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Long-Term Trend Analysis and Prediction of Freight Volume in Beijing Using ARIMA-LSTM Model

Xuejun Li[a], Dianzheng Zhuang[b]

Shenyang University of Technology, Shenyang 110000, China

[a]lxj1050@gmail.com, [b]zhuangdianzheng@sut.edu.cn

Abstract

To study the relationship between freight volume in Beijing and various economic factors and reveal the underlying reasons for changes in freight volume, we selected five sets of data highly correlated with freight volume, namely milk production, vegetable and edible fungus production, furniture production, steel production, and cement production in Beijing, as input features for the prediction model based on the results of Pearson correlation coefficient (PCC) analysis. After data preprocessing and feature engineering, we trained these data using the Autoregressive Integrated Moving Average - Long Short-Term Memory Hybrid (ARIMA-LSTM) model and predicted the freight volume in Beijing for the first quarter of 2024. Meanwhile, we established a BP neural network model as a comparison benchmark. By comparing the prediction performance of different models, the results indicated that the ARIMA-LSTM model performed better in handling long-term sequence data and capturing nonlinear relationships, providing more accurate and reliable freight volume prediction results. Finally, we observed a significant downward trend in the freight volume in Beijing in recent years.

Keywords

ARIMA-LSTM Model; Beijing Freight Transportation Forecast; Pearson Correlation Coefficient; BP Neural Network Model.

1. Introduction

Beijing, as the capital and political center of China, attracts a large number of permanent residents and resources. The freight transport industry is an important part of the urban economy, and its development trend and operation dynamics are key indicators for measuring the urban economy. The freight volume directly reflects the efficiency and scale of urban material circulation, and is closely related to aspects such as industrial development, infrastructure construction, and residents' consumption. Conducting an in-depth study on the relationship between the changes in Beijing's freight volume and economic factors is of great significance for understanding the impact of the relocation policy on the urban economy, evaluating the adaptability of the freight transport industry, and formulating relevant policies. Against this backdrop, it is extremely important to clarify the changing trend of Beijing's freight volume and its influencing factors. This study analyzes long-term time series data to explore the interaction between freight volume and multiple economic factors, providing data and policy support for the healthy development of Beijing's freight transport industry. Many scholars have conducted research on the changes in urban freight volume and its relationship with economic development. Chang Zhihong et al. [1], through their research on urban freight volume in China, found that among economic factors, the added value of the construction industry has the greatest impact on road freight volume. Pu Xueming [2] conducted an overall analysis of the factors influencing road freight volume using the entropy weight grey correlation analysis method, and

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introduced the grey correlation analysis method into the analysis of freight volume in this paper. In addition, some scholars have also studied the relationship between urban freight volume and the output of characteristic industries. Jia Chunmiao et al. [3] adopted a method combining the ARMA model and the multiple linear regression model to analyze and predict the annual railway freight volume in the Ningxia-Gansu region, and concluded that the freight volume in the Ningxia-Gansu border region is mainly affected by coal output. Moreover, Gui Wenlin [4], through the analysis of the monthly data of railway passenger and freight volumes in China from 2002 to 2009, reached the conclusion that China's railway passenger and freight volumes have obvious linear trends and seasonal characteristics. However, in previous studies, scholars mainly focused on traditional statistical methods or simple machine learning models to predict freight volume. But these methods often fail to capture the long-term dependencies and complex nonlinear relationships in time series data. In recent years, with the rapid development of big data and artificial intelligence technologies, time series prediction models have been widely applied in freight volume prediction [5]. Among them, the Autoregressive Integrated Moving Average - Long Short-Term Memory Hybrid (ARIMA-LSTM) model, as a deep learning algorithm, has the ability to process and predict long sequence data, and thus has great potential in the field of freight volume prediction [6]. All manuscripts must be in English

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2. Research Methods

2.1 Research Steps

(1) Data collection and preprocessing: Collect the freight volume data of Beijing from 1978 to 2023, as well as the output data of steel, cement, furniture, milk, vegetables and edible fungi in the same period. Clean the data, remove outliers, fill in the missing values, and then perform normalization processing.

(2) Pearson correlation analysis: Use Pearson correlation analysis to determine the correlation between the freight volume and various economic factors, and clarify the magnitude of the correlation by calculating the correlation coefficient.

(3) ARIMA-LSTM model: Select the ARIMA-LSTM model for training to predict the freight volume in Beijing. ARIMA-LSTM is a variant of the Recurrent Neural Network (RNN), which has advantages in processing long time series data and capturing nonlinear relationships. Take the economic factors that are highly correlated with the freight volume as input features, and after training through the ARIMA-LSTM model, predict the freight volume in Beijing in the first quarter of 2024.

(4) Model comparison and evaluation: Establish a Backpropagation (BP) neural network model as a control group to compare the prediction performance of the ARIMA-LSTM model. Evaluate the prediction accuracy and reliability of each model by calculating indicators such as the Mean Squared Error (MSE) and the Mean Absolute Error (MAE).

(5) Result analysis: Analyze the prediction results of the models, compare the performance of different models, discuss the changing trend of the freight volume in Beijing under the background of relieving non-capital functions, and provide a reference for policy-making.

Through the above research methods, we can comprehensively analyze the long-term trend of the freight volume in Beijing, and predict the freight volume in the first quarter of 2024 based on the ARIMA-LSTM model. This method not only takes into account the impact of economic factors on the freight volume, but also fully considers the complexity and nonlinear relationships of the time series data.

 Volume 11 Issue 5, 2025
DOI: 10.6919/ICJE.202505_11(5).0002

2.2 Sources and Selection of Associated Variables

In order to analyze the factors closely related to the freight volume in Beijing, based on experience, monthly data from 1978 to 2023 are collected, including thirteen groups of data such as Beijing's GDP, the number of industrial enterprises above a designated size, and steel output. These data are sourced from the Beijing Municipal Bureau of Statistics, the RESSET Macro Database, and the official website of the National Bureau of Statistics. Calculate the Pearson correlation coefficients between these factors and the freight volume, and draw a heatmap to display the relationships.

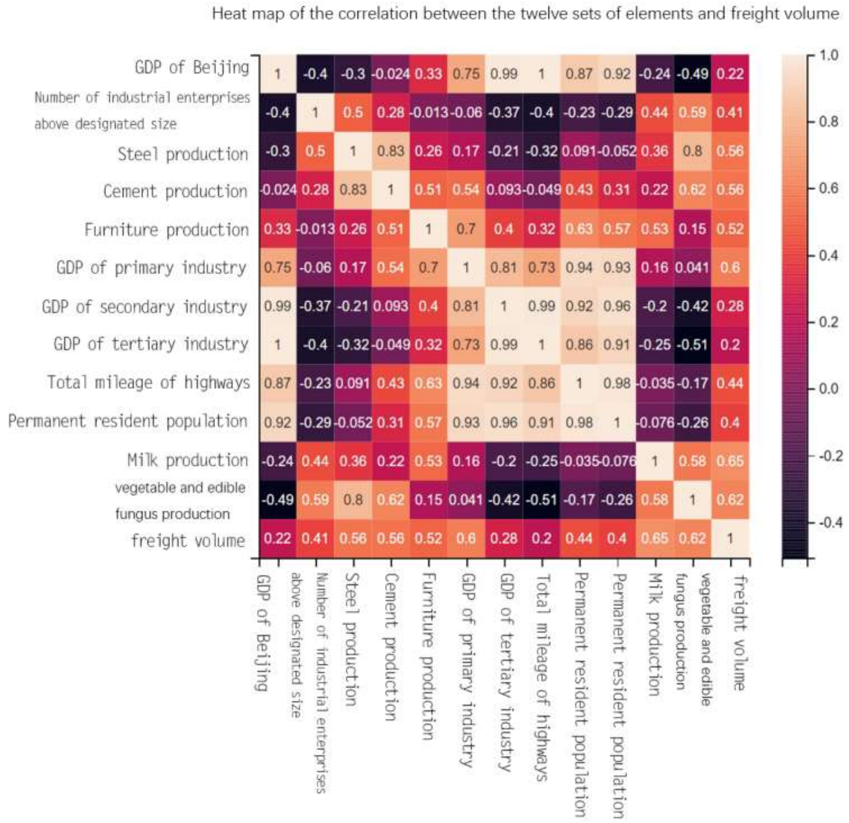

Figure 1. Twelve sets of correlation heat maps between elements and freight volume

As can be seen from Table 1, the factors with the highest correlation degrees with the freight volume in Beijing are milk output, the output of vegetables and edible fungi, and the GDP of the primary industry, with the correlation degrees being 0.65, 0.62, and 0.60 respectively. However, the overall GDP, the GDP of the secondary industry, and the GDP of the tertiary industry have relatively low correlation degrees with the freight volume. Through analysis, the factors with a correlation degree exceeding 0.5 and being closely related to the freight volume include milk output, the output of vegetables and edible fungi, the GDP of the primary industry, steel output, cement output, and furniture output. Due to the large population in Beijing and the huge demand for daily necessities, these factors are mostly related to daily needs. Considering that the GDP of the primary industry covers many elements and its changing trend is not obvious, it is excluded when selecting associated variables. Finally, this study selects five groups of data, namely milk output, the output of vegetables and edible fungi, furniture output, steel output, and cement output, as associated variables. During the data processing, it was found that there were missing values in some data. To ensure the integrity of the data and the accuracy of the research, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model combined with the interpolation method was used to fill in the missing data. After filling in the missing data, the Pearson correlation coefficients between the monthly data of these five

 Volume 11 Issue 5, 2025
DOI: 10.6919/ICJE.202505_11(5).0002

variables and the freight volume M were calculated again, and a correlation heatmap (Figure 2) was drawn to visually display the correlations among them.

Table 1. Summary of the correlation between the twelve sets of elements and freight volume

Serial Number	Variable Name	Unit	Correlation Degree
1	GDP of Beijing City	Hundred million yuan	0.22
2	Number of Industrial Enterprises above a Designated Size	Unit	0.41
3	Steel Output	Ton	0.56
4	Cement Output	Ton	0.56
5	Furniture Output	Piece	0.52
6	GDP of the Primary Industry	Hundred million yuan	0.60
7	GDP of the Secondary Industry	Hundred million yuan	0.28
8	GDP of the Tertiary Industry	Hundred million yuan	0.20
9	Total Length of Highways	Kilometer	0.44
10	Permanent Resident Population	Ten thousand people	0.40
11	Milk Output	Ton	0.65
12	Output of Vegetables and Edible Fungi	Ton	0.62

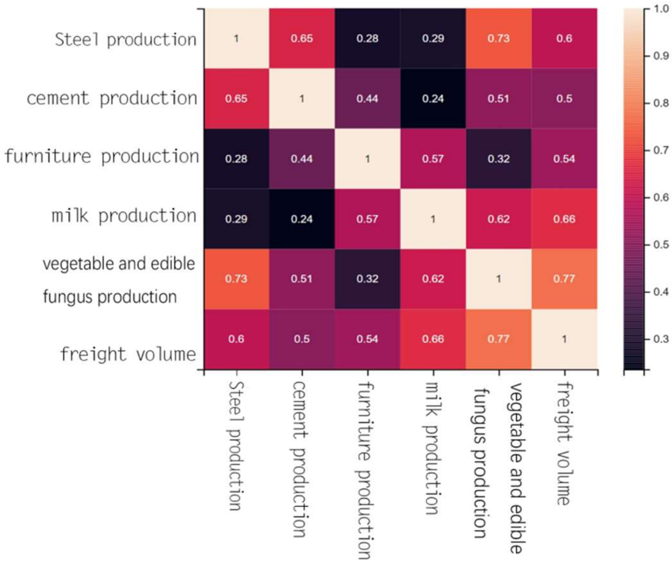

Figure 2. Heat map of steel production, cement production, furniture production, milk production, vegetable and edible fungi production and freight volume in Beijing

The results of the correlation analysis show that there is indeed a high degree of correlation between these five variables and the freight volume, which can be applied in the prediction of the model.

3. Prediction of Freight Volume Using the BP Neural Network Model

The Back Propagation (BP) neural network is a widely used machine learning method, especially suitable for modeling and predicting nonlinear relationships [7]. It consists of an input layer, one or more hidden layers, and an output layer. Each neuron converts the input signal into an output signal through an activation function and is connected through weights and biases [8]. The BP algorithm updates the weights and biases of the network by backpropagating the error to minimize the difference between the predicted value and the actual value [9]. In this study, we use the BP neural network model to capture the complex nonlinear relationships between the freight volume in Beijing and economic factors, and use these factors as input features and the freight volume as the output target for modeling.

3.1 Prediction Steps of the BP Neural Network Model:

(1) Data collection and preprocessing: Clean the collected data, remove outliers and missing values, and perform normalization or standardization processing.

(2) Construct the BP neural network model: Determine the number of nodes in the input layer and the output layer, and select the number of hidden layers and nodes. Usually, a complex problem requires 2 hidden layers [10].

(3) Train the neural network: Use historical data to train the network, select an appropriate activation function, such as the Sigmoid function, and adjust the network weights through the backpropagation algorithm [11].

(4) Determine hyperparameters such as the learning rate and the number of iterations to minimize the error between the predicted value and the actual value.

(5) Test and evaluate the model: Use the data that has not been involved in the training to test the model, and calculate the prediction error indicators, such as the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

3.2 Evaluation of the BP Neural Network Model

The comparison chart between the actual value of the freight volume M and the predicted value of the BP neural network model is as follows:

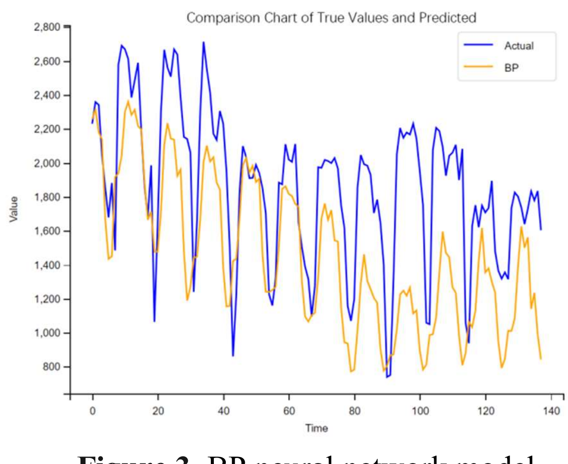

Figure 3. BP neural network model

This figure shows the prediction results obtained by using the remaining 25% of the influencing factor data after training the Back Propagation (BP) neural network model with the first 75% of the influencing factor data. The figure is a comparison chart between the predicted values and the true

Volume 11 Issue 5, 2025
DOI: 10.6919/ICJE.202505_11(5).0002

values. It shows that the BP neural network model can roughly capture the overall trend of the actual values. However, the model has deficiencies in terms of accuracy, which indicates that the BP neural network algorithm has limited effectiveness when simulating the degree of correlation among these data.

4. Construction and Evaluation of the ARIMA-LSTM Model

4.1 Construction and Parameter Setting of the ARIMA-LSTM Model

Principle:

ARIMA for handling linear features: ARIMA is proficient in capturing the linear trends and seasonal components of time series, and eliminates non-stationarity through differencing.

LSTM for handling nonlinear residuals: The prediction residuals of ARIMA are used as the input of LSTM to capture nonlinear patterns (such as the impacts of unexpected events like the COVID-19 pandemic shock and sudden policy changes).

The final predicted value is obtained by superimposing two parts:

$$\hat{y}_t = ARIMA(y_t) + LSTM(\epsilon_t) \tag{1}$$

$\epsilon_t = y_t - ARIMA(y_t)$ represents the prediction residual of the ARIMA model.

When constructing the ARIMA-LSTM model, it is necessary to determine the structure and parameters of the model. The structure of the ARIMA-LSTM model includes an input layer, hidden layers, and an output layer [12]. The input layer receives the preprocessed data, the hidden layers are composed of multiple LSTM units, and the output layer is used to generate the prediction results. In terms of parameter setting, we need to determine the number of LSTM units, the number of hidden layers, the learning rate, the batch size, etc. The selection of these parameters has an important impact on the performance of the model [13]. First, the data is normalized using the MinMaxScalar method in the sklearn library of Python. Subsequently, in the PyTorch environment, an ARIMA-LSTM neural network model is built, and the processed data is fed into the network model for training. The number of training iterations is 100, the optimization algorithm used is the Adma algorithm, and the learning rate is set to 0.01.

The calculation process of ARIMA-LSTM is shown in Formulas (2)-(7):

$$\mathrm{I_t} = \sigma(\mathrm{X_t W_{xi}} + \mathrm{H_{t-1} W_{hi}} + \mathrm{b_i}) \tag{2}$$

$$\mathrm{F_t} = \sigma(\mathrm{X_t W_{xf}} + \mathrm{H_{t-1} W_{hf}} + \mathrm{b_f}) \tag{3}$$

$$\mathrm{O_t} = \sigma(\mathrm{X_t W_{xo}} + \mathrm{H_{t-1} W_{ho}} + \mathrm{b_o}) \tag{4}$$

$$\mathrm{C_t} = \tanh(\mathrm{X_t W_{xc}} + \mathrm{H_{t-1} W_{hc}} + \mathrm{b_c}) \tag{5}$$

$$\mathrm{C_t} = \mathrm{F_t} \odot \mathrm{C_{t-1}} + \mathrm{I_t} \odot \mathrm{C_t} \tag{6}$$

$$H_{\mathrm{t}} = \mathrm{O_t} \odot \mathrm{Tanh}\ (\mathrm{C_t}) \tag{7}$$

Volume 11 Issue 5, 2025
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In the formulas, X_t is the input feature at time step t。 I_t,F_t and O_t represent the values of the input gate, forget gate, and output gate at time step respectively [14]. $W_{xi}W_{hi}$, $W_{xf}W_{hf}$ and, $W_{xo}W_{ho}$are the weight coefficients of the input gate, forget gate, and output gate respectively, and， b_i,b_f, b_o are the bias coefficients of the input gate, forget gate, and output gate respectively; W_{xc} and W_{hc} are the weight parameters of the candidate memory cell , b_c is the bias parameter of the candidate memory cell ; $\odot$ represents element-wise multiplication;; tanh represents a function;σ represents the sigmoid function [15].

4.2 Model Training and Validation

After determining the structure and parameters of the ARIMA-LSTM model, we trained the model using the training dataset. During the training process, we employed the backpropagation algorithm and the gradient descent method to optimize the weights of the model. In order to prevent overfitting, we adopted techniques such as regularization and dropout.

Once the model training was completed, we validated the model using the validation dataset. The validation dataset is used to evaluate the generalization ability of the model, that is, how the model performs on unseen data. We calculated the prediction error of the model and relevant indicators, such as the Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), to assess the performance of the model.

4.3 Model Evaluation

Through the above steps, we successfully established the ARIMA-LSTM model and plotted the comparison and fitting graph for the test dataset.

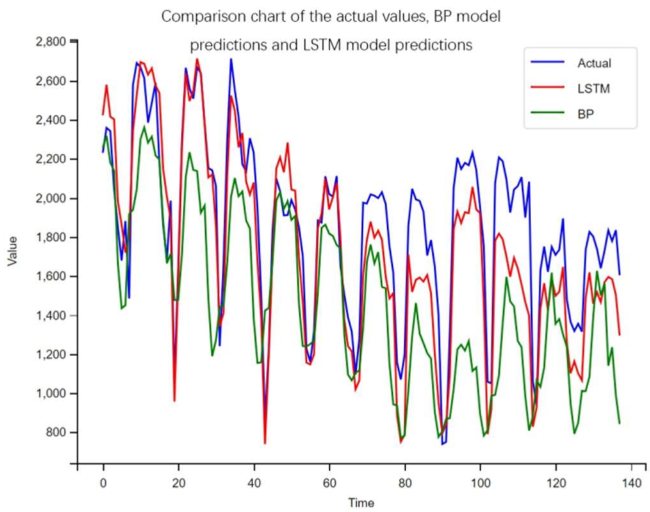

Figure 4. Comparison of the prediction results between the BP and ARIMA-LSTM models

Analysis of the Fitting Effect of the ARIMA-LSTM Model: It can be seen from the model fitting graph that the fitting effect in the first 65 months is excellent, with extremely high fitting accuracy. However, the fitting effect in the last part is slightly insufficient. This may be due to the comprehensive influence of various non-economic factors, including the COVID-19 pandemic, industrial transfer under the policy guidance, and the relocation of central and state-owned enterprises. At the same time, it can be observed from the graph that both the actual freight volume and the predicted freight volume generally show a downward trend, indicating that under the background of Beijing's efforts to relieve non-capital functions, there is a significant decline in Beijing's freight volume. According to the evaluation results of the prediction accuracy indicators of each model in Table 2 below, the prediction performance of the ARIMA-LSTM model is significantly better than that of the BP model, and it has higher prediction accuracy. The ARIMA-LSTM model performs excellently in the prediction of Beijing's freight volume.

Table 2. Comparative performance evaluation of the two models

Evaluation Indicator	BP	ARIMA-LSTM
MSE	0.1954	0.0726
RMSE	0.4421	0.2694
MAE	0.3966	0.2082

5. Conclusion

5.1 Research Conclusion

This study analyzed the correlations between the freight volume in Beijing and multiple economic factors, and the following conclusions were drawn:

(1) The study found that five groups of data, namely milk output, the output of vegetables and edible fungi, furniture output, steel output, and cement output, have a significant correlation with the freight volume in Beijing.

(2) The ARIMA-LSTM model performs more excellently in handling long time series data and capturing the nonlinear relationships among data, providing a reliable method for accurately predicting the freight volume in Beijing. In future research, by expanding the sample data and considering more influencing factors, the prediction accuracy and reliability of the model can be further improved.

5.2 Research Limitations and Prospects

This study has certain limitations when discussing issues related to the freight volume in Beijing. On the one hand, only the relationships between some economic factors and the freight volume were considered. Potential factors that affect the freight volume, such as the growth of the permanent resident population, urban planning, and environmental protection, were not included in the study. On the other hand, the research perspective mainly focused on economic factors, and the discussion of the impact of the policy of relieving non-capital functions was relatively simple, without involving other factors such as technology and the environment. In future research, by including more potential factors, the impacts of different models and parameter settings on the prediction performance can be further explored, and the research perspective can be expanded to comprehensively consider the impacts of multiple factors on the freight volume, so as to improve the research on the freight volume in Beijing.

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