

# The Influence and Prediction Analysis of Cargo Volume Under the Change of Logistics Route Based on LSTM Neural Network

Chuyu Yu<sup>\*,#</sup>, Haodi Zhu<sup>#</sup>

Institute of finance and economics, Qinghai University, Xining, China, 810000

\* Corresponding Author Email: 19357620585@163.com

<sup>#</sup>These authors contributed equally.

**Abstract.** With the vigorous development of e-commerce, logistics industry has put forward higher requirements for the management efficiency of sorting center. Accurately predicting the cargo volume of the sorting center is the key to optimizing personnel scheduling and improving operational efficiency. Aiming at the problem of cargo volume prediction in sorting center of logistics network, this paper constructs a prediction model based on LSTM model. The LSTM model can effectively capture the long-term dependence relationship in the time series data, and the predicted results have a high degree of fitting with the actual results. The research results of this paper show that the cargo volume prediction model based on LSTM model can effectively predict the cargo volume of the logistics network sorting center, and provide decision support for the operation and management of logistics enterprises.

**Keywords:** LSTM model, Cargo volume prediction, Logistics network, Sorting center.

## 1. Introduction

As an important basic and strategic industry supporting national economic and social development, logistics industry has ushered in vigorous development under the promotion of e-commerce. As the core node of the logistics network, the sorting center undertakes the important functions of receiving, sorting, packaging and transshipment, and its operational efficiency directly affects the efficiency and service quality of the entire logistics network<sup>[1]</sup>. With the rapid growth of the order volume and the increasing demand of consumers for the timeliness of logistics, the sorting center is faced with great challenges. How to predict accurately.

The cargo volume of the sorting center has become a key issue to improve the operational efficiency of the sorting center.

The traditional cargo volume prediction method mainly relies on historical data statistics and experience judgment, which is difficult to deal with the complex and changeable logistics environment. In recent years, with the rapid development of artificial intelligence and big data technology, the prediction model based on machine learning has achieved remarkable results in various fields. Among them, long short-term memory network (LSTM), as a special recurrent neural network, has a strong series modeling ability and can effectively capture the long-term dependence relationship in the time series data, showing great potential in the field of cargo volume prediction<sup>[2]</sup>.

This paper aims to explore the cargo volume prediction method of logistics network sorting center based on LSTM model. First, this paper will analyze the characteristics of the cargo volume data of the sorting center, and pre-process the data to provide a reliable data basis for model training. Secondly, this paper will build a cargo volume prediction model based on LSTM, and verify the superiority of LSTM model in cargo volume prediction by comparing different time series prediction models. Finally, this paper will analyze the impact of the change of transportation line on the cargo volume of the sorting center, and according to the changed line data, the LSTM model is used to forecast again, and the prediction result of the cargo volume of the sorting center after the change of transportation line is obtained.

The research results of this paper will provide an effective model and method for the cargo volume prediction of the logistics network sorting center, which will help improve the operational efficiency

of logistics enterprises, reduce operating costs, improve service level, and provide theoretical and technical support for promoting the intelligent development of the logistics industry.

## 2. Data and methods

### 2.1. Acquisition of data

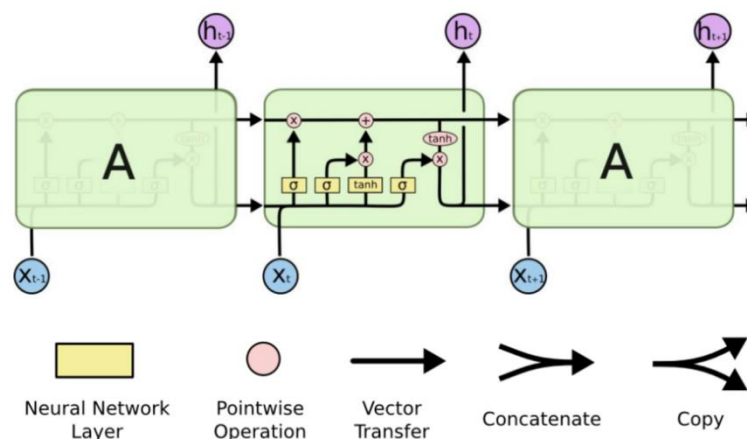
The data in this research are sourced from the open-source website (<http://mathorcup.org/>).

The data included 57 sorting centers in the logistics network, shipments per unit for each center over the past four months and shipments per hour over the past 30 days.

### 2.2. LSTM

Long Short-Term Memory (LSTM) is a type of temporal recurrent neural network (RNN) suitable for processing and predicting important events in time series with very long intervals and delays [3]. LSTM is a powerful time series prediction tool to manage the flow of control information through cell state and gating mechanism, which enables it to effectively capture long-term dependencies in time series data [4].

The LSTM also has a similar chain structure to the RNN, but the difference is that its repetitive module structure is different, and it is four neural networks that interact in a special way [5-6].

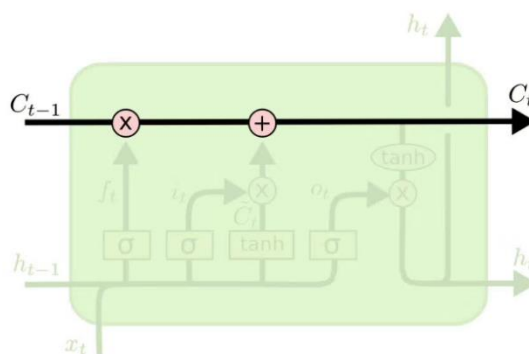


**Figure 1.** Diagram of the LSTM model1

In Figure 1, each line passes a complete vector from the output of one node to the input of the other. The pink circles represent pointwise operations, such as node summing, while the yellow boxes represent the neural network layer used for learning. The two merged lines indicate connections, and the two separate lines indicate that the information is copied into two copies and will be passed on to different locations [7].

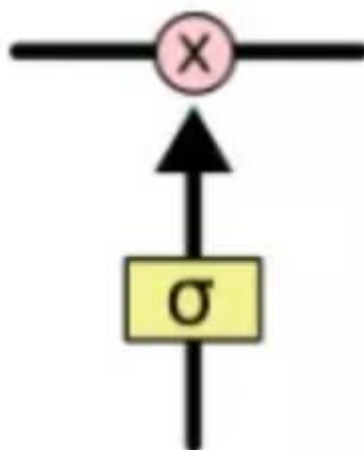
The key to the LSTM is the state of the cell, the horizontal line that runs through the top of the schematic [8].

The cell state is a bit like a conveyor belt (Figure 2) in that it runs through the chain with only minor linear interactions. This is where the information is remembered, so it can easily flow through it in an unchanging form.



**Figure 2.** Cell state diagram2

In order to add/remove information in the cell, there are some control gates (gates) in the LSTM (Figure 3). They determine how information passes through and contain a sigmoid neural network layer and a pointwise dot multiplication operation<sup>[9]</sup>.



**Figure 3.** gate diagram3

The sigmoid layer outputs numbers between 0 and 1. The dot multiplication operation determines how much information can be transmitted, and when it is 0, it is not transmitted; When it's 1, it sends it all.

There are three LSTMS like this to protect and control the cell state.

The main advantages can be summarized as:

1. Long-term memory ability: introducing internal cellular states, capturing and retaining long-term dependencies in sequences;
2. Gating mechanism: the gating units of forgetting gate, input gate and output gate control the flow of information through learning to effectively manage the updating of cell states and selective forgetting;
3. Back propagation stability: Due to the gating mechanism of LSTM, it usually does not have the problem of gradient disappearance or explosion when back propagation, and training is easier<sup>[10]</sup>.

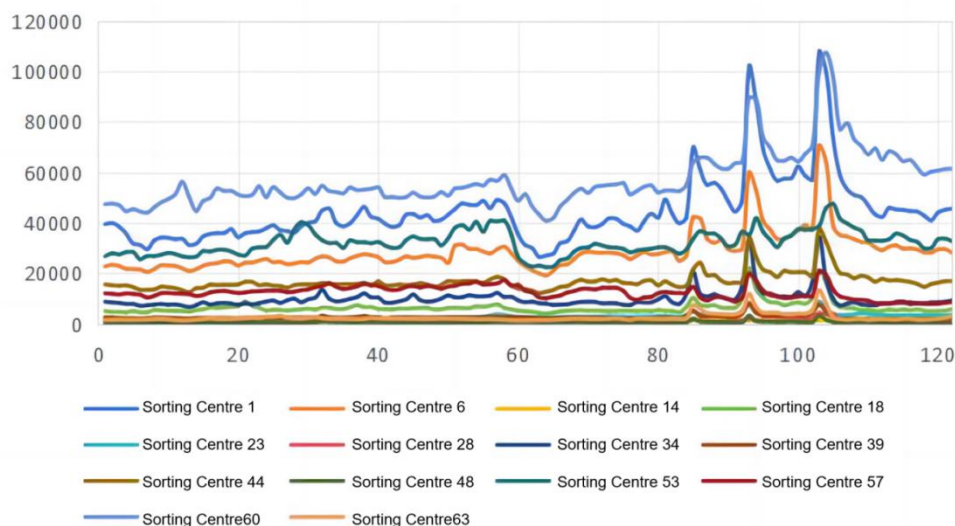
### 2.3. Selection of model evaluation indexes

Since the range of mean square error, root mean square error and mean absolute error is closely related to the size of the data itself, it is impossible to intuitively understand the effect of the model, so this paper mainly considers R square as the evaluation index, while referring to MSE, RMSE and MAE comprehensive evaluation.

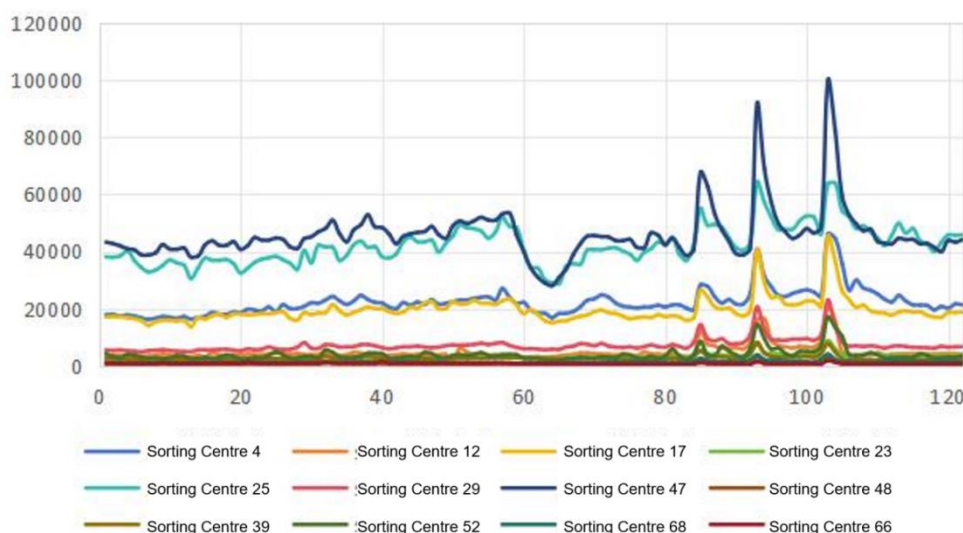
### 3. Results and analysis

#### 3.1. Data Preprocessing

First of all, this paper makes a visual analysis of the routes generated by different nodes and the total amount of goods distributed on the nodes, and cleans the data, zeroes out the missing value of the amount of goods per hour, considers the abnormal value to be the real data, and considers the corresponding time node to be the "Double Eleven" promotion period, so no exponential smoothing, denoising and other processing are carried out. The daily cargo volume and visualization of some nodes are shown in Figure 4 and Figure 5:



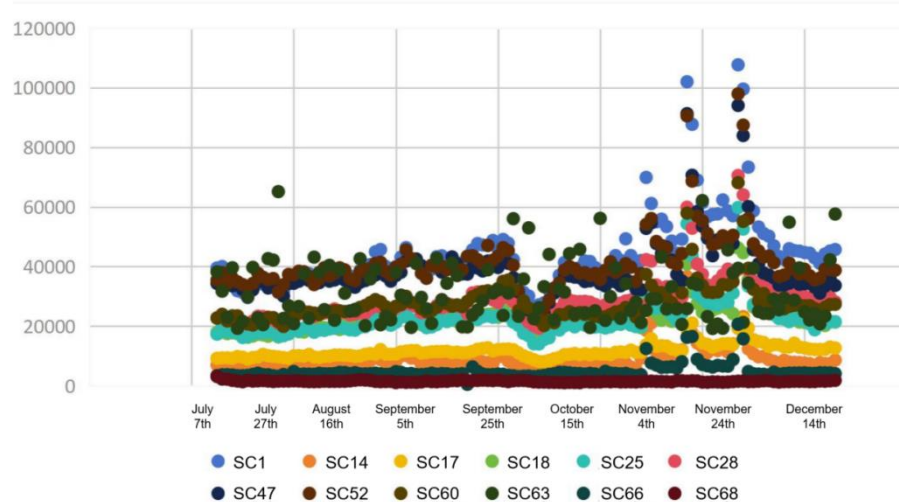
**Figure 4.** Cargo volume of sorting center 14



**Figure 5.** Cargo volume of sorting center 25

It can be seen from Figure 4 and Figure 5 that the change trend of the daily cargo volume of some sorting centers shows a rising trend on the whole, and most of the sorting centers are demarcated on October 1. Before October 1, it showed a slow trend of change, and after October 1, there was a more obvious peak situation, and some picking center points did not change significantly, such as SC21, SC28, SC46 and so on.

The cargo volume of some important nodes as well as their monthly changes and trends are shown in Figure 6.

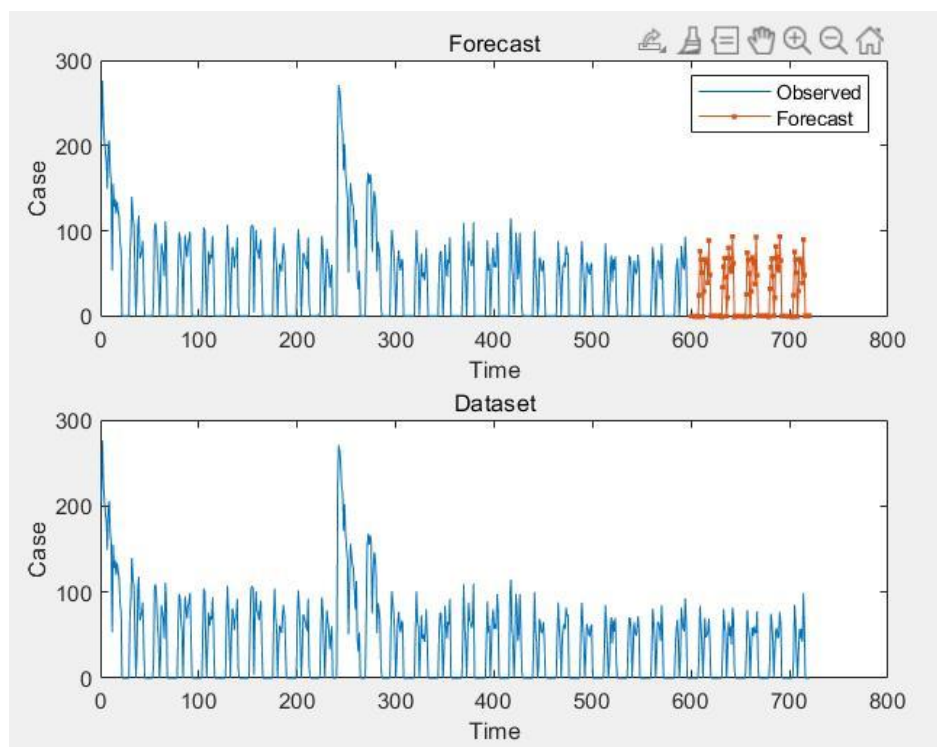


**Figure 6.** Scatter diagram of cargo volume of typical sorting center6

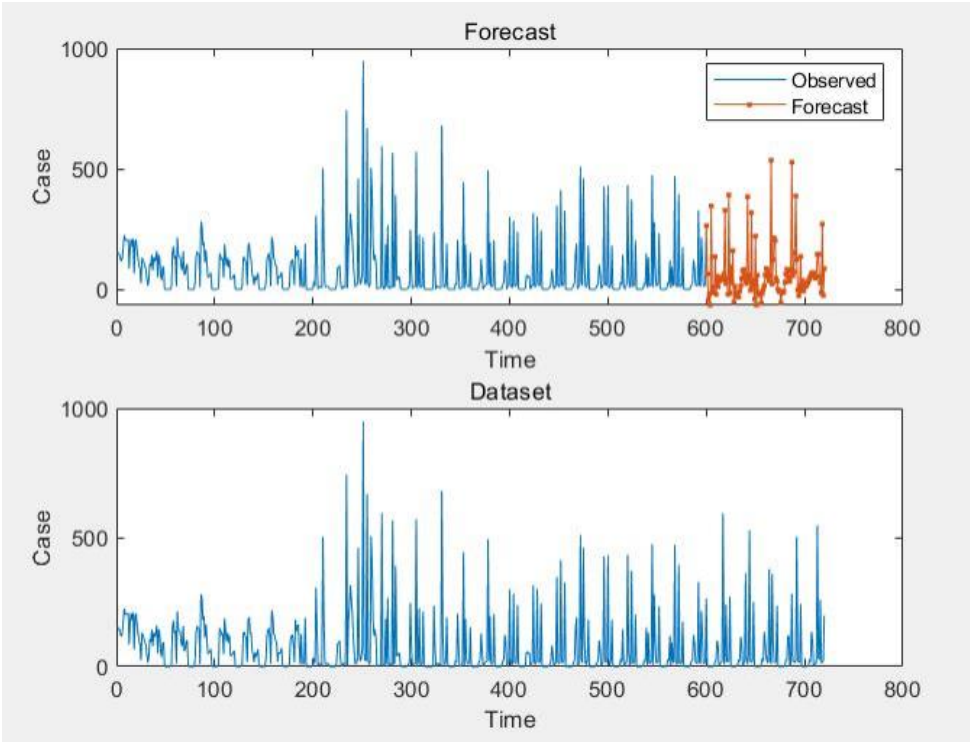
From the perspective of the trend of total cargo volume (Figure 6), the total cargo volume showed a steady and slow growth trend from August to October 1. After October 1, it showed an overall upward trend, and there were obvious fluctuations at special time nodes, such as October 24, November 1 and November 11. This time node is the corresponding "Double Eleven" shopping carnival period, so the growth rate of goods is fast.

### 3.2. Future cargo volume prediction of logistics network sorting center based on LSTM model

After data analysis, the prediction results and model prediction accuracy are shown in the Figure 7 and Figure8 below.

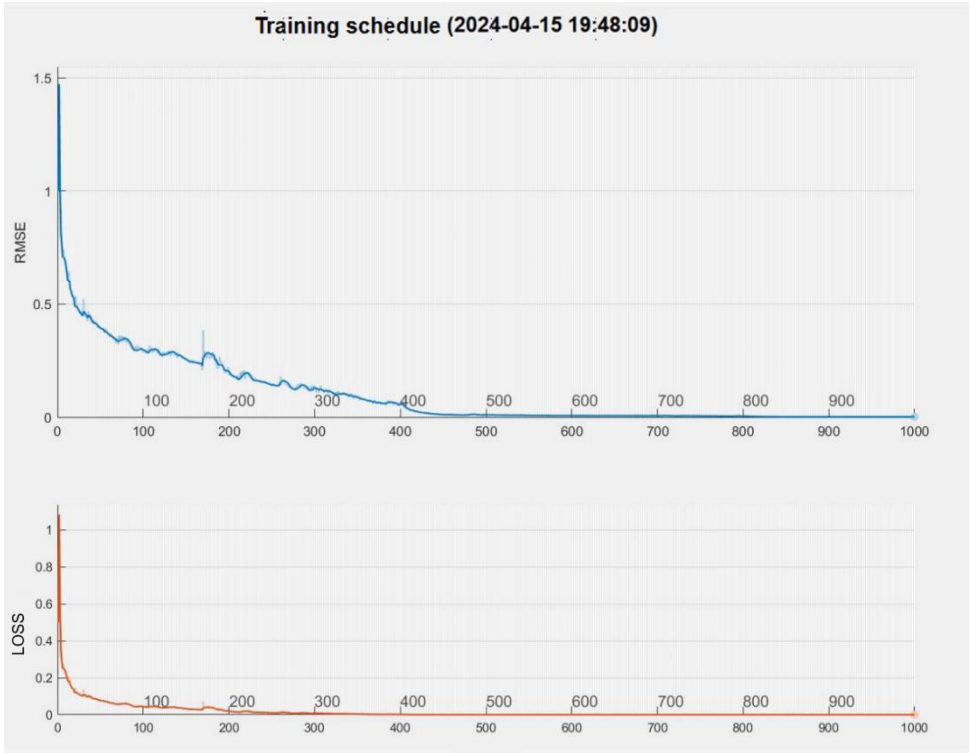


**Figure 7.** Prediction result 17



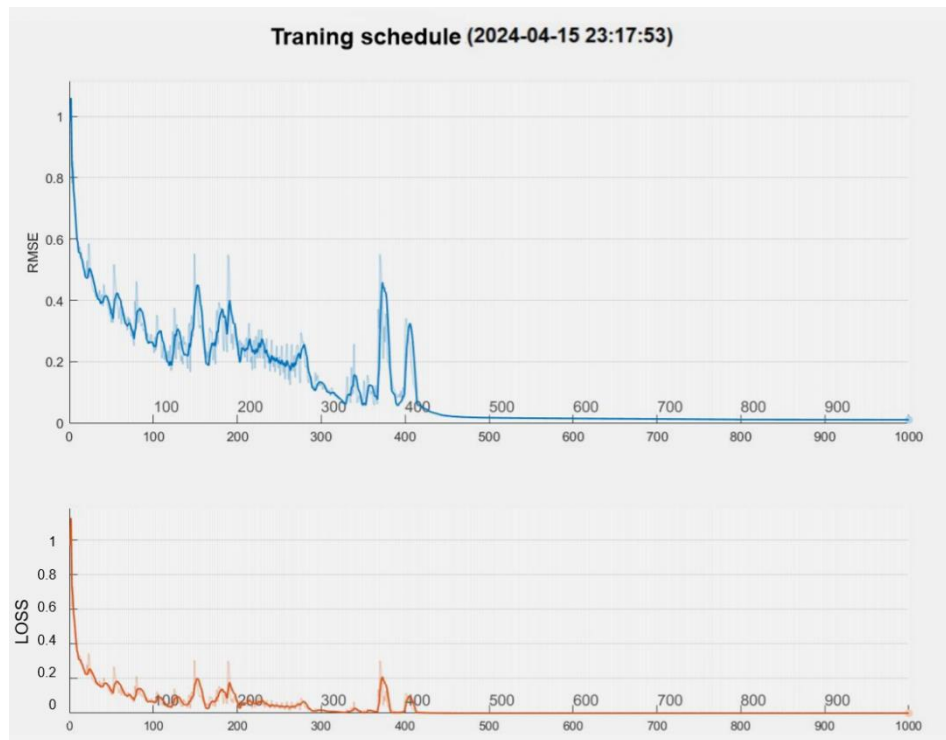
**Figure 8.** Predicted result 28

The comparison between the observed value and the predicted value calculated by the program is shown in Figure 7 and Figure 8. It can be clearly found through the comparison chart that there is a strong correlation between the observed value and the predicted value. The change trend and amplitude of the predicted value are strongly correlated with the observed value, which indicates that the predicted value can better reflect the actual amount of goods in the future period.



**Figure 9.** Training progress 19



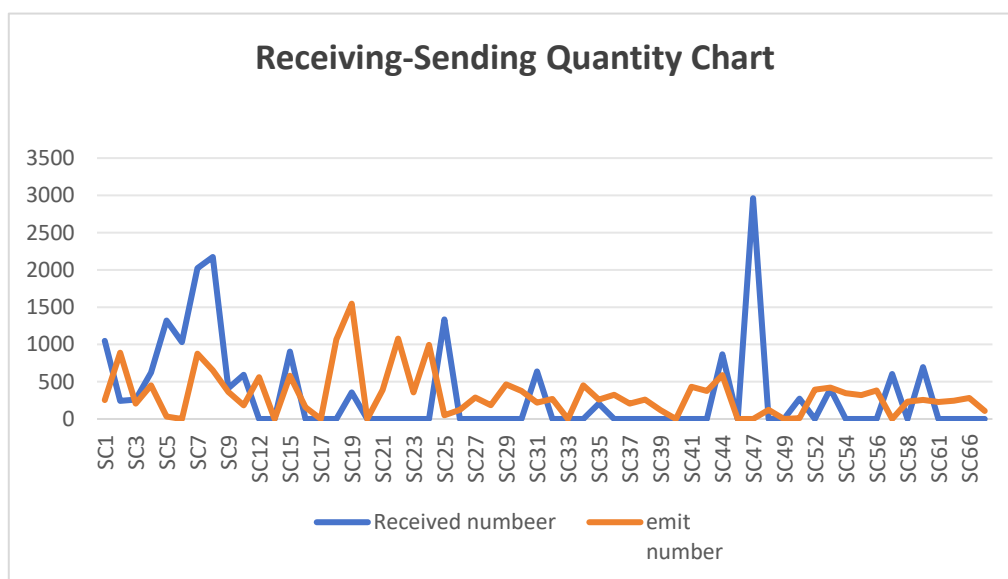


**Figure 10.** Training progress 210

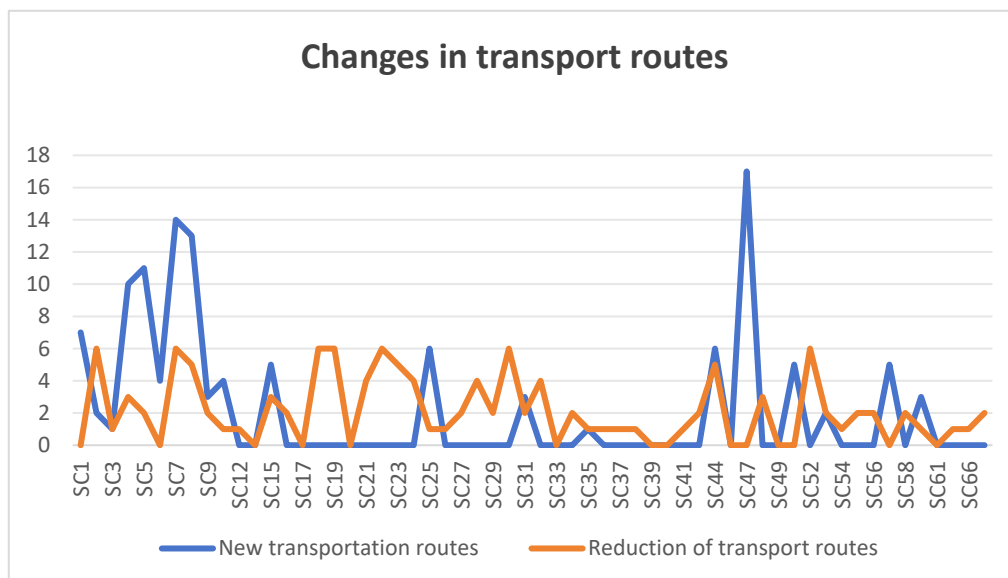
As can be seen from the training progress in Figure 9 and Figure10, as the number of iterations increases, RMSE decreases and the loss function decreases, and RMSE approaches 1 when the iteration is about 600 times, indicating that the prediction accuracy of your model has been improved to the best level. The predicted results using this method are in good comparison with the original results. The predicted results are similar to the actual results, and the predicted results are relatively accurate.

### 3.3. Cargo volume prediction of logistics network sorting center based on transport route changes

On the basis of sorting out the quantity of goods received and sent out by different sorting centers, the change of transportation routes of each sorting center is further analyzed, as shown in Figure. 11 and 12.



**Figure 11.** Change of cargo volume in sorting center11



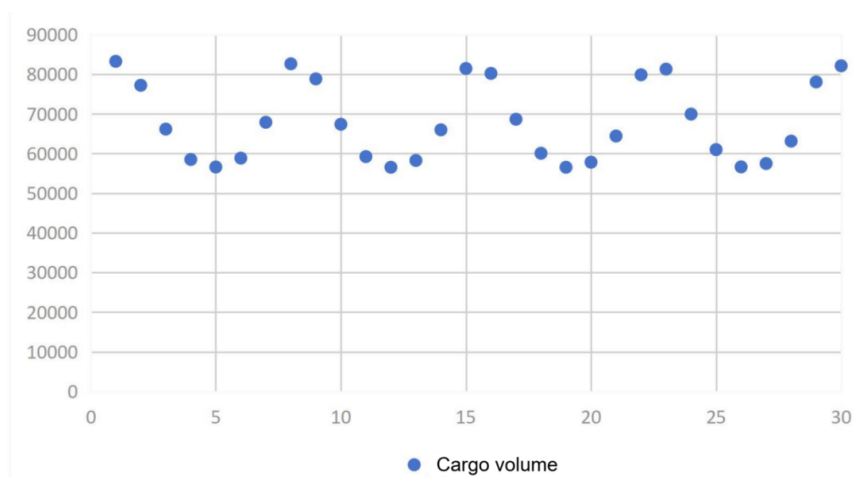
**Figure 12.** Change of sorting center line

**Table 1.** The degree of change in cargo volume12

| Sorting Center | The degree of change in the volume of goods |
|----------------|---------------------------------------------|
| SC5            | Reduced to 89.55 percent before change      |
| SC7            | Reduced to 93.67% before change             |
| SC8            | Reduced to 95.54% before change             |
| SC9            | Reduced to 125.05% before change            |
| SC10           | Reduced to 61.49 percent before change      |
| SC15           | Reduced to 59.99% before change             |
| SC25           | Reduced to 67.37% before change             |
| SC47           | Reduced to 96.53% before change             |
| SC51           | Reduced to 94.86% before change             |

According to the data of the quantity of goods before the change of the route and the change of the transportation route, the degree of change of the quantity of goods in Table 1 is sorted out, and the corresponding change of the quantity of goods is inferred according to the change of the route after the change. The LSTM model is used again to forecast the data according to the quantity of goods in the first 90 days.

The quantity of goods predicted in the next 30 days is shown in Figure 13:



**Figure 13.** Scatterplot of forecast cargo volume for the next 30 days13



## 4. Conclusion

Based on the LSTM model, this paper makes an in-depth study of the cargo volume prediction of the logistics network sorting center, and draws the following conclusions: The LSTM model can effectively predict the cargo volume of the logistics network sorting center, and the predicted results have a high degree of fitting with the actual results. The change of transportation route has a significant impact on the cargo volume of the sorting center, so it is necessary to adjust the cargo volume prediction model in time according to the change of the line. The research results of this paper provide an effective model and method for the cargo volume prediction of logistics network sorting center, which is helpful to improve the operating efficiency of logistics enterprises and reduce the operating cost. In real situations, future cargo volume can be predicted based on historical data. Meanwhile, appropriate adjustments should be made according to different seasonal factors. By predicting future changes in a timely manner and adjusting transportation routes, the operation of the logistics network can be made more systematic and efficient.

## References

- [1] Xia Jing. Research on business process simulation modeling and optimization of Sorting center of S Logistics Company based on Anylogic [D]. Anhui University of Science and Technology, 2024.
- [2] Le Hengtao, Zhao Kangkang, Wu Song-Lin, et al. A different space hand-eye calibration method for robot based on LSTM network [J]. Journal of Wuhan Institute of Technology, 2024, 46(05): 574-578.
- [3] Yan T. (2023). Positioning of logistics and warehousing automated guided vehicle based on improved LSTM network. Int. J. Syst. Assurance Eng. Manage. 14, 509–518.
- [4] Ul B I, Forruque S A. Short-Term Electrical Load Demand Forecasting Based on LSTM and RNN Deep Neural Networks [J]. Mathematical Problems in Engineering, 2022, 2022.
- [5] Mounir G, Francisco G, Francisco R, et al. A Soft Sensor to Estimate the Opening of Greenhouse Vents Based on an LSTM-RNN Neural Network [J]. Sensors, 2023, 23(3): 1250-1250.
- [6] Huang YC, Chen YH. Use of Long Short-Term Memory for Remaining Useful Life and Degradation Assessment Prediction of Dental Air Turbine Handpiece in Milling Process. Sensors (Basel). 2021 Jul 22; 21 (15): 4978.
- [7] Dai Y, Wei J, Qin F. Recurrent neural network (RNN) and long short-term memory neural network (LSTM) based data-driven methods for identifying cohesive zone law parameters of nickel-modified carbon nanotube reinforced sintered nano-silver adhesives [J]. Materials Today Communications, 2024, 39: 108991-.
- [8] Liu C, Wang C, Tran N M, et al. A long short-term memory enhanced realized conditional heteroskedasticity model [J]. Economic Modelling, 2025, 142: 106922-106922.
- [9] Smagulova, K., James, A.P. A survey on LSTM memristive neural network architectures and applications. Eur. Phys. J. Spec. Top. 228, 2313–2324 (2019).
- [10] Zhou L, Wang T, Chen Y. Bridge temperature prediction method based on long short-term memory neural networks and shared meteorological data [J]. Advances in Structural Engineering, 2024, 27(8): 1349-1360.