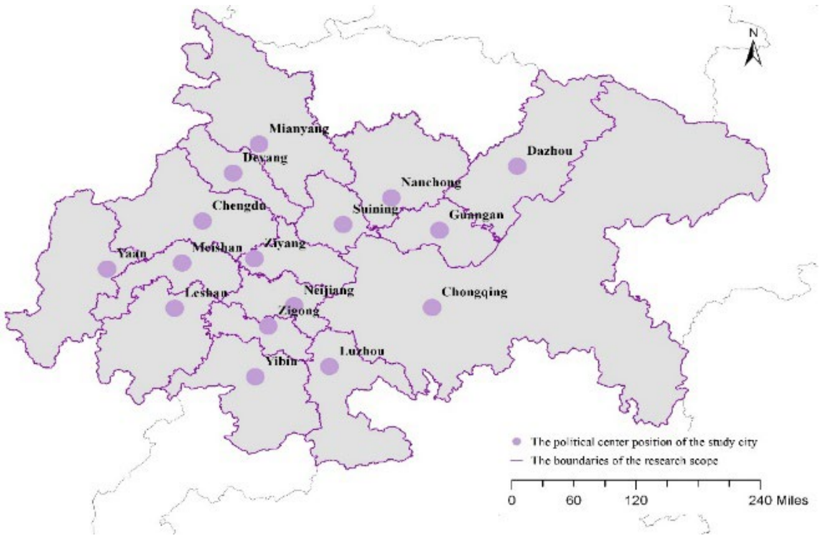

Figure 3: The study area and cities involved in the Chengdu-Chongqing urban agglomeration.

The data spans the period from November 1, 2017, to March 7, 2018. The total number of data entries is 85,766. The format of some data fields is shown in *Table 1*:

ISSN 2616-5775 Vol. 8, Issue 1: 71-79, DOI: 10.25236/AJCIS.2025.080110

Table 1: Freight OD Data Set Fields and Descriptions.

Field Name	Description
Date	The data type is datetime64[ns], and the calculation unit is days
Departure City	The scope of the cities covers 16 cities in the Chengdu-Chongqing region
Arrival City	The scope of the cities covers 16 cities in the Chengdu-Chongqing region
Total Distance	The total highway trunk mileage for cargo transportation, in kilometers
Cargo Weight	The data type is float64, and the unit is tons

4.2. Parameters

Considering the influence of freight volume history over the q days immediately preceding date t, this study incorporates the OD freight volume data from the previous q days along with other influencing factors as inputs to the model. Given the periodic nature of freight activities and the importance of prediction accuracy, we set q=7.

After normalizing the data, the dataset is split into a training set and a validation set with a ratio of 70%:30%. The training set is used for learning and optimizing model parameters, while the validation set is used to evaluate the model's performance on unseen data, ensuring that it demonstrates good generalization ability. The Adam optimization algorithm is employed for model training, replacing the traditional stochastic gradient descent method.

We chose Mean Squared Error (MSE) as the loss function for the prediction model. The formula for calculating the MSE of a two-dimensional matrix is as follows:

$$MSE = \frac{1}{m * n}\sum_{i=1}^{m \cdot n}(\hat{y}_i - y_i)^2 \tag{10}$$

Here, m and n denote the length and width of the input matrix, respectively. $\hat{y}_i$ represents the predicted value, while y_i refers to the actual value.

Given the limited data volume, the 2D DWT-ConvLSTM model begins with a 2D convolutional layer featuring a 3×3 kernel, 64 filters, a stride of 1, and zero padding. This Conv2D layer is responsible for extracting fused high-frequency feature information. Subsequently, the data stream passes through two 2D DWT-ConvLSTM layers to capture the integrated feature flow of both high-frequency and low-frequency components, each consisting of 64 units. The first ConvLSTM layer utilizes a convolutional kernel of 5×5, while the second layer employs a 3×3 kernel. Both layers apply the ReLU activation function and use 'same' padding to maintain the dimensionality across the layers. To mitigate potential shifts in data distribution between network layers, a Batch Normalization (BN) layer is incorporated after each ConvLSTM layer. Moreover, to prevent overfitting during training, Dropout layers are integrated into the model, with a random dropout rate set to 0.3, thereby enhancing the model's generalization capabilities.

The model's performance is evaluated using two metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The formulas for calculating these two metrics are provided below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{11}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{12}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{13}$$

Here, n denote the length of the input matrix, $\hat{y}_i$ represents the predicted value, while y_i refers to the actual value.

ISSN 2616-5775 Vol. 8, Issue 1: 71-79, DOI: 10.25236/AJCIS.2025.080110

5. Result and Discussion

5.1. The prediction results and carbon emissions calculation.

We input the historical freight volume data for each OD pair in the Chengdu-Chongqing urban cluster from March 8 to March 14, 2018, into the model. Using ConvLSTM prediction, the forecasted freight volume for the main OD pairs in the Chengdu-Chongqing urban cluster for the following week is shown in *Figure 4*.

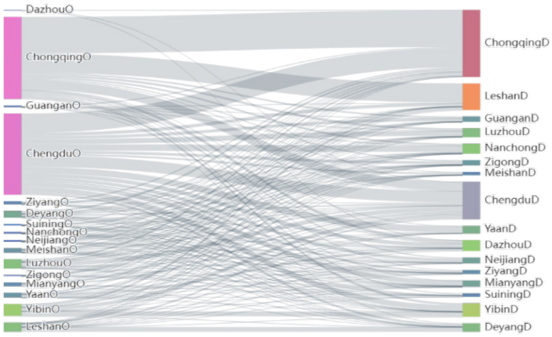

Figure 4: Total cargo volumes for major OD pairs in the coming week.

For the calculation of carbon emissions, this study assumes that all road freight vehicles in the Chengdu-Chongqing urban cluster use diesel as fuel. According to data from the "China Transportation Yearbook 2006-2016" and the "China Logistics Yearbook," the energy consumption per unit turnover of diesel is 8.6L/100 ton-kilometers. Based on the "Guidelines for the Calculation of Greenhouse Gas Emissions from Energy Consumption, Tool Version 2.1" by the World Resources Institute, the CO2 emission coefficient of diesel is 3.0959 kgCO2/kg. By substituting the predicted freight turnover data into *Equation (9)*, the corresponding carbon emissions are calculated. The predicted total daily carbon emissions in the Chengdu-Chongqing urban cluster for the next 7 days are presented in *Table 2*.

Table 2: Predicting freight turnover and measuring carbon emissions.

Date	Freight turnover (100 ton-kilometers)	Carbon emissions (tons)
2018.03.08	38715707.87	164518.58
2018.03.09	27689184.37	117662.46
2018.03.10	42963534.95	182569.30
2018.03.11	35441614.87	150605.65
2018.03.12	55116330.74	234211.41
2018.03.13	65774783.94	279503.46
2018.03.14	39145837.96	166346.38

5.2. Effect of parameters on freight Demand Prediction Performance

To assess the effect of hidden layer size on the model's predictive performance, we fixed the learning rate at 0.008, set the convolutional kernel size to 3×3, and used a batch size of 16. The hidden layer size was varied across several iterations of training. *Table 3* presents the influence of different hidden layer unit configurations on the model's prediction accuracy.

Table 3: Effect of hidden size on LSTM and ConvLSTM prediction.

Hidden layer Size	LSTM			ConvLSTM		
	RMSE	MAE	R^2	RMSE	MAE	R^2
2	14.821	11.534	0.136	11.463	3.212	0.143
4	13.235	10.144	0.142	11.454	3.737	0.144
8	11.2	8.132	0.288	4.749	2.620	0.312
16	7.546	5.468	0.459	3.708	2.021	0.581
32	5.632	3.445	0.543	3.170	1.685	0.633
64	**3.221**	**2.137**	**0.782**	**2.215**	**1.158**	**0.850**
128	4.573	3.288	0.633	2.972	1.534	0.730

ISSN 2616-5775 Vol. 8, Issue 1: 71-79, DOI: 10.25236/AJCIS.2025.080110

The experimental results show that predictive performance improves with hidden layer size, though LSTM and ConvLSTM differ significantly. LSTM performs best with a hidden layer size of 64 (RMSE: 3.2, MAE: 2.1, R^2: 0.782) but degrades at 128 due to overfitting. ConvLSTM consistently outperforms LSTM, achieving optimal results at 64 (RMSE: 2.215, MAE: 1.158, R^2: 0.850) and maintaining greater robustness even at 128. These findings highlight ConvLSTM's superior ability to capture complex spatiotemporal features, offering higher accuracy and stability with well-tuned hidden layer sizes.

Similarly, to evaluate the effect of input length on the model's predictive performance, we maintained a learning rate of 0.008, a convolutional kernel size of 3×3, and a batch size of 16. The input length underwent multiple modifications, and the model was trained accordingly. The impact of varying input lengths on the model's prediction performance is summarized in *Table 4*

Table 4: Effect of input length on LSTM and ConvLSTM prediction.

Input length	LSTM			ConvLSTM		
	RMSE	MAE	R^2	RMSE	MAE	R^2
1	15.221	11.531	0.201	14.920	6.357	0.214
3	10.462	7.345	0.266	10.004	3.058	0.275
5	5.385	4.323	0.626	3.340	1.979	0.676
7	2.437	1.890	0.779	**2.437**	**1.390**	**0.848**
9	6.782	5.432	0.528	3.863	2.702	0.545

The experimental results emphasize the importance of input sequence length in LSTM and ConvLSTM models. For LSTM, shorter sequences (1 and 3) lack sufficient temporal context, leading to higher errors and lower R^2. Performance peaks at a length of 7, capturing longer-term dependencies, but degrades at 9 due to redundant information. ConvLSTM follows a similar trend, with optimal performance at 7, achieving lower RMSE and MAE and higher R^2 than LSTM across all lengths. ConvLSTM also shows greater stability with longer sequences, making it a more robust and accurate choice for capturing spatiotemporal dynamics.

6. Conclusion

This study developed a ConvLSTM-based spatiotemporal freight volume prediction model for highway transportation in the Chengdu-Chongqing urban cluster, achieving promising results. Compared to LSTM, ConvLSTM, which incorporates spatial features, showed significantly better performance. The predicted freight volumes for key OD pairs were used to calculate carbon emissions via a top-down method, analyzing short-term trends and pinpointing emission peaks. These findings support precise regulation of road freight emissions and promote green, low-carbon transportation. The key findings of this study are as follows:

(1) This study applies ConvLSTM to the freight domain, fully considering both spatiotemporal information of freight flows. In terms of accuracy, the ConvLSTM model achieves a prediction accuracy of 85%, significantly outperforming common classical models, and improving by approximately 9% compared to the basic LSTM model.

(2) The hidden layer size influences the prediction of OD freight flow. As the number of hidden layer units increases from 2 to 128, the model's predictive performance first improves, then declines. Under similar conditions, setting the number of hidden layer units to 64 yields the best predictive performance for both LSTM and ConvLSTM models, with the ConvLSTM model consistently showing higher predictive accuracy than the LSTM model.

(3) The input length affects the prediction of OD freight flow. As the input length varies from 1 to 9, the model's performance initially increases, then decreases. Under similar conditions, setting the input length to 7 yields the best predictive performance for both LSTM and ConvLSTM models, with the ConvLSTM model consistently outperforming the LSTM model in predictive accuracy.

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