Multi-Model Fusion Optimization for Cargo Volume Forecasting and Sorting Efficiency in E-Commerce Logistics Networks

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Abstract: With the rapid development of the logistics industry and the growing material needs of the people, the rational planning of e-commerce logistics networks has become increasingly important. In the process of studying e-commerce logistics networks, the sorting efficiency of sorting centers is also one of the research directions that cannot be ignored. Both cargo prediction and sorting efficiency prediction have great research value for logistics networks. This article focuses on the sorting center of e-commerce logistics network, mainly studying the prediction of cargo volume and the scheduling of sorting center employees. This article establishes an LSTM neural network model for prediction, and imports data from different sorting centers into the LSTM neural network model for prediction training. At the same time, new and deleted routes were identified, corresponding data was extracted, and an additional Analytic Hierarchy Process (AHP) model was established to explore the relationships between logistics network sorting centers and between sorting centers, as well as between sorting centers and goods. The weights of edge weight coefficients, edge weight coefficients, and sorting center strength were determined.

Keywords: LSTM neural network model, Analytic Hierarchy Process, Multivariate Linear Constraint Model, Sorting Center Scheduling Model.

1. Introduction

With the rapid development of the logistics industry and the growing material needs of people, the rational planning of e-commerce logistics networks has become increasingly important. The e-commerce logistics network consists of three parts: warehouses, sorting centers, and business departments. The sorting center, as an intermediate link in the network, carries the majority of the pressure of the entire e-commerce logistics network. Therefore, optimizing the cargo volume prediction of the sorting center has always been an important research problem in the e-commerce logistics network. Accurate prediction of the cargo volume of the sorting center is the basis for subsequent management and decision-making. Of course, in the process of studying e-commerce logistics networks, the sorting efficiency of sorting centers is also one of the research directions that cannot be ignored. Both cargo prediction and sorting efficiency prediction have great research value for logistics networks.

In the process of studying the e-commerce logistics network, it is necessary to consider the volume and sorting efficiency of the sorting center[1]. In this paper, the model establishes a multivariate linear programming model, selects the time series model to predict the cargo volume, and establishes the model by analyzing the corresponding data characteristics and constraints. The volume of goods refers to the quantity of logistics sent by the warehouse and other sorting centers to the sorting center, and the sorting efficiency refers to the sum of the logistics quantity that the sorting workers of the sorting center can sort and process in a unit time. This paper studies the sorting center in the e-commerce logistics network, and explores the problems related to sorting efficiency and cargo volume[2].

2. Analysis of Sorting Center Data Based on LSTM Neural Network Model

2.1. Model establishment and solution

This article collects 90 days of sorting center data from e-commerce logistics networks. Based on this sorting center data, a Python program was used to visualize the e-commerce logistics network. The data source (90-day sorting center data) includes: sorting center, warehouse, business center, three parts of the goods; Specific time range (December 2023 to February 2024), data frequency (data frequency is counted on a daily basis)

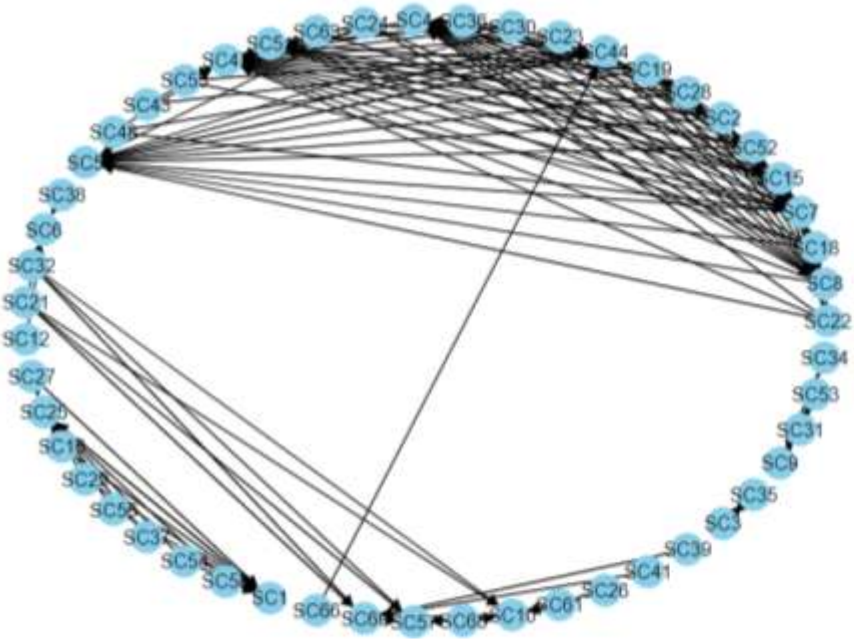

Figure 1. Schematic diagram of e-commerce logistics network

From Figure 1, it can be seen that there are many sorting centers that are not interconnected with other nodes. It is necessary to consider the issue of keeping the existing e-commerce logistics network unchanged[3].

This article analyzes the volume of goods on the same day and draws a three-dimensional image of the date hour cargo volume for some sorting centers, as shown in Figure 2-5.(The horizontal coordinate is" Time (hour)", the vertical coordinate is "Cargo Volume (units)")

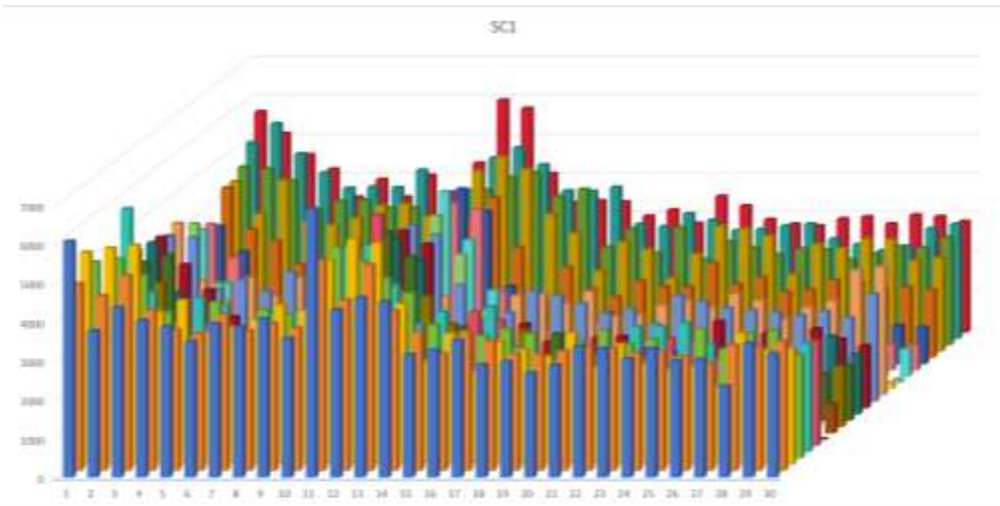

Figure 2: Hourly Cargo Volume Distribution of SC1 in November 2023

Figure 3: Hourly Cargo Volume Distribution of SC10 in November 2(

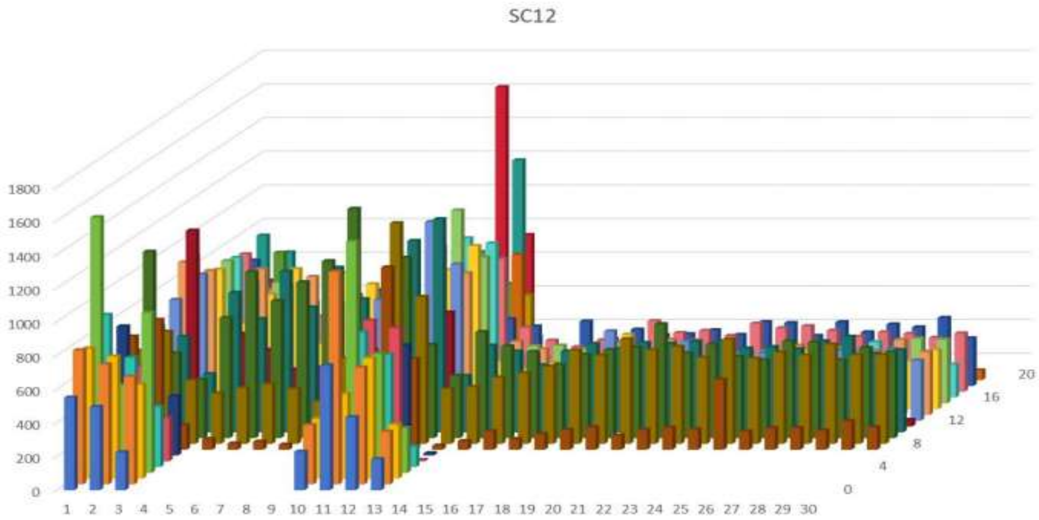

Figure 4: Hourly Cargo Volume Distribution of SC12 in November 2023

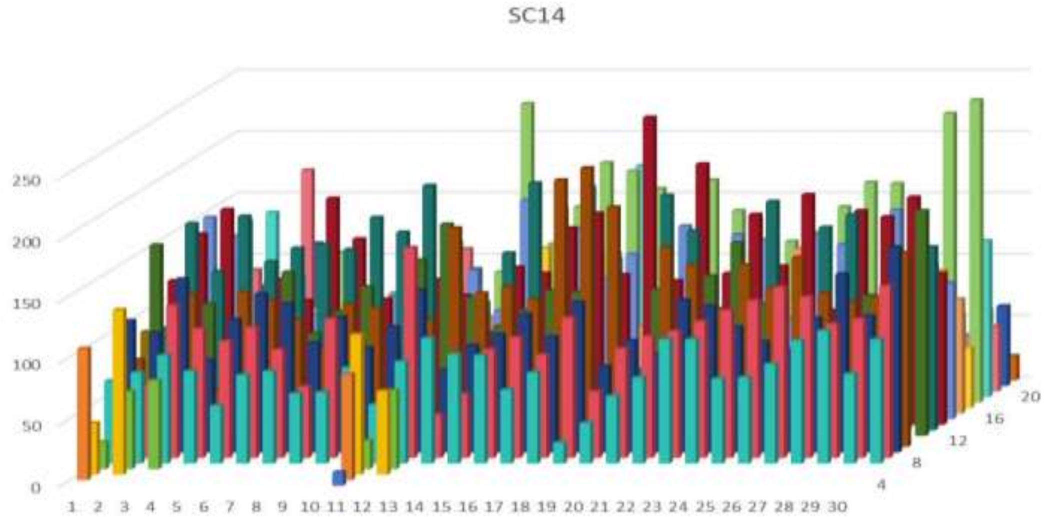

Figure 5: Hourly Cargo Volume Distribution of SC14 in November 2023

From the above figure, it can be seen that there is a peak logistics period in early Novembe[4]. It may be due to the shopping festival, but this article does not analyze the logic behind it. Instead, this article predicts the volume of goods in the sorting center.

2.2. Solution of the model

This article establishes an LSTM neural network model for predictive analysis of continuous time series data, namely cargo volume time data [5]. The LSTM neural network model is suitable for long time series data, and can remember information between a small amount of data and feature values. It can also remember information throughout the entire dataset and eliminate a series of problems such as data errors during training. The LSTM neural network model consists of an input layer, a hidden layer, and an output layer, which perform directed loops between internal neural units. During the training process, the target value is determined by the feature values of the current target and the data sequences from the previous and later stages. Neural units are the core units of the hidden layer, used to remember the associated information of long-term sequence data. And through the input gate, output gate, and forget gate, a non-linear activation function is used to control the transmission state of the IO stream, achieving selective and long-term memory, forgetting, or updating of memory parameter information. The key to the LSTM neural network model is the neural unit state, and its logical architecture is shown in Figure 6:

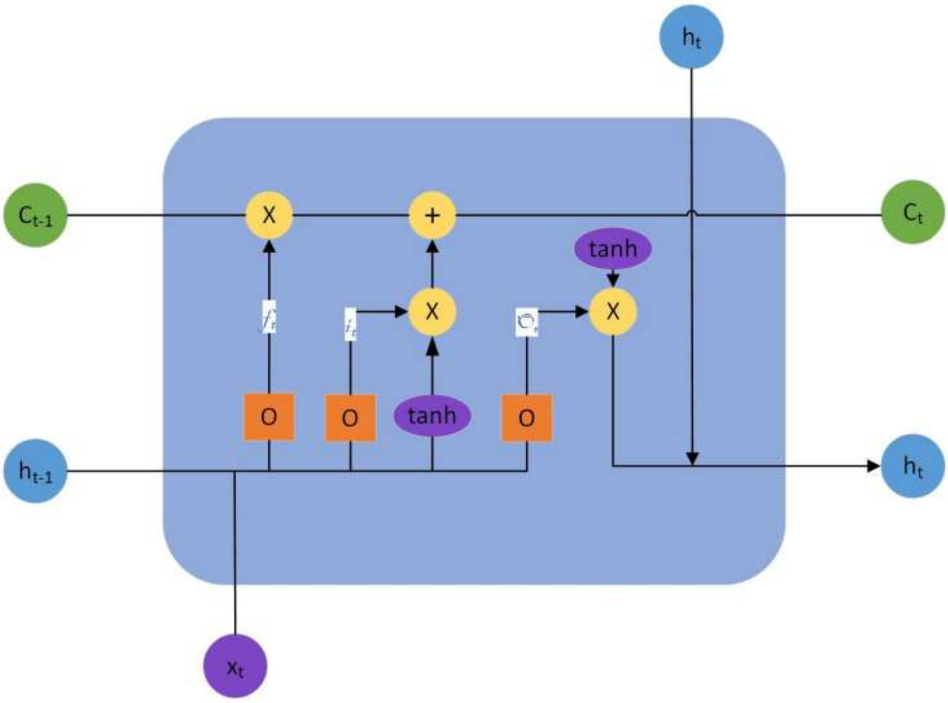

Figure 6: Structure diagram of LSTM neural unit

The forget gate determines whether to retain or forget the information in the unit state, and uses equation (1) to save the required parameters of the Ci-1 state 1; The function of the input gate is opposite to that of the forget gate. The input saved to Ci is determined by equations (2) and (3), and the selected information is placed in the cell state. The output gate controls the information output by equations (4), (5), and (6), and updates the information before each output, discarding some information from the old state; The activation functions are equations (7) and (8） [6].

$$f_t = \sigma \cdot \left(W_f \cdot [h_{t-1}, x_t] + b_f \right) \tag{1}$$

$$i_t = \sigma \cdot \left(W_i \cdot [h_{t-1}, x_t] + b_i \right) \tag{2}$$

$$o_t = \sigma \cdot \left(W_o \cdot [h_{t-1}, x_t] + b_o \right) \tag{3}$$

$$\tilde{c}_t = \tanh \cdot \left(W_o \cdot [h_{t-1}, x_t] + b_c \right) \tag{4}$$

$$h_t = o_t \cdot \tanh(c_1) \tag{5}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \tag{6}$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{7}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{8}$$

In the formula: A, B, and C are the outputs of the forget gate, input gate, and output gate, respectively; DDD is the internal function of the LSTM neural unit; W and b are the weight parameter matrix and bias parameter matrix, respectively. HT and CT are the internal memory vectors of the neural unit at time t. The basic structure of a multi-layer stacked LSTM neural network model is shown in the figure. The neural network architecture shown in the figure consists of three hidden layers of LSTM. The blue circles in the figure represent the neural units, and each hidden layer is composed of a chain of neural units as shown in Figure 7.

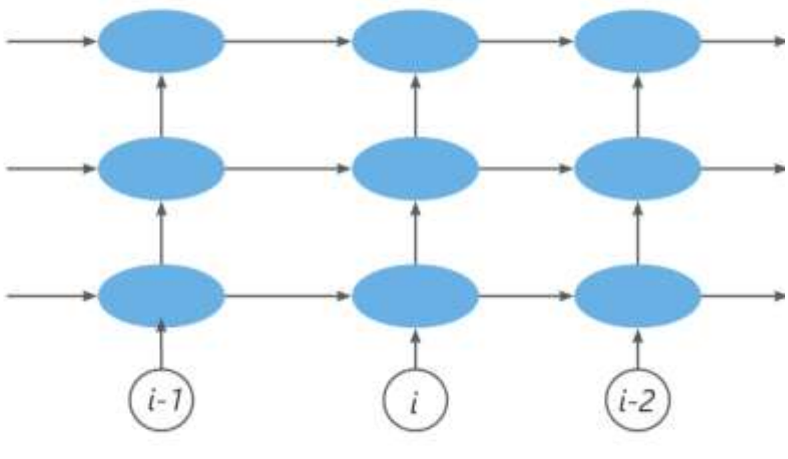

Figure 7: Schematic diagram of LSTM neural network model structure

The establishment process of the LSTM neural network prediction model for the sorting center cargo volume in e-commerce logistics networks is as follows:

(1) Data preprocessing: For the three data of cargo volume, hour, and date, mainly focusing on the secondary integration of cargo volume data, establish sample datasets corresponding to the three types of data, and divide the training and testing sets in an 8:2 ratio.

(2) The training set is used as input to establish the neural network model, and then the error of the model is detected using the test set. When the error meets the requirements, the model is saved, otherwise the parameters need to be adjusted and retrained.

(3) Establish a dataset with the same format as (1) and input it into a saved neural network model, and calculate the output of the model.

Before using the LSTM neural network model, it is necessary to normalize and standardize the mechanical energy of the data. During the training process of the neural network, the cargo volume and time series of each sorting center are used as the training set.

During the training process of LSTM neural network models, the convergence speed of the model slows down when the short-term sequence length is large, while the underfitting of the model and poor memory performance of fluctuation points are caused by the sudden increase in dataset fluctuations when the sequence length is small; When the long-term memory batch is large, it is exactly opposite to when the sequence length is large. The model converges quickly, but it may lead to poor convergence, while smaller long-term memory batches also result in unsatisfactory learning results for fluctuation points. When selecting the activation function, the Sigmoid activation function has a large computational load, and during backpropagation, it is easy to encounter gradient vanishing, making it impossible to complete the training of deep networks[7]. The Relu function is prone to gradient zeroing during the training process, so Tanh is chosen as the activation function. Dropout parameters can effectively reduce overfitting in deep neural network training.

Table 1: Dropout values and fitting effects

Dropout	fitting effect
0	overfitting
0.1	just right
0.2	under-fitting

As shown in Table 1, the Dropout value is crucial. If the Dropout value is 0, the fitting effect is overfitting, and if the Dropout value is 0.2, the fitting effect is underfitting. Therefore, in order to achieve optimal accuracy in training the LSTM neural network model, the Dropout is set to 0.1 using regularization methods. Finally, Adam was chosen as the optimization algorithm for the model. The Adam algorithm is not affected by gradient scaling and is suitable for applications in large-scale data and parameter scenarios[8].

When the Dropout of each layer is set to 0.1, it is also necessary to select the appropriate number of hidden layers. During the training process, the mean square error is used to represent the training loss at each time step.

The training loss formula is:

$$loss = \frac{1}{n}\sum_{i=1}^{n}\left(\overline{u_i} - u_i\right)^2 \tag{9}$$

In the formula, U1 and U2 represent the training cargo volume and actual cargo volume, respectively. As shown in the figure, the training loss of different layers of hidden layers in neural networks is compared. Among them, 4 layers of hidden layers have higher accuracy in training, with the smallest loss value after 300 iterations (epochs)[9].

In the formula, U1 and U2 represent the training cargo volume and actual cargo volume, respectively. As shown in Figure 8, the training losses of different layers of hidden layers in neural networks are compared. Among them, 4 layers of hidden layers have higher accuracy in training, with the smallest loss value after 300 iterations (epochs).

For the hourly cargo volume prediction of sorting nodes, this article selects the cargo volume prediction data of the sorting center for the next 30 days and the LSTM neural network prediction model established in the previous text to predict the hourly cargo volume for the next 30 days. By utilizing the data characteristics in Attachment 2, the LSTM neural network model is further trained to obtain the corresponding hourly cargo volume prediction data[10].

2.3. Result analysis

Based on the LSTM neural network model established in the previous text, data can be predicted to analyze and obtain the forecast of cargo volume for the next 30 days, As shown in Figure 9-13.

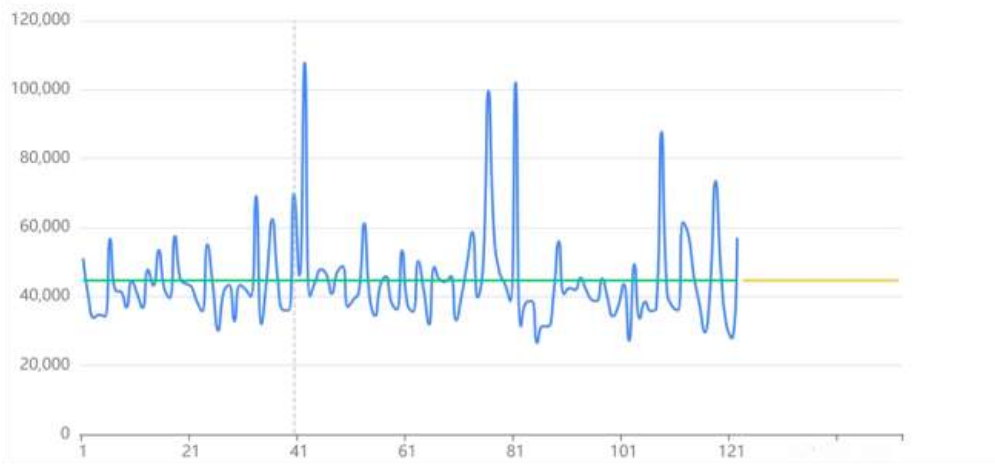

Figure 9: 30 day forecast of SC1 cargo volume

Based on the established LSTM neural network model, a schematic diagram of the prediction for the next 30 days of the SC1 sorting center can be seen.

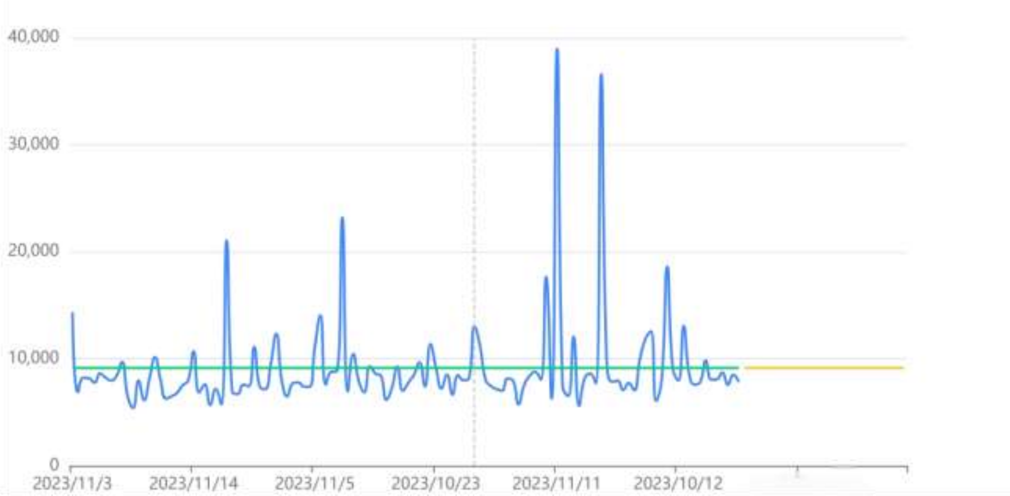

Figure 10: SC2 Cargo Volume 30 Day Forecast

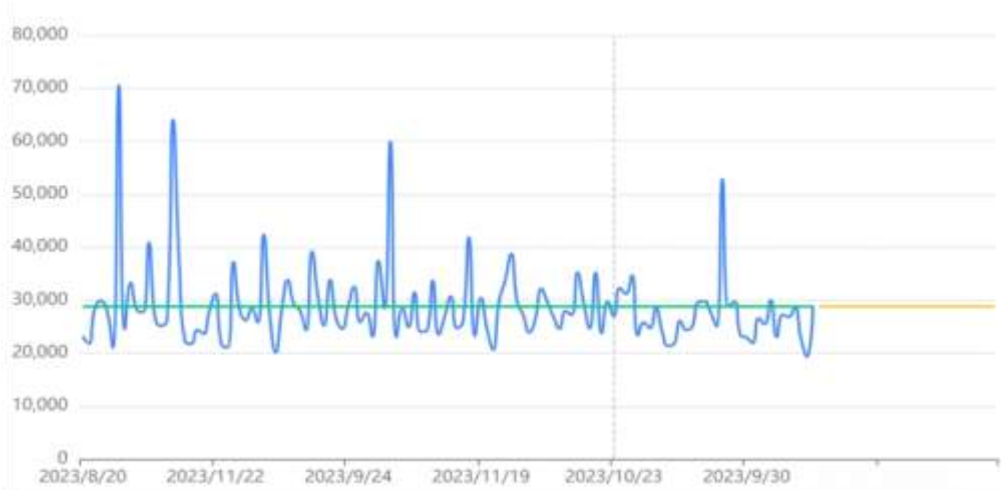

Figure 11: SC6 Cargo Volume 30 Day Forecast

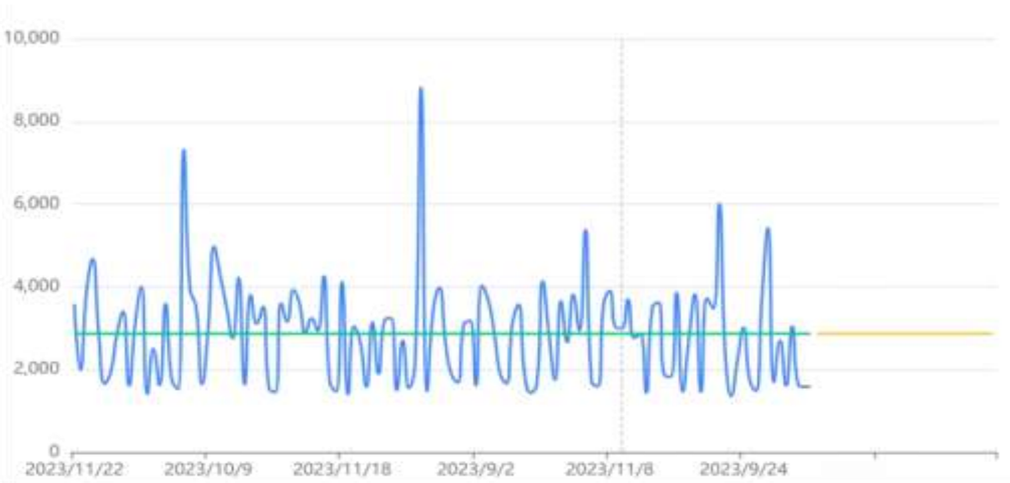

Figure 12: SC24 30 day cargo volume forecast

The hourly cargo volume data of each sorting center in November extracted from this article is imported into the LSTM neural network model for analysis. At the same time, predict the daily and hourly cargo volume of each sorting center based on the predicted data, As shown in Figure 14-17.

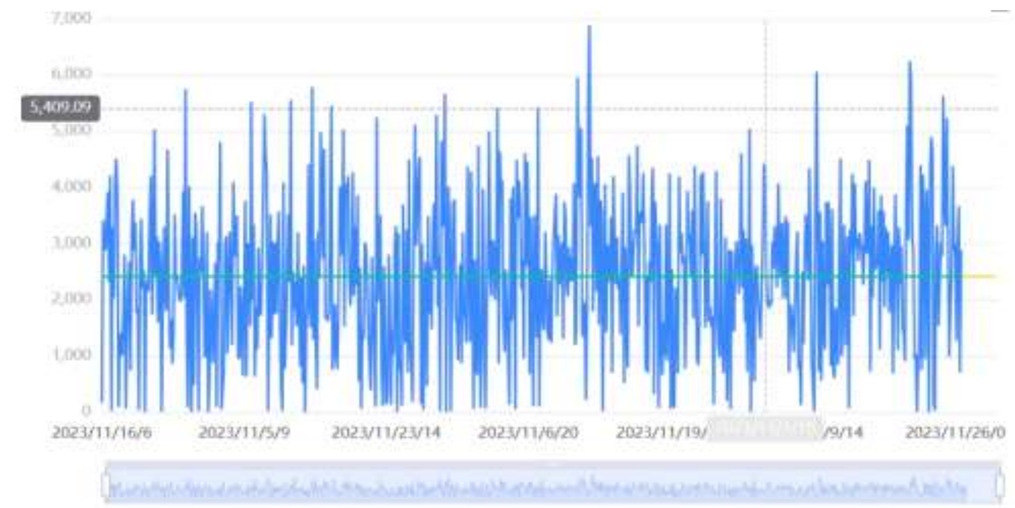

Figure 13: Prediction of daily and hourly cargo volume for the next 30 days for SC1

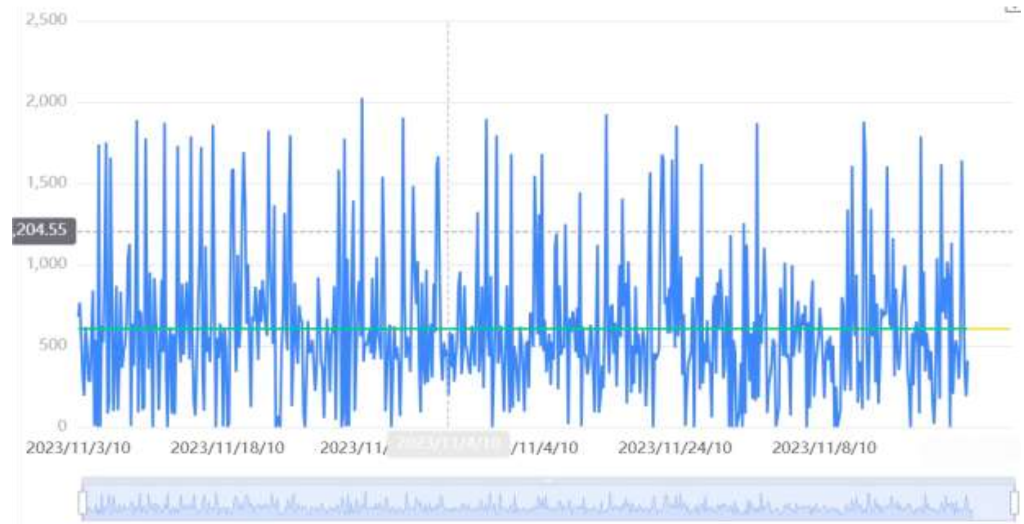

Figure 14: SC2's daily hourly cargo volume forecast for the next 30 days

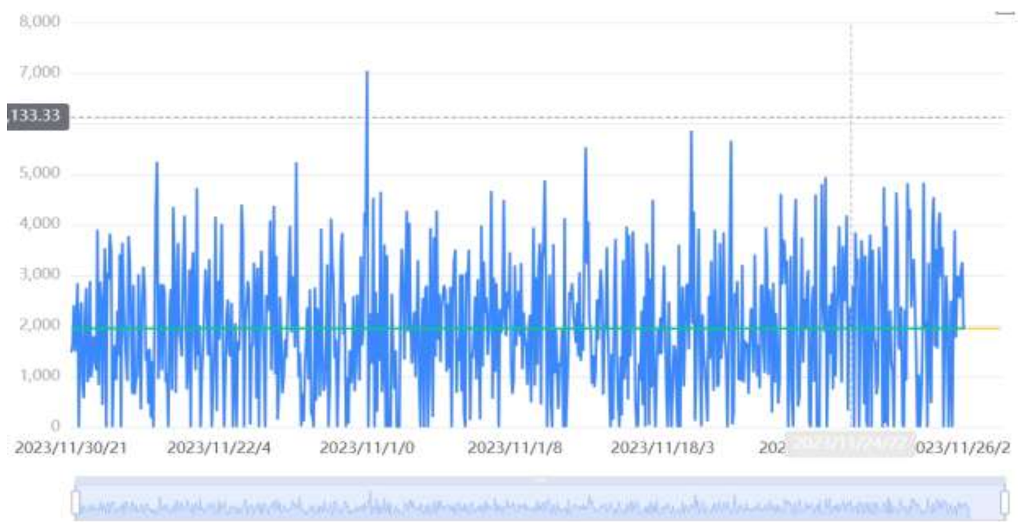

Figure 15: SC6's daily hourly cargo volume forecast for the next 30 days

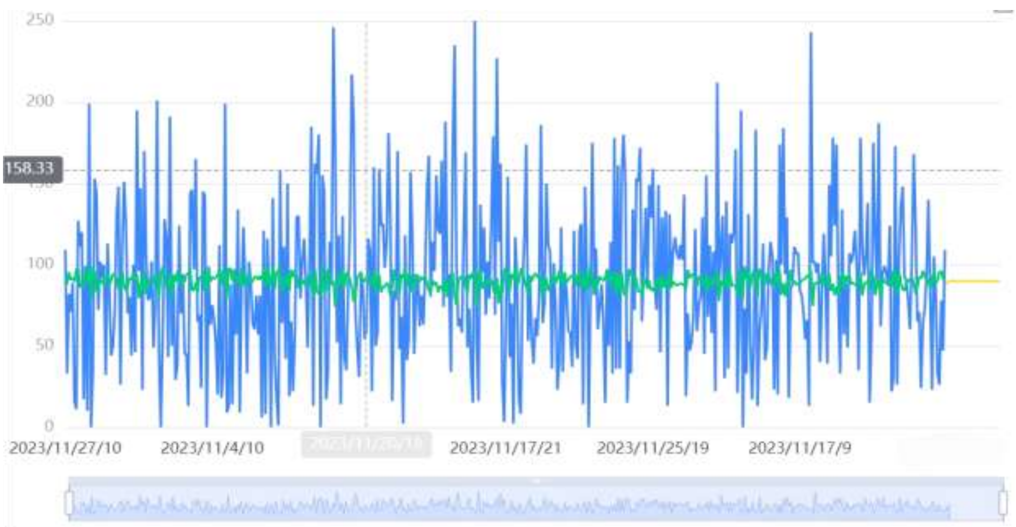

Figure 16: SC14's daily hourly cargo volume forecast for the next 30 days

3. Conclusions

The LSTM neural network model established in this article can effectively predict short - and long-term time series data; The established Analytic Hierarchy Process model has the characteristics of simplicity, speed, and accuracy, and plays a key role in the evaluation of sorting center factors in e-commerce logistics networks in this paper; The multivariate linear programming model can efficiently and quickly optimize practical problems. In the process of satisfying constraints, the multivariate linear programming model can be used for objective optimization planning. In this paper, the volume of each sorting center is predicted for the new e-commerce logistics network, and a systematic analysis of the cargo index model is established, which can further conduct a comprehensive analysis of the entire logistics process.

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