International Journal of Information Technologies and Systems Approach
Volume 16 • Issue 3

Demand Forecast of Railway Transportation Logistics Supply Chain Based on Machine Learning Model

Pengyu Wang, Zhengzhou Railway Vocational and Technical College, China
Yaqiong Zhang, Zhengzhou Railway Vocational and Technical College, China
Wanqing Guo, SIAS University, China*

ABSTRACT

The deep learning method based on long short-term memory (LSTM), gated recurrent unit (GRU), and bidirectional LSTM (Bi-LSTM) was constructed by researching the factors affecting railway transportation logistics. Moreover, a simulation study on Tianjin Station was conducted. The deep learning model suitable for the logistics demand forecasting of Tianjin Station was established, and the changing trend of logistics supply chain demand in Tianjin Station in the future was analyzed. Moreover, a strategy for railway construction and regional cooperation was proposed. In this study, three deep learning neural networks, namely LSTM, GRU, and Bi-LSTM, were used to construct a demand forecasting model for the logistics supply chain in Tianjin Station. Bi-LSTM, which has bidirectional storage performance and the highest prediction accuracy, is superior to the traditional neural network structure in terms of period and fluctuation.

KEYWORDS

Deep Learning, Demand Forecast, Logistics Supply Chain, Machine Learning, Rail Transport

INTRODUCTION

The continuous development of machine learning has brought new vitality to all walks of life. In recent years, new technologies, such as the Internet and e-commerce, have been widely used with the rapid development of China's economy. In such a large environment, the industrial structure of Chinese enterprises has been continuously optimized, and the competition among various modes of transportation has become increasingly fierce. Consumers have new development needs for timeliness, speed, convenience, information transparency, differentiation, and many other aspects of logistics. Railway transportation is the key to social and economic development. The development of the railway transportation industry must be given attention, and the adjustment of the scale and structure of the railway should meet the needs of sustainable development. The widespread use of the Internet has

DOI: 10.4018/IJITSA.323441
*Corresponding Author

led to the rapid development of e-commerce and network economy, and online shopping has been widely accepted as a new way of shopping. Online shopping uses real money, not conceptual money, virtual money, or metal money. Given the large amount of repeated information on the Internet, people cannot easily obtain comprehensive information. Nevertheless, machine learning models can obtain considerable information in the shortest time. Improving the efficiency of obtaining and utilizing information on demand data of railway transportation supply chain has great practical value. This approach is an important guarantee for sustainable and healthy development and the survival and competitiveness of China's railway freight transportation industry. Therefore, this study has certain research value. In particular, the application of machine learning to the demand forecasting of railway transportation is crucial for optimizing resource allocation and improving the efficiency of railway logistics transportation.

As the foundation of the national economy and social development, railways have been studied by many researchers. Li (2017) took the railway intermodal service supply chain as the research object. They concluded that the railway is still better than other modes of transportation. Gogrichiani and Lyashenko (2021) believed that the important role of railway transport logistics remains. They suggested that a method should be developed to rationalize the criteria for railway line selection. Jayakrishnan, Mohamad, and Yusof (2020) concluded that digitalization brought challenges to the establishment, maintenance, security, and reliability of the Railway Supply Chain (RSC), and the research of machine learning model considerably impacts the demand for railway transportation logistics supply chain. Lustig (2019) believed that research on railway transportation is essential because most railways outside North America are still state-owned. Many scholars have conducted comprehensive and in-depth research on railway transportation. They have comprehensively investigated the economic benefits of railway transportation and the demand for a logistics supply chain. However, they paid considerable attention to the cost of railway transportation but did not consider the demand for logistics supply. However, they neglected the need for logistical supply compared to the cost of rail transport.

A machine learning model is an expression of an algorithm that combs through massive amounts of data to find patterns or make predictions. Many people apply it to research in other fields. Gang (2017) studied the problem of railway logistics demand with machine learning model construction and data mining algorithm. Shruthishree (2021) developed a deep mixed feature machine learning model named AlexResNet+ for the railway logistics demand problem. Sudarmaji (2021) applied machine learning to the demand forecasting process of the railway logistics supply chain to develop a scoring model. Madar (2021) used machine learning to classify and analyze factors from various aspects, such as the economy and railway networks. Machine learning models are used to study demand forecasting in railway transportation logistics supply chains. The research in the field of machine learning has developed to a certain extent. This field can be improved by researchers in many ways. However, machine learning in the logistics supply chain still needs further research.

In response to this concern, the present study presents the following innovations. Most of the previous studies used the economic level and demand for railway logistics in each region as the input indicators for prediction. The present study takes Tianjin Station as an example and predicts its logistics demand from the economic conditions of its radiation area. Given the lack of data mining and prediction accuracy in the prediction processes of traditional mathematical models, this study uses deep learning neural networks, namely, long short-term memory (LSTM), gated recurrent unit (GRU), and bidirectional LSTM (Bi-LSTM), to analyze the data characteristics affecting the railway operation volume and local economic conditions. Using these deep learning neural networks can effectively improve forecast accuracy. Moreover, technical support for the correct judgment of the development trend of Tianjin Station and the formulation of railway transportation planning and construction strategies can be provided. Based on machine learning, this study aims to predict the future development trend through accurate forecasting of logistics and distribution supply chain demand in

Tianjin Station. The prediction model method of Bi-LSTM is mainly used. It can effectively solve the transportation problem in railway transportation and is rarely involved in past studies.

DEMAND FORECASTING METHOD OF RAILWAY TRANSPORTATION LOGISTICS SUPPLY CHAIN

Railway Transport Logistics Survey

Integrating enterprise logistics, household logistics, non-profit organization logistics, and green logistics, we can call it a complete logistics chain or a complete supply chain. To put it simply, the logistics supply chain can be understood as an organic logistics chain, which is formed by all the logistics activities involved in the economic activities in the time range from the product or service market demand to the demand satisfaction. The ideal state of a well-functioning logistics chain is green logistics.

Railway transportation has the advantages of fast speed, a large supply of goods, and safety, and plays an important role in logistics transportation. Railway transportation supply is the infrastructure and services built to meet the needs of railway transportation. Among them, railway transportation supply includes rail transportation planning and rail transportation supply. Railway transportation has the advantages of high speed, large capacity for the supply of goods, and safety. It plays a vital role in logistics transportation. The railway transportation supply includes the basic facilities and services built to meet the needs of railway transportation. It involves the planning of rail transportation and the resources for rail transportation. The railway lines in the research area are mainly investigated during the railway traffic planning, which adopts the survey method mainly based on atlases and data research. The main sources of the atlas method are the national railway atlas and the regional railway atlas, as shown in Figure 1. The data survey method is the same as the demand survey method. Materials such as feasibility analyses of railway projects can also be used as references.

The surveys of railway supply are mainly obtained from the literature. The quantity to be transported is generally expressed by the carrying capacity of the transport vehicle. The supply capacity of transport depends mainly on two aspects: transport infrastructure and means of transport. The transportation capacity of each railway grade, that is, the passenger and freight capacity, is determined according to the actual situation of China's railways. Railways are organized and operated by trains. During logistics transportation, trains may need to be organized and redistributed, so railway logistics transportation takes a long time, and the efficiency is not high. The cargo damage rate in railway transportation is high, and due to the loading and unloading. There are usually more damage or loss accidents than other modes of transportation. Door-to-door transportation cannot be realized and usually rely on the cooperation of other modes of transportation to complete the transportation task, unless both the shipper and the consignee have iron.

Figure 1. Railway transportation

Prediction Algorithm of Railway Logistics Demand

In statistics, regression analysis refers to a statistical analysis method that determines the interdependent quantitative relationship between two or more variables. According to the number of variables involved, regression analysis can be divided into simple regression analysis and multiple regression analysis. According to the number of dependent variables, it can be divided into simple regression analysis and multiple regression analysis. According to the relationship between independent variables and dependent variables, it can be divided into Linear regression analysis and nonlinear regression analysis. The railway logistics demand forecast is a simple measure of the transportation volume. Moreover, the paste and roll transportation is related to the lives of residents along the line. The railway transportation demand forecast uses certain technical means and methods to estimate the railway transportation demand for each traffic district in the next few years and plan the railway network. The first three stages in the four-stage method (Kozachenko et al., 2017), which forecasts the demand for railway transportation, include trip generation prediction, trip distribution prediction, and trip mode division prediction.

Trip Generation Prediction

Given the advantages and disadvantages of railway transportation and the importance of railway transportation in life, the total railway demand between different regions is analyzed according to the development of society and economy. The trip generation forecast is the most basic work in the traffic demand forecast. The present study summarizes the main factors affecting railway transportation: first, the level of the industry and the speed of industrial development; second, the transportation coefficient of industrial and agricultural products; third, the distribution of industrial and agricultural production and resource allocation; fourth, the import and export commodities; fifth, the country's economic policy and other irresistible factors.

Regression analysis, a widely used data analysis method in statistics, is simple and fast in terms of prediction. The present study proposes a railway logistics forecasting method based on regression analysis. The impact factors of logistics are easy to quantify. The yearbook also simplifies the data query. An accurate forecast result is obtained by analyzing the logistics demand and the existing relationships. This study uses the multiple linear regression method to investigate each factor and the relationship between logistics demand and production volume.

The railway demand T is presumably a linear function of n influencing factors $X_1, X_2, X_3, \cdots, X_n$. The multiple regression model can be determined as follows (Irannezhad, 2019):

$$T = a_0 + a_1 X_1 + a_2 X_2 + a_3 X_3 + \cdots + a_n X_n \tag{1}$$

where $a_1, a_2, a_3, \cdots, a_n$ is the undetermined coefficient.

Trip Distribution Prediction

The origin–destination (OD) matrix has all traffic zones sorted by row (starting area) and column (destination area). The resident or vehicle travel volume (OD volume) between any two zones is considered the element. According to the form, rectangular and triangular matrices exist. The former can distinguish the travel volume in different directions of the two sections, whereas the latter represents only the sum of the travel volume in two directions of two sections. The second stage of the four-stage method is trip distribution prediction, which aims to find the traffic flow between regions during the forecast year. The essence of the row assignment problem is to solve the specific value of each cell in the OD matrix with the rows and columns of the assignment matrix (Abdellaoui & Pache, 2020).

As shown in Formula 2, the present study adopts a new growth function model, namely, the Fratar method (Sabath, 2019), to predict the data accurately. This approach assumes that the increase in traffic between two regions is not only related to the connection between the two regions but also to the growth of the region as a whole; this assumption is in line with the reality of the regional railway network (Wilson, 2017):

$$f\left(o_i^k \cdot fd_j^k\right) = fo_i^k fd_j^k \frac{\dfrac{O_i^k}{\sum_j q_{ij}^k fd_j^k} + \dfrac{D_j^k}{\sum_i q_{ij}^k fd_i^k}}{2} \tag{2}$$

Travel Mode Division Prediction

The third stage in the four-stage method is the division of travel modes. The targets of railway transportation are passengers and goods. The following introduces the selection of transportation modes. The existing railway transportation modes are divided into passenger-dedicated line transportation and ordinary passenger transportation. The factors that affect shipping patterns include arrival and departure time, speed, the geographic location of the shipment, and the region to which the shipment is being shipped. The freight line has the characteristics of cost-saving and no empty load. However, the departure time is uncertain, and it cannot cope with urgent demands. The ordinary line starts on time and covers a wide range. Employers can choose according to the needs of the goods.

Trip generation refers to traffic generation or traffic occurrence when specifically referring to vehicle travel. It is the sum of the number of departures and arrivals of people or vehicles traveling in a specified area and within a specified time. Represents the total amount of travel activities in a region, and its unit is usually person-times per day or train-times per day. The amount of trip generation is determined by land use. Current travel generation is obtained by a travel survey, and future travel generation is calculated by the travel generation forecasting model. It is the first step of the four-step model.

Establishing the railway transport mode is difficult. Collecting data is challenging, and some data are unavailable. Therefore, according to the daily logistics volume of railway transportation lines and ordinary railways, predicting methods based on expert experience is feasible. On the basis of the collected data, the method analyzes the adaptability of ordinary railway traffic capacity. If the transportation capacity of ordinary railways is less than the current capacity, factors such as the economy and transportation distance must be comprehensively considered. Moreover, some goods and the appropriate ratio of goods from ordinary railways must be separated, and they should be transported via railway freight lines. When the transport capacity of the ordinary railway exceeds its existing transport capacity, the cooperation between the ordinary railway and the freight line must be considered. Moreover, the sharing ratio of the two should be carefully analyzed. In any case, decisions cannot be made blindly and hastily, and the apportionment ratio must be discussed repeatedly with experts.

The railway system has always been an important pillar industry of the national economy. Railway-related information systems, such as the computer interlocking system and the train operation control system, have been developed and promoted in China. China's economic and social development is inseparable from railway development. Many countries have further developed railway freight transportation by continuously improving information technology. In such a large environment, the present study proposes a demand forecasting method for a railway transportation logistics supply chain based on a machine learning model to adapt to the times and historical trends and make this supply chain increasingly scientific and refined.

Machine Learning Models

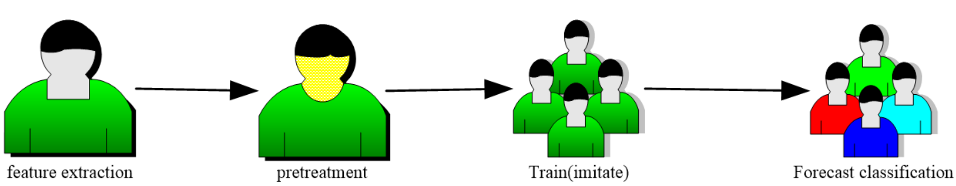
The concept of machine learning has been proposed since the 1950s. However, it has not been well developed because of the limitation at the technical level. Since the 1990s, machine learning has developed rapidly, and breakthroughs have been made in algorithms and applications. Algorithms such as decision trees, support vector machines, and logistic regression have emerged; a variety of algorithms have been widely used in many fields (Hartzel & Wood, 2017). Different machine learning algorithms have different effects in the same environment. Various methods reflect different advantages and disadvantages of various algorithms.

Data mining has been influenced by many disciplines, among which database, machine learning, and statistics are undoubtedly the most influential. Roughly speaking, databases provide data management techniques, and machine learning and statistics provide data analysis techniques. Because the statistics field is often obsessed with the beauty of the theory and ignores the practical utility, many techniques provided by the statistics field usually have to be further studied in the machine learning field and can only enter the field of data mining after becoming effective machine learning algorithms. In this sense, statistics mainly exert influence on data mining through machine learning, and machine learning and database are the two supporting technologies of data mining. Data collection and storage methods constantly develop with the rapid development of information technology, such as computers, communications, and sensing. The popularity of the Internet has exponentially increased the amount of data. Millions or even hundreds of millions of valuable data exist because of the nature of data and the complexity of topology, such as text data and image data. How to mine useful information effectively from massive and high-dimensional data has become a problem to be solved at present. Traditional data analysis methods cannot adapt to data analysis and processing because of the large amount of high-dimensional data. The huge amount of information causes the considerable pressure of an information explosion. In an ocean of data, obtaining useful information from massive data is already a huge problem. People use machine learning, mathematical statistics, and other means to analyze data and explore their characteristics, thereby expanding the research scope of data mining. Machine learning provides considerable technical support for data mining. Given the expansion of the application range, the amount of data increases rapidly, and the structure becomes increasingly complex. Thus, machine learning has become increasingly important. However, early machine learning objects are relatively simple, low dimensional, slightly classified, and small in scale. When processing a large amount of data, traditional machine learning algorithms encounter problems, such as difficulty in labeling, high dimension, many types, and large scale. The main application areas of machine learning mainly include two aspects: problem-solving and classification. Problem-solving can be transformed into categorization problems. An improved model, which can effectively describe and predict some crucial data, can be obtained using the classification method. As shown in Figure 2, the classification is generally divided into four stages (Rudakov et al., 2017): feature extraction, preprocessing, simulation, and prediction.

LSTM Neural Network Prediction Model

LSTM neural networks are a special form of recurrent neural networks (RNNs). They are good at analyzing trends in long-term time series and are similar to traditional RNN models. The present

Figure 2. Classification steps



study proposes to use the recurrent connection patterns between neurons and the intrinsic correlation between time series data for processing (Yin et al., 2017). LSTM is a special neuron structure called a *memory unit*. The hidden layer of the LSTM network established with this structure can save the data at any time and obtain an accurate time series model, efficiently solving the problem of gradient disappearance and burst in long sequences (Norouzi Nav et al., 2018).

As shown in Figure 3, the memory cell module consists of three gates: a forget gate, an output gate, and a cell state update unit. The core idea is to use the nonlinear activation function to realize the switching of each gate. Thus, the control and protection of the storage unit can be realized. Therefore, the core problem in the LSTM network is storing data information in memory for a long time.

Compared with other neural networks, the LSTM neuron system uses threshold units to control the selection information. LSTM adds input, forget, and output gates to the gated unit control. The input of the memory cell module is presumably x_t at time t; the output is h_t; the unit state is c_t. Therefore, the formulas of the input, forget, output gates, the input transition (Bai et al., 2021), the unit state update, and the structure of the output memory block are controlled as follows:

$$i_t = \sigma\left(W^i x_t + R^i h_{t-1} + U^i \cdot c_{t-1} + b^i\right) \tag{3}$$

$$f_t = \sigma\left(W^f x_t + R^f h_{t-1} + U^f \cdot c_{t-1} + b^f\right) \tag{4}$$

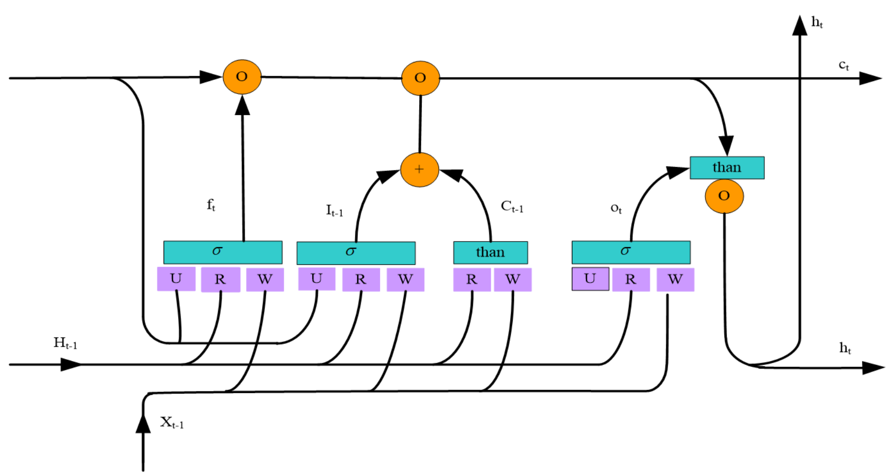
$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh\left(W^c x_t + R^c h_{t-1} + b^c\right) \tag{5}$$

$$O_t = \sigma\left(W^o x_t + R^o h_{t-1} + U^o \cdot c_t + b^o\right) \tag{6}$$

$$h_t = o_t \cdot \tanh\left(c_t\right) \tag{7}$$

In the formulas, σ is the sigmoid function; tanh is the hyperbolic tangent function; i_t, f_t, o_t, c_t are the input gate, forgetting gate, output gate, and input transformation to the unit input; $W^i x_t, W^f x_t, W^c x_t, W^o x_t$ and R^i, R^f, R^c, R^o are the weight matrices of the input gate, forget gate, output gate, and input transform, which correspond to x_t and h_{t-1} respectively; b^i, b^f, b^c, b^o are the input gate, forget gate, output gate, and input transform offset vector, respectively.

Figure 3. Schematic diagram of LSTM neurons



GRU Neural Network Prediction for the GRU Model

Gated recurrent units are also derived from LSTMs. The main reason for the popularity of GRU is the computational cost and the simplicity of the model, as shown in the figure. GRU is a lighter version of RNN than standard LSTM in terms of topology, computational cost, and complexity. This technique combines the forget and input gates into a single update gate and incorporates cell state, hidden state, and some other changes. The simpler GRU model is gaining popularity. GRU is similar to LSTM. It is an improved model based on the RNN structure. The concept of *gate* is also introduced. The input data maintain important data characteristics through different gate functions. This method can effectively solve the shortcomings of gradient disappearance and explosion in RNN. GRUs use fewer gates than LSTM models, and the functions of gates are different (Jitsuishi & Yamaguchi, 2022). Therefore, the performance of LSTM and GRU varies in different applications.

GRU is at the neuron level. It contains two kinds of gates. The first is the update gate, and the second is the reset gate. The update gate can be interpreted as a gate after fusing the input and forget gates. Its main function is determining which data have been added and which have been forgotten. The main function of the reset gate is to forget much information from the past. The gates are merged into a whole, and GRU requires smaller tensors and parameters than LSTM. From a training point of view, GRU takes up less computing power than LSTM and trains faster. A schematic diagram of its neuron is shown in Figure 4. Its calculation formulas are as follows (Zhang & Jia, 2021):

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1,} x_t\right]\right) \tag{8}$$

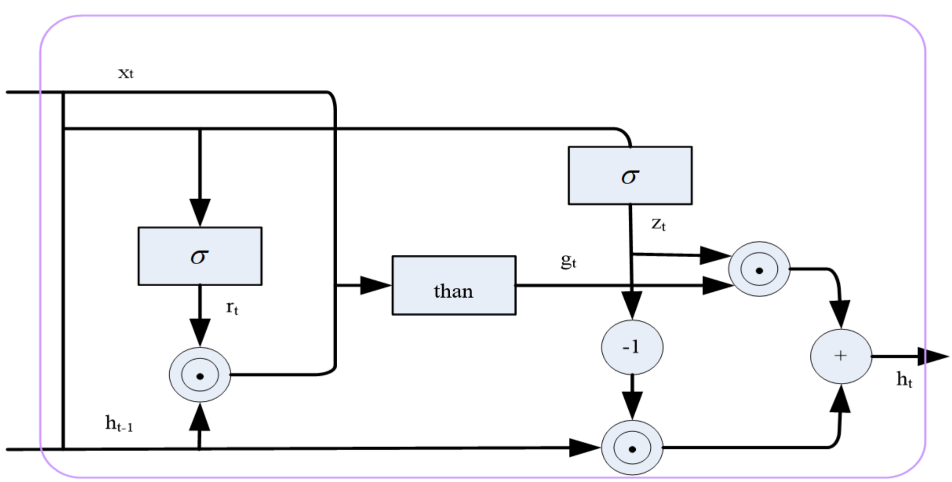
$$\tilde{h}_t = \tanh\left(W \cdot \left[r_t \otimes h_{t-1,} x_t\right]\right) \tag{9}$$

The function of the reset gate is single. Thus, it is used to judge whether to save or discard the previous vector information. The formulas are as follows:

$$r_t = \sigma\left(W_z \cdot \left[h_{t-1,} x_t\right]\right) \tag{10}$$

$$h_t = \left(1 - z\right) \otimes h_{t-1} + z_t \otimes \tilde{h}_t \tag{11}$$

Figure 4. Schematic diagram of GRU neurons



GRU Neural Network Prediction for the Bi-LSTM Model

Although the LSTM model has a memory unit structure, the prediction mode of LSTM involves prediction by time series. Moreover, future data cannot be added to the prediction model. Therefore, the present study uses the Bi-LSTM model of the Bi-LSTM network (Homchan & Gupta, 2021). This model concatenates two backpropagated hidden layers and points to the same output layer. In this way, the neural network can obtain information from the past and future time series, as shown in Figure 5. This finding shows that the Bi-LSTM neural network can learn data information from two directions to improve prediction accuracy. The hidden layer state H_t of Bi-LSTM at time t contains $\overrightarrow{h_t}$ in the forward direction and $\overrightarrow{h_t^{'}}$ in the backward direction:

$$\overrightarrow{h_t} = \overrightarrow{LSTM}\left(h_{t-1}, x_t, c_{t-1}\right) \tag{12}$$

$$\overrightarrow{h_t^{'}} = \overrightarrow{LSTM}\left(h_{t+1}, x_t, c_{t+1}\right) \tag{13}$$

$$H\left(t\right) = \left|\overrightarrow{h_t}, \overleftarrow{h_t}\right| \tag{14}$$

where T is the sequence length; h_t, x_t, c_t are the input of the input transition, the output gate, and the input transition to the unit, respectively.

EXPERIMENT AND EVALUATION ON DEMAND FORECASTING OF RAILWAY TRANSPORTATION LOGISTICS SUPPLY CHAIN

Experimental Data

Tianjin Railway Station is one of the largest railway stations in China. It plays a vital role in China and even the world. The present study took Tianjin Station as the research object, and the impact of macroeconomics, port transportation, and other aspects on railway transportation was considered. The input index set included the economic and railway transportation indices. The selected economic indicators were the investment in fixed assets and the total imports and exports. The railway transportation index included the two aspects of goods and trade from other countries. This study used the experimental data of the National Bureau of Statistics of China and mainly collects the statistical data of Tianjin. A total of 220 pieces of data were found from January 2005 to December 2020. Based on Barrett's Law, this study selected 173 items from January to June 2005 as the prediction model test data set. A total of 47 items from June 2015 to December 2020 were used as the prediction model test data set, as shown in Table 1.

Figure 5. Overview of the model of the Bi-LSTM neural network

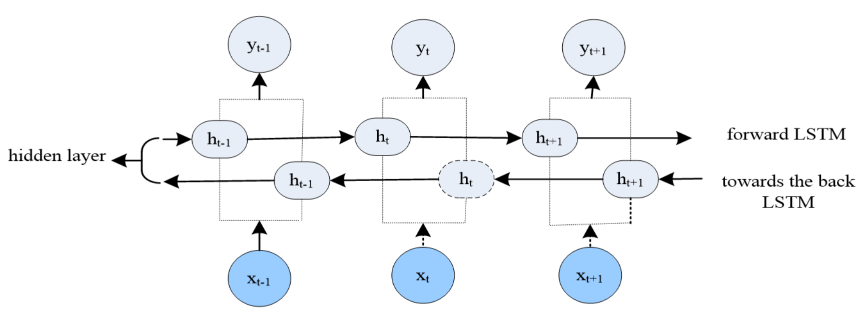


Table 1. Indicators related to railway logistics transportation volume

Indicator Name	Unit	Meaning
Fixed asset investment	Billion RMB	The construction and purchase of fixed assets by regional enterprises within a certain period Changes in workload and related costs
Total value of logistics	Billion RMB	The actual total amount of railway logistics in China
Logistics cargo volume	Billion tons	The scope of railway transportation and the quantity of goods transported

The experimental result of this study is a nonlinear time series data suitable for a neural network prediction model of deep learning. It can be used to study the relationship between high-dimensional nonlinear input vectors and prediction targets comprehensively. Therefore, the prediction effect of the prediction result mainly depends on the selection of the input vector. Properly gaining the input data dimensionality allows predictive models to learn the input index data efficiently and accurately. In this study, the method of using deep learning to predict the demand for railway transportation is mainly discussed. The high- and low-frequency signals can be separated by the information gain of the input variables. According to this finding, wavelet decomposition technology, used for decomposing one-dimensional data into high-dimensional data, can reflect the changing trend of the data and effectively extract the characteristics of the input signal, thereby improving prediction accuracy. In particular, wavelet decomposition technology can conduct multiscale analysis of data. Thus, the computational complexity of the algorithm is greatly reduced, and the overall performance of the algorithm is improved.

Deep Learning Prediction Model Construction

In this study, the deep learning neural network model was used to predict the railway logistics demand model. The neuron model has multiple neuron structures. Thus, the neural networks of different structures have different learning characteristics. Therefore, different neuron structures were established in each of the three selected neural network models. The best predictive model was finally obtained by comparing the smallest errors in each model to facilitate the selection of the best predictive structure among different models.

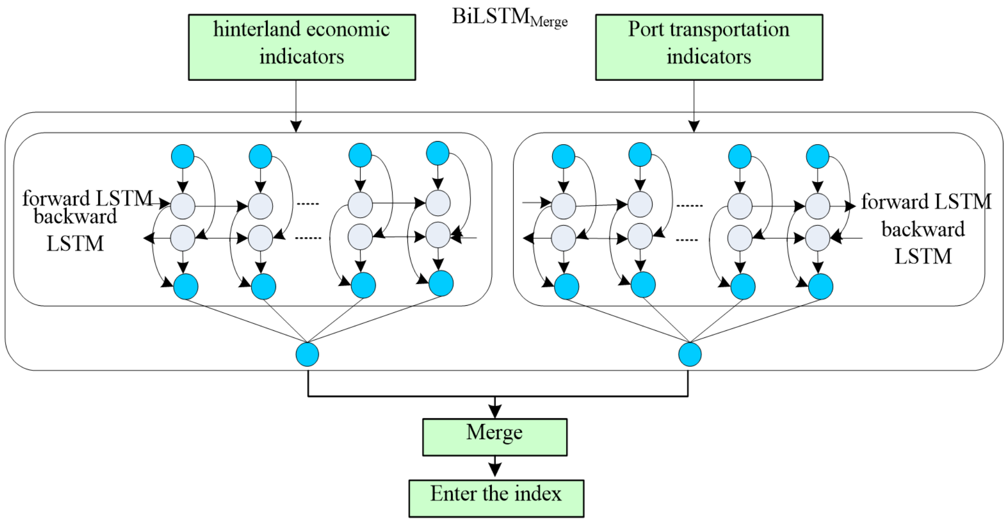
Unlike the Bi-LSTM mode, the LSTM and GRU models are unidirectional sequential neuron systems. In the LSTM and GRU models, linear neuron networks with the same structure are constructed: LSTM1, LSTM2, and LSTM3 and GRU1, GRU2, and GRU3. Among them, LSTM1 and GRU1 are single-level network structures. After the index was input into the prediction model, the structure of a neural network layer was used for learning and output.

The Bi-LSTM network used in this study connected two hidden layers with different transmission directions in series and makes them develop toward the same output layer. In this way, the neural network could obtain information from past and future time series. Therefore, only the merge algorithm was used for the Bi-LSTM neural network structure with two neural network layers to realize the fusion of different input hidden layers. Finally, the demand forecast result of the logistics supply chain in Tianjin Station was obtained, as shown in Figure 6.

Evaluation of the Forecast Results of Logistics Supply Chain Demand

In actual demand forecasting, the software functions must be used to make the forecasting model superior in performance and realize complex operations. The prediction and prediction models of multiple structures were established based on the establishment and derivation of the deep learning prediction model of the neural network. In Ubuntu, the Python language was used in calling the TensorFlow library to build an experimental environment for deep learning. The experimental

Figure 6. Schematic diagram of the Bi-LSTM neural network structure model



parameters were individually adjusted according to the model construction method in the previous section. On this basis, the divided and gained data were processed and introduced into the prediction model. This study adopted three forecasting modes and forecasts them to select the optimal logistics transportation mode of Tianjin Station.

LSTM Model Prediction Results

The results show that the mean absolute percentage error (MAPE) was 8.38%, and the LSTMMerge model has obvious advantages. As shown in Table 2, the average MAPEs of the prediction models of the four network structures were 9.46%, 16.49%, and 11.36%, indicating that the model has high prediction accuracy.

The degree of fitting between the experimental data and the real data indicates that the prediction effects of the four neural network models had obvious differences. Figure 7 shows how well the experimental and real data match: Figures 7A–7C represent the relationship between the predicted value and the true value in LSTM1, LSTM2, and LSTM3; Figure 7D shows the relationship between the predicted value and the true value in the LSTMMerge neural network. The chart shows that in the test data stage, the trends of the three indicators of LSTM1, LSTM2, and LSTM3 vary, but they were all significantly different from the actual values. In 2016, the mutation value of LSTM1 occurred; the prediction of LSTM2 changed in stages; the prediction of LSTM3 had noticeable changes before and after the actual value. The prediction effect of the LSTMerge model was the best, and its change

Table 2. LSTM model error

	MAPE (%)	MAE	RMSE
LSTM1	9.39	11.29	15.41
LSTM2	9.75	11.36	17.69
LSTM3	10.33	12.41	18.51
LSTMMerge	8.38	10.12	14.34
Average value	9.46	11.36	16.49

trend was consistent with the actual situation. However, the first and last two prediction results also had certain deviations.

Based on the above results, the evaluation indicators of the LSTM model were lower than those of other LSTM models—the comparison between Figure 7D and Figs. 7A to 7C shows that the LSTMMerge model had the best fitting effect, the trend was basically the same, and most of the points were concentrated near the true value. The fit was particularly high elsewhere, except that the head and tail show a trend that was different from the true value.

GRU Model Prediction Results

Table 3 shows that the error values of the GRU model are all within a good range. However, compared with the LSTMMerge model, the GRU model had a certain gap. The maximum value of the MAPE index is 13.41, and the minimum value is 9.07, which can be considered good.

Figure 7. LSTM model fitting of different architectures

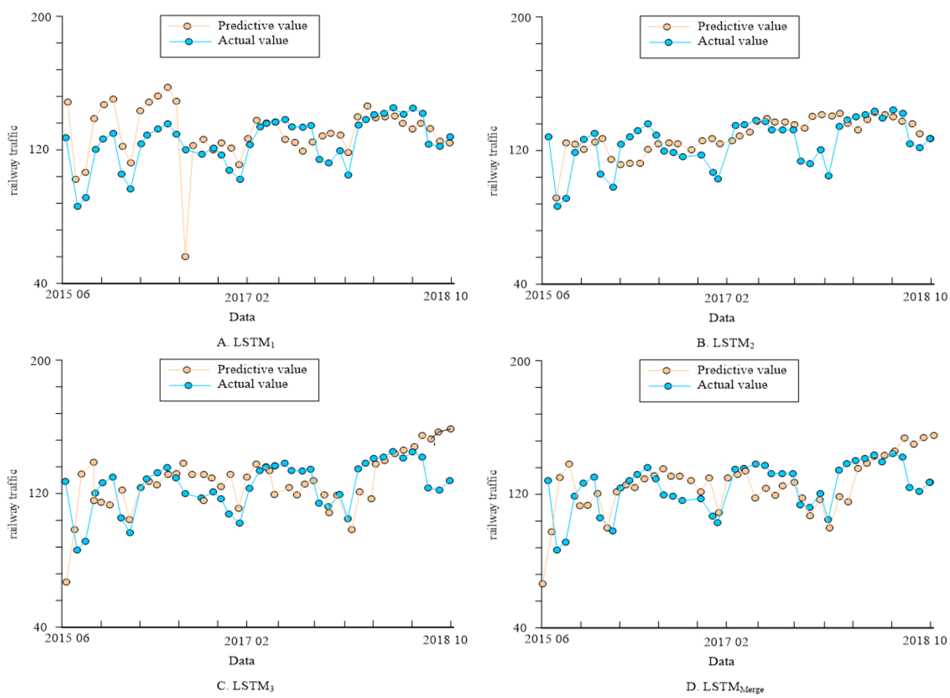


Table 3. GRU model error

	MAPE (%)	MAE	RMSE
GRU1	9.31	11.28	15.85
GRU2	10.14	11.35	15.13
GRU3	13.41	13.32	18.38
GRUMerge	9.07	10.45	13.70
Average value	10.56	11.6	16.30

Figure 8 shows that the three neural networks, GRU1, GRU2, and GRUMerge, had a good fitting. The learned data were close to the real data. However, the deviation of GRU2 was large, and the gap and offset can be clearly seen. GRU1 and GRU3 had different prediction trends in the test data phase. Figure 8 shows that the two had a large difference. The GRU1 after the prediction was lower than it was at the beginning of the prediction. GRU3 is generally worse than the actual forecast during the forecast period, and GRU2 has different stages before and after the forecast period. The prediction effect of the GRUMerge model was the best, and its change trend was close to the actual situation.

Based on the above results, the MAPE, mean absolute error (MAE), and root mean square error (RMSE) of the GRU model are lower than those of the other GRU models. The line chart shows that the fitting effect of this method is better than that of other GRU models, which further shows that the prediction effect of the deep learning prediction model using the merge algorithm is better than that of a single algorithm. The results of the LSTM prediction model indicate that the prediction effect of the multilayer neural network is poorer than that of the single neural network.

Bi-LSTM Model Prediction Results

On the basis of the Bi-LSTM model, a Bi-LSTM neural network structure based on LSTM was established and connected with the neural network. The preprocessed input index was fed into the Bi-LSTM model, and its predicted value was 5.25%, MAE was 6.21%, and RMSE was 8.89%. This finding shows that the method has a good prediction effect.

Figure 8. GRU model fitting of different architectures

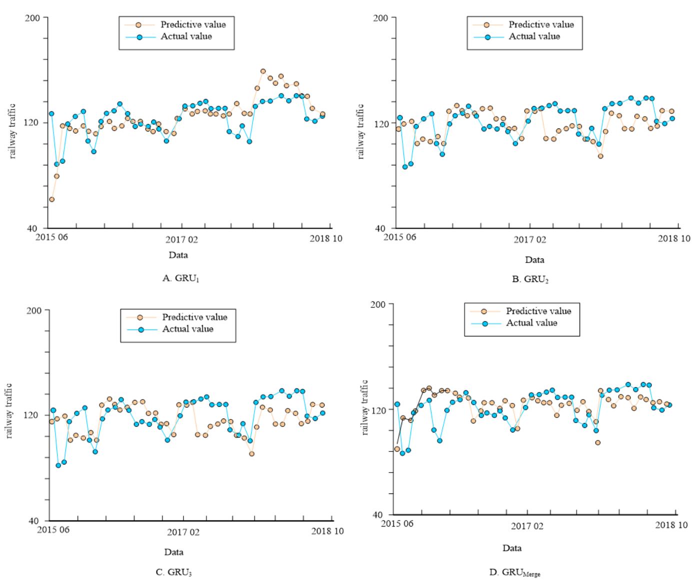


Table 4. Bi-LSTM model error

Serial Number	Index	Bi-LSTM
1	MAPE (%)	5.25
2	MAE	6.21
3	RMSE	8.89

In terms of the match between the test results and the real data, the prediction results made by the Bi-LSTM method are close to the actual situation. Given its bidirectional input of time series data, Bi-LSTM's prediction results in the data testing phase are the closest to the actual situation in both cases. Moreover, the change trend of the overall prediction was consistent with the change trend of the real situation. On the basis of the above reasons, this study selects the Bi-LSTM neural network model as the prediction model for the transportation demand of Tianjin Station.

Prediction Model Performance Evaluation

On the basis of deep learning prediction for Tianjin Station, a prediction model based on Bi-LSTM neural network was established. A performance comparison method based on the deep learning model was adopted to evaluate the prediction effect of the Bi-LSTM prediction model objectively and efficiently. The economic indicators of the six regions were input into the forecasting model, and forecasting was assessed by indices such as MAPE, MAE, and RMSE.

The traffic indices of the six regions and the economic indices of each region are input into the prediction model of Bi-LSTM, as shown in Figure 10. The MAPE, RMSE, and MAE scores of each index input into the prediction model were compared with the LSTM and GRU models by adjusting the test parameters of the prediction model many times. The optimal model of the logistics system of Tianjin Station was also obtained. This study analyzes several aspects, such as data preprocessing, time series data, and data segmentation, to eliminate parameter interference in various model experiments.

Six regions were used as input indices. The complete prediction results show that the MAPE values of LSTM, GRU, and Bi-LSTM were all below 0.1. This finding shows that the three deep learning methods proposed in this study can all be used for logistics demand forecasting in Tianjin Station. The prediction effect of the Bi-LSTM model is better than the prediction effects of LSTM and GRU prediction models in reflecting the learning and memory of long-term nonlinear time series data. The reason is that the algorithm designed in this study integrates the self-learning technology of neural networks in the calculation. Thus, it has excellent adaptive ability and is better than other algorithms.

According to the perspective of the prediction effect of the deep learning prediction mode on a single regional indicator, the Bi-LSTM with Tianjin Station as the example had the best performance. Given the division of Tianjin Station and its own economic and railway transportation advantages, the influence of logistics demand and supply chain demand of Tianjin Station is much greater than that of other provinces and cities. The data analysis of Beijing Station and Hebei Station shows that after the model was entered as an input index, the predicted values of Beijing Station and Hebei Station

Figure 9. Bi-LSTM model fitting

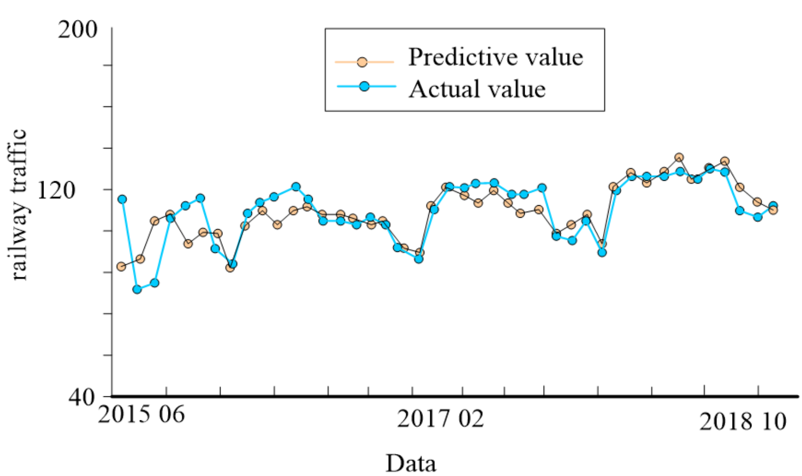
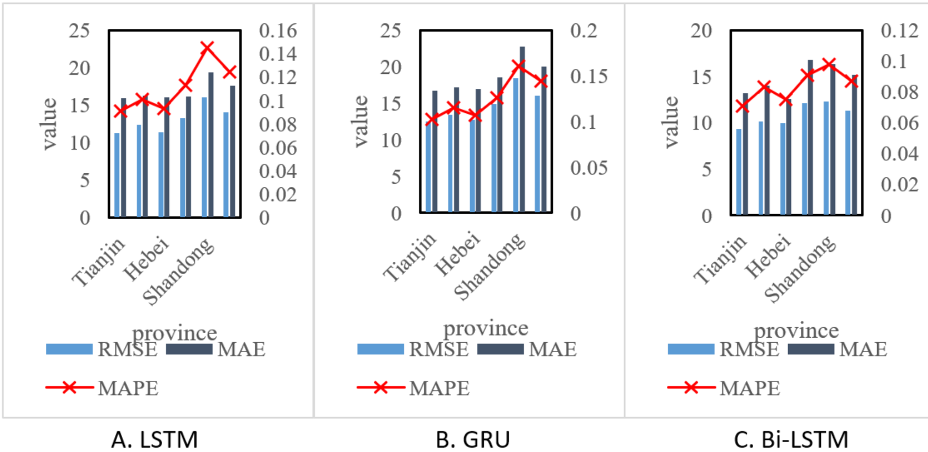


Figure 10. Predicting the performance evaluation results of a single hinterland index deep learning model



were lower than the predicted value of Tianjin Railway Station but better than those in other cities. This scenario may be related to the economic strength of Tianjin Station. Moreover, the logistics supply chain demands of Shanxi Station and Shandong Station were input into the forecasting model because of their weak economic capacities. The worst performance results were obtained when the logistics supply chain demand was fed into a predictive model as input metrics. When it was fed into the predictive model as input metrics, the results were the worst.

CONCLUSION

In this study, the historical evolution trend of the logistics industry development and logistics flow in Tianjin Station was sorted out. The factors that affect the logistics traffic were selected according to the logistics industry and regional economic conditions of Tianjin Station. Moreover, wavelet decomposition changes were used to decompose the influencing factors. The value of the supply chain demand forecast under the training of the machine learning model is more accurate, and the model stability is high. The demand forecasting model of the Tianjin Station logistics supply chain was constructed using deep learning neural networks, namely, LSTM, GRU, and Bi-LSTM. According to the experimental results, the Bi-LSTM model constructed based on machine learning in this study had the highest prediction accuracy. It could well predict the demand for RSC. However, the present research has certain flaws. For example, the supply chain demand analysis for railways has no empirical data. Therefore, in the follow-up experiments, China's railway network will be deeply analyzed for perfect results.

FUNDING

Special Course on Innovative Application of Virtual Simulation Technology in Vocational Education Teaching by the Ministry of Education (ZJXF2022006). Key Research Project Plan for Higher Education Institutions in Henan Province (23A580006). Henan Vocational Education Teaching Reform Research and Practice Project (Yu Jiao [2023] 03141). Henan Province Lifelong Education Special Project (Yu Jiao [2022] 45760). General Research Projects of Zhengzhou Railway Vocational and Technical College (2023KY007).

REFERENCES

Abdellaoui, M. E., & Pache, G. (2020). Effects of disruptive events within the supply chain on perceived logistics performance. *Economic Bulletin*, *39*(1), 32–51.

Bai, Y., Rong, Y., Sun, J., Chen, L., Zhang, D., & Yin, Z. (2021). Seamount age prediction machine learning model based on multiple geophysical observables: Methods and applications in the Pacific Ocean. *Marine Geophysical Researches*, *42*(3), 1–11. doi:10.1007/s11001-021-09451-z

Gang, L. (2017). Toward a progress indicator for machine learning model building and data mining algorithm execution: A position paper. *SIGKDD Explorations*, *19*(2), 13–24. doi:10.1145/3166054.3166057 PMID:29177022

Gogrichiani, G. V., & Lyashenko, A. N. (2021). Choosing the best solutions for multimodal oil transportation. *Transportation Systems and Technology*, *7*(2), 76–86. doi:10.17816/transsyst20217276-86

Hartzel, K. S., & Wood, C. A. (2017). Factors that affect the improvement of demand forecast accuracy through point-of-sale reporting. *European Journal of Operational Research*, *260*(1), 171–182. doi:10.1016/j.ejor.2016.11.047

Homchan, S., & Gupta, Y. (2021). Short communication: Insect detection using a machine learning model. *Nusantara Bioscience*, *13*(1), 68–72.

Inamul, H. M., Ghazala, S., Iftikhar, A. T., Atif, N. H., Bandana, P., Anjali, R., Pravitha, K. S., Tamizhini, L., Mahamuda, B., & Sneha, R. (2021). Identification of marker genes in Alzheimer's disease using a machine-learning model. *Bioinformation*, *17*(2), 348–355. PMID:34234395

Irannezhad, E. (2019). Is blockchain a solution for logistics and freight transportation problems? *Transportation Research Procedia, 48*, 290–306.

Jayakrishnan, M., Mohamad, A., & Yusof, M. M. (2020). Digitalization Railway Supply Chain 4.0: Enterprise architecture perspective. *International Journal of Advanced Trends in Computer Science and Engineering*, *9*(5), 9056–9063. doi:10.30534/ijatcse/2020/310952020

Jitsuishi, T., & Yamaguchi, A. (2022). Searching for optimal machine learning model to classify mild cognitive impairment (MCI) subtypes using multimodal MRI data. *Scientific Reports*, *12*(1), 1–14. doi:10.1038/s41598-022-08231-y PMID:35277565

Kozachenko, D. M., Vernigora, R. V., & Rustamov, R. S. (2017). Creation of export-oriented network of grain elevators in Ukraine. *Science and Transport Progress Bulletin of Dnipropetrovsk National University of Railway Transport*, *68*(2), 56–70. doi:10.15802/stp2017/99952

Li, J. (2017). Research on benefit coordination mechanism of service supply chain of highway and railway combined transportation based on pricing game model. *Boletin Tecnico/Technical Bulletin, 55*(10), 643–648.

Lustig, D. (2019). Ripples in the supply chain. *Railway Gazette International*, *175*(1), 32–35.

Nav, H. N., Motlagh, M. R. J., & Makui, A. (2018). Modeling and analyzing the chaotic behavior in supply chain networks: A control theoretic approach. *Journal of Industrial and Management Optimization*, *14*(3), 1123–1141. doi:10.3934/jimo.2018002

Rudakov, K. V., Strizhov, V. V., Kashirin, D. O., Kuznetsov, M. P., Motrenko, A. P., & Stenina, M. M. (2017). Selecting an optimal model for forecasting the volumes of railway goods transportation. *Automation and Remote Control*, *78*(1), 75–87. doi:10.1134/S0005117917010064

Sabath, R. (2019). U.S. truck transportation: Solving the industry's challenges will separate leaders from laggards! *Supply Chain Brain*, *23*(2), 52–53.

Shruthishree, S. H., Tiwari, H., & Verma, C. D. (2021). AlexResNet+: A deep hybrid featured machine learning model for breast cancer tissue classification. *Turkish Journal of Computer and Mathematics Education*, *12*(6), 2420–2438.

Sudarmaji, E., Achsani, N. A., Arkeman, Y., & Fahmi, I. (2021). Credit-worthiness prediction in energy-saving finance using machine learning model. *Asia Proceedings of Social Sciences*, *8*(2), 88–92. doi:10.31580/apss.v8i2.1899

Wilson, S. (2017). The advantages of a pop up supply chain. *Inbound Logistics, 37*(4), 93–93.

Yin, H., Hu, L., Yeh, J. S., & Pan, Y. (2017). Collaborative demand forecasting model and simulation for supply chain integration based on multi-agent Petri net. *C e Ca*, *42*(5), 1915–1919.

Zhang, R., & Jia, H. (2021). Production performance forecasting method based on multivariate time series and vector autoregressive machine learning model for waterflooding reservoirs. *Petroleum Exploration and Development*, *48*(1), 201–211. doi:10.1016/S1876-3804(21)60016-2

Pengyu Wang was born in Xinyang, Henan, P.R. China, in 1992. He received the master's degree in transportation management and logistics from St. Petersburg State Transportation University, Russia. Director of the office of the college. Research interests: railway freight, logistics and supply chain, multimodal transport, the Belt and Road, etc.

Yaqiong Zhang was born in Handan, Hebei, P.R. China, in 1981. She received the Doctoral Degree in Management Science and Engineering from North China University of Water Resources and Electric Power, China. Now, she works in School of transportation management, ZhengZhou Railway Vocational & Technical College. Research interests: railway freight, logistics and supply chain, multimodal transport, the Belt and Road, etc.

Wanqing Guo was born in Zhengzhou, Henan, P.R. China in 1992. She received Master Degree in Money and Banking from University of Exeter, UK. Now she works in Business School, Zhengzhou SIAS University. Research interests: finance, economics, supply chain management, etc.