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Logistics Sorting Center Volume Prediction Based on Time Series Prediction LSTM Model

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Abstract: With the rapid development of e-commerce and global trade, logistics sorting centers are faced with increasing cargo volume volatility and complexity, and traditional cargo volume prediction methods are difficult to cope with such changes. In this study, a cargo volume prediction model based on Long Short-Term Memory (LSTM) neural network is proposed by utilizing the logistics data from Jinan City's Caijiao Post. First, the historical data are preprocessed, including missing value filling and outlier processing. Then, the daily cargo volume of each sorting center is predicted based on the LSTM model, and the results show that the model performs well in capturing the long-term dependence in the time series data, and the deviation between the predicted cargo volume data and the actual value is small. Finally, based on the prediction results, suggestions are made to optimize the resource allocation and operation process of the sorting center. The study shows that the LSTM model has important practical significance and application prospects in improving the accuracy of cargo volume prediction and the overall efficiency of the logistics system.

1. Introduction

In the modern logistics industry, logistics sorting centers, as an important link in the supply chain, have a direct impact on the operational efficiency of goods distribution speed and accuracy. With the rapid development of e-commerce and global trade, logistics sorting centers are facing increasing volatility and complexity of cargo volume. This makes it difficult to cope with the traditional methods of cargo volume prediction, which in turn affects the operational efficiency and customer satisfaction of the entire logistics chain. Therefore, how to accurately predict the cargo volume of logistics sorting centers has become a key issue to be solved in the logistics industry. Time series forecasting technology can provide scientific prediction of future trends by analyzing time dependencies and patterns in historical data. As a special kind of Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) network has significant advantages in processing time series data.LSTM effectively solves the gradient vanishing and gradient exploding problems of traditional RNN in the processing of long series data through its gating structure, making it a good solution to the problem of gradient vanishing and gradient exploding in the processing of long series data. LSTM effectively solves the gradient disappearance and gradient explosion problems of traditional RNN in long sequence data processing through its gating structure, which makes it perform well in dealing with complex time series prediction tasks. Applying LSTM to the cargo volume prediction of logistics sorting centers can make full use of its powerful modeling ability on time series data, thus improving the accuracy and reliability of cargo volume prediction. This not only helps optimize the resource allocation and operation process of the sorting center, but also significantly improves the overall efficiency of the logistics system, reduces the operation cost, and enhances the customer service level. Therefore, the research and application of LSTM model based on time series prediction in the estimation of cargo volume in logistics sorting centers has important practical significance and broad application prospects.

2. Related Works

In recent years, the importance of physical flow prediction in logistics management has become increasingly prominent, and many scholars have conducted in-depth research on this. Ji Zhaonan [1] predicted the material flow in Guizhou Province based on Gray-Markov model, which proved the effectiveness of gray system theory in material flow prediction. Cai et al [2] established a model for predicting the recycling volume of used home appliances in reverse logistics and proposed a new method for predicting the recycling volume in reverse logistics. Lin Yafei and Yang Yingming [3] carried out a reverse logistics study based on end-of-life volume prediction for used home appliances in Beijing, which further enriched the content of the study of waste material logistics. He Siyun [4] predicted the suitable amount of logistics parks based on the circle structure, which provided a scientific basis for the planning of logistics parks. Liu Lijun and Hou Weilei [5] studied the development of logistics industry in Shijiazhuang from the perspective of material flow prediction and industrial correlation analysis, which is of guiding significance for the planning of regional logistics industry. Xu Xiaohui and Li Junxiang [6] used wavelet transform and PSO-BP method to predict the task volume of logistics contact center, and proposed a method combining intelligent algorithm and time series analysis. Huijun Dong [7] predicted the material flow in Jiangsu Province based on the gray GM(1,1) model, and verified the applicability of the gray prediction model in regional logistics prediction. Wang Yan and Guo Jinyan [8] studied the application of combined model in material flow prediction and proposed a comprehensive method to improve the prediction accuracy. Chunying Jiang [9] predicted the recycling volume of reverse logistics of electronic equipment and improved the calculation of time and cost to provide an optimization scheme for reverse logistics management. Shan Baowei [10] studied the planning of railroad logistics center based on the material flow prediction, and put forward a new idea of railroad logistics center planning.

3. Theory and Method

3.1 Data Preprocessing

All the data were subjected to ADF test, and the data were cleaned, transformed and integrated, missing values were filled with zeros, and according to the corresponding time nodes, the outliers were considered to be real data to a certain extent by taking into account factors such as festivals, seasons, etc., and the daily shipments of some nodes were visualized as shown in Figure 1 below.

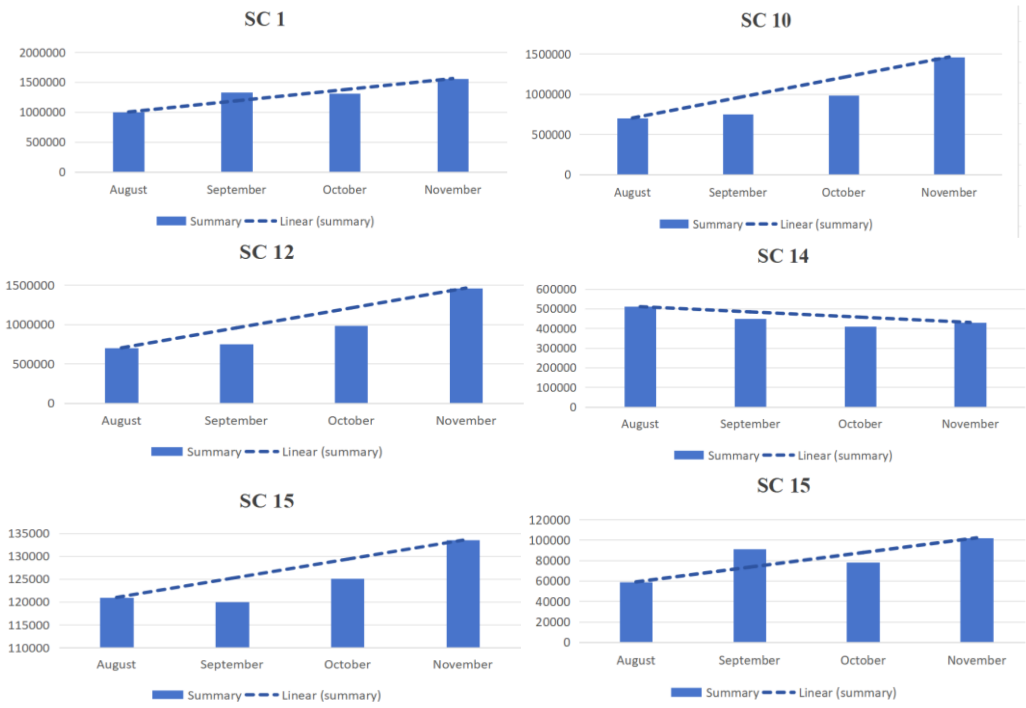

Figure 1: Visualization of daily cargo volume

As can be seen from the above chart, part of the sorting center's daily cargo volume growth trend is upward trend, the first three months of growth is relatively flat, November cargo volume growth trend is more pronounced, the peak, but there are some sorting centers, cargo volume growth is not obvious, or even a downward trend, such as sorting centers SC14, SC20, to consider the impact of certain unavoidable objective factors.

3.2 Daily Cargo Volume Prediction Based on LSTM Deep Learning Neural Network

There are three gates in the LSTM neural network, which are "Forgetting Gate", "Output Gate", and "Output Gate" respectively:

(1) Oblivion gate *f*: The oblivion gate is a key component in LSTM, which controls how much information needs to be obliviated from the previous moment's memory unit state, and decides which information should be retained to the current moment's memory unit state. The forgetting gate uses a sigmoid function to produce an output between 0 and 1, indicating the importance of each element of the memory cell state. An output close to 0 indicates that the element should be forgotten, while an output close to 1 indicates that the element should be retained. Through the use of forgetting gates, LSTM can selectively forget or retain the memory of the previous moment in order to better handle long-term dependencies in sequential data. This is an important improvement of LSTM over traditional recurrent neural networks (RNN).

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

(2) Input gate *i*: The input gate is another important part of the LSTM model. The input gate determines how much of the input information candidate state needs to be saved to the current memory cell state at the current moment. The input gate also generates an output between 0 and 1 by using a sigmoid function, which indicates the importance of each element. This importance level will determine whether the corresponding candidate state is saved to the current memory cell state. The input gate works in a similar way to the forget gate. It accepts the output of the previous moment and the input of the current moment as inputs, and then linearly transforms them with a

weight matrix and bias, and inputs the result into a sigmoid function, whose output indicates the importance of each element in the candidate state. The candidate states are transformed by a tanh function, which maps the values to a range of values between $[-1,1]$. The candidate states are transformed by a tanh function, which maps the values into the range of values that are more favorable for information retention. Then, the output of the input gate is multiplied by the candidate states element by element, and the result is added to the current memory cell state. Through the control of the input gate, the LSTM can selectively save the input information of the current moment into the current memory cell state, so as to adapt and utilize the new input information.

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_i \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \tag{2}$$

By adding the results of the two methods together, the redundant information can be deleted, and then new data can be added to obtain information about the next state.

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C_t} \tag{3}$$

(3) Output Gate o: The output gate is another key component of the LSTM model. The output gate determines how much information about the state of the memory cell at the current moment needs to be output to the external state. The output gate also uses a sigmoid function to generate an output between 0 and 1, indicating the importance of each element in the output. This level of importance determines whether or not the corresponding memory cell state is output to the external state. The output gate works in a similar way to the forgetting and input gates. It accepts the output of the previous moment and the input of the current moment as inputs, and then linearly transforms them with a weight matrix and bias, and inputs the result into a sigmoid function, the output of which indicates the importance of each element in the state of the memory cell. The state of the memory cell is transformed by a tanh function, which maps the values to a certain range. Then, the output of the output gate is multiplied element-wise with the state of the memory cell, and finally, we obtain the output state. Finally, the output state is further processed by an output layer to obtain the final output result. The output layer is designed according to the requirements of specific tasks, for example, in language modeling, it can be a softmax layer for predicting the next word. Through the control of the output gate, LSTM can selectively output the information of the current state of the memory unit to the external state, realizing the effective modeling and prediction of sequence data.

$$\begin{aligned} o_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \times \tanh(C_t) \end{aligned} \tag{4}$$

4. Results and Discussions

4.1 Results of Daily Cargo Volume Prediction Based on LSTM Deep Learning Neural Network

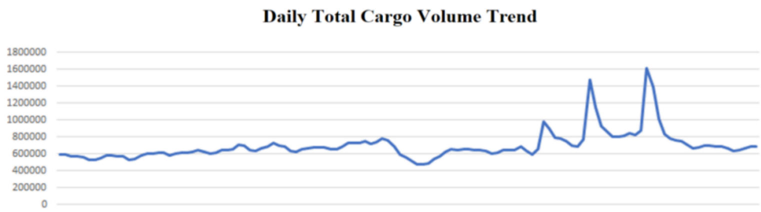

Figure 2: Trends in total daily cargo volume

As seen in Figure 2 above, from the perspective of the development trend of the total volume of goods, there are noticeable peaks on October 30 and November 14. Between August 1 and October 30, the trend in the total volume of goods remained relatively stable, with an overall upward trajectory. However, from October 30 to mid-November, there was a more pronounced fluctuation. This fluctuation is closely related to the Double Eleven shopping festival, which significantly impacted the growth rate of goods. For the daily prediction of cargo volume, the cargo volume data of each sorting center is characterized by time series dependence, and the use of a deep learning model, the Long Short-Term Memory Network (LSTM), is considered. LSTM (Long Short-Term Memory) is a deep learning model used to deal with sequential data, which is especially effective in tasks such as natural language processing and speech recognition. Compared to traditional Recurrent Neural Networks (RNN), LSTM introduces a gating mechanism to better capture and utilize long-term dependencies in sequences. Training the LSTM model with historical shipment data can predict the future daily shipment data. The gating mechanism and lattice parameters of the LSTM model are shown in Table 1 below.

Table 1: Gating mechanism and grid parameters for LSTM modeling

Parameters	Hidden meaning	Parameters	Hidden meaning	Parameters	Hidden meaning
x_t	Input at the current moment	f_t	Oblivion gate control signal	C_{t-1}	Previous Momentary Memory Unit
$\tilde{C}_t$	Information Candidate Status	i_t	Input door control signal	C_t	current moment memory cell
h_{t-1}	Previous external state	o_t	Output gate control signal	h_t	Current external state

The LSTM neural network structure as well as the hyperparameter settings are shown in Table 2 below.

Table 2: LSTM neural network structure and hyperparameter settings

Parameters	Numerical value
NumFe	1
NumRe	1
NumHiDu	150
MaxE	300
GraTH	1
IniRate	0.005
LearnRateDrPeriod	120
LearnRateDropFactor	0.25

Set up the parameters shown in the above figure, and then use MATLAB to program the solution, set the horizontal axis as time and the vertical axis as the cargo volume, and set the historical data of the cargo volume of each sorting center (August-November) the change of the cargo volume, as well as the cargo volume prediction is shown in Figure 3 and Figure 4 below.

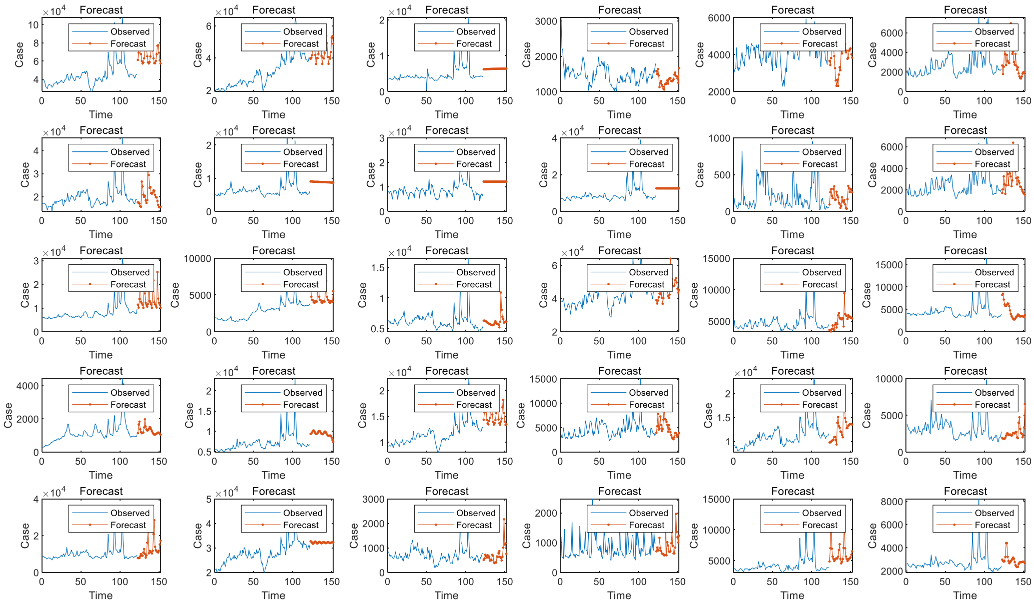

Figure 3: Forecast results of each sorting center

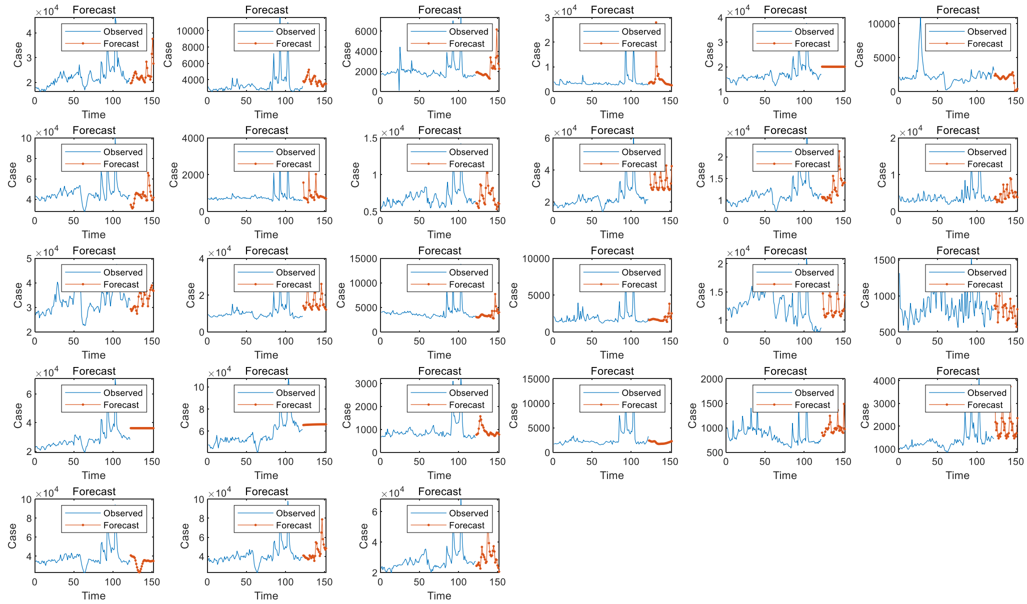

Figure 4: Forecast results of each sorting center

The above figure shows that the LSTM neural network model gives a series of predicted values for the coming month, and the predicted values show a certain degree of volatility, which also reflects to a certain extent that the cargo volume in the coming month will be affected by a variety of uncertain objective factors. The actual value and the predicted value also show a certain degree of deviation, which furthermore the sorting centers are subject to a variety of unpredictable factors in the actual operation, resulting in the actual performance of the cargo volume is poor. Generally speaking, LSTM can better handle sequence data with long-term dependencies and nonlinear characteristics, and effectively captures and remembers past information through its memory unit when processing sequence data, which makes the cargo volume prediction show high accuracy. Therefore, by training and optimizing the LSTM model, we can predict the daily cargo volume for the next 30 days, and it can be seen that these predicted values reflect the trend and fluctuation of the cargo volume to a certain extent. Table 3 below shows the results of daily cargo volume prediction for the next 30 days for some sorting centers.

Table 3: Daily Volume Forecast Results for Selected Sorting Centers for the Next 30 Days

Sorting center	Date	Quantity of goods	Sorting center	Date	Quantity of goods
SC16	2023/12/1	2633.522541	SC17	2023/12/1	17365.56293
SC16	2023/12/2	1764.362966	SC17	2023/12/2	17321.89852
SC16	2023/12/3	2502.881455	SC17	2023/12/3	16861.97197
SC16	2023/12/4	4655.529141	SC17	2023/12/4	15728.52639
SC16	2023/12/5	3761.737273	SC17	2023/12/5	15494.65436
SC16	2023/12/6	2668.86791	SC17	2023/12/6	26305.96289
SC16	2023/12/7	3697.03125	SC17	2023/12/7	24196.16655
SC16	2023/12/8	3104.21896	SC17	2023/12/8	20690.88205
SC16	2023/12/9	2928.289482	SC17	2023/12/9	19702.53914
SC16	2023/12/10	2867.989153	SC17	2023/12/10	20211.77813
SC16	2023/12/11	4618.277974	SC17	2023/12/11	18210.74836
SC16	2023/12/12	6892.8692	SC17	2023/12/12	17148.13224
SC16	2023/12/13	4556.463882	SC17	2023/12/13	18384.52043
SC16	2023/12/14	3806.297424	SC17	2023/12/14	39917.17898
SC16	2023/12/15	4038.756482	SC17	2023/12/15	29043.72668
SC16	2023/12/16	2970.118674	SC17	2023/12/16	23602.61707
SC16	2023/12/17	2711.446611	SC17	2023/12/17	23956.573
SC16	2023/12/18	3800.55175	SC17	2023/12/18	21334.07461
SC16	2023/12/19	2621.393349	SC17	2023/12/19	21118.59686
SC16	2023/12/20	2203.938435	SC17	2023/12/20	21530.45619
SC16	2023/12/21	2447.02259	SC17	2023/12/21	22554.49325
SC16	2023/12/22	1836.137966	SC17	2023/12/22	22354.0047
SC16	2023/12/23	1540.070925	SC17	2023/12/23	20615.16832
SC16	2023/12/24	1352.239211	SC17	2023/12/24	19591.99172
SC16	2023/12/25	1319.162915	SC17	2023/12/25	19554.47227
SC16	2023/12/26	1519.309084	SC17	2023/12/26	17975.05295
SC16	2023/12/27	1806.688608	SC17	2023/12/27	16312.33829
SC16	2023/12/28	1937.831463	SC17	2023/12/28	15344.31357
SC16	2023/12/29	1962.37771	SC17	2023/12/29	15271.48283
SC16	2023/12/30	1820.727345	SC17	2023/12/30	15492.81357

5. Conclusion

In this study, the cargo volume of logistics sorting centers was accurately predicted by using a long short-term memory (LSTM) neural network model. The experiment proves that the LSTM model can effectively capture the long-term dependence in time series data and shows high accuracy and reliability in cargo volume prediction. The prediction results based on this model can significantly improve the resource allocation efficiency of the sorting center and optimize the operation process, thus enhancing the operation efficiency and customer service level of the whole logistics system. Future research can further combine other deep learning models and algorithms to explore more factors affecting the change of cargo volume, in order to further improve the accuracy of prediction and the breadth of application. This study provides important technical support and theoretical basis for intelligent and refined management in the logistics industry.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

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