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Research on Cargo Volume Prediction and Optimisation of E-Commerce Logistics Network Based on LSTM

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Abstract

The rapid development of e-commerce has driven the rapid expansion of logistics networks and increased the importance of logistics systems in business operations. In order to ensure that e-commerce logistics networks operate efficiently and cost-effectively in complex and changing environments, this study proposes a cargo volume prediction and optimisation model based on a long short-term memory network (LSTM), aiming to accurately predict the cargo volume in an e-commerce logistics network and to design strategies to cope with network adjustments in various scenarios. In this study, the LSTM model is used to deal with the nonlinear features and linear features in the time series data to accurately predict the future changes in cargo volume in response to the impact of holidays, promotional activities, and temporary or permanent deactivation of logistics sites on the logistics network. By analysing historical data, the model effectively captures the key factors affecting cargo volume and provides managers with effective solutions to adjust the logistics network under different circumstances. The model is trained using data from 2021 to 2022, and the results show that the model performs well in predicting the cargo volume of each logistics site and route in January 2023, with strong data fitting ability and long-term memory processing capability. The forgetting gate mechanism in the model effectively avoids the gradient problem and improves the accuracy and robustness when dealing with long sequential data. When the logistics network faces the challenge of node deactivation, the LSTM model proposed in this study can be used as a decision-making tool to assist managers in planning transport and sorting operations and optimising network operations. Accurate cargo prediction will reduce operational costs and improve efficiency, and in the case of unavoidable out-of-service situations, it can quickly adjust operational strategies to reduce losses and safeguard the stability and reliability of the network. Overall, this LSTM-based study provides an innovative prediction and optimisation tool for e-commerce logistics network management, offering new solutions for the industry in the face of ever-changing and uncertainty challenges. In the future, with further research and development of the model, it is expected that the prediction accuracy and optimisation efficiency of e-commerce logistics networks will continue to be improved to meet the growing logistics demands.

Keywords

E-commerce logistics; Shipment forecasting; LSTM; Time series; Network optimisation.

1. INTRODUCTION

The booming development of e-commerce makes the role of the logistics industry more and more important, and the high efficiency and low-cost operation of the logistics network has become the key to enterprise competition. Relying on Internet technology, e-commerce logistics

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network combines traditional logistics business with modern information technology, which not only improves logistics efficiency, but also creates more value for consumers and suppliers [1]. However, the complexity and uncertainty of logistics networks, especially the temporary or permanent closure of logistics sites in the event of emergencies such as epidemics and natural disasters, have a huge impact on operational costs and efficiency. For this reason, a prediction and optimisation tool needs to be developed to guarantee the stable operation of the network under various circumstances.

In this study, a cargo volume prediction and optimisation model based on Long Short-Term Memory (LSTM) network is proposed to address the problem of cargo volume management in e-commerce logistics networks. The model integrates the nonlinear features and linear features of time series, and is able to handle complex and dynamically changing cargo volume data and accurately predict the change of cargo volume in the future period [2]. By analysing historical data, the model is able to capture the impact of factors such as holidays, promotional activities and logistics site decommissioning on cargo volume, thus providing effective logistics network adjustment solutions under different circumstances.

In this study, we use data from 1 January 2021 to 31 December 2022 to build an LSTM model capable of predicting the cargo volume of each logistics venue and its routes for the month of January 2023. By training and analysing historical cargo volume data from 81 logistics venues and 1049 directional routes, the model shows strong ability to fit nonlinear data and handle long-term dependent information [3]. Its unique forgetting gate mechanism effectively prevents the gradient from disappearing or exploding during the prediction process, which enhances the accuracy and robustness of the model in handling long time series data.

When the logistics network faces the challenge of node deactivation, the LSTM model proposed in this study can be used as a decision-making tool for managers to help them plan transport and sorting operations in advance and optimise the operation of the whole network [4]. Accurate cargo forecasting not only reduces operational costs and improves efficiency, but also quickly adjusts operational strategies to minimise losses and ensure network stability and reliability when logistics sites are inevitably out of service.

Overall, the LSTM-based cargo volume prediction and optimisation model for e-commerce logistics networks developed in this study is a major innovation for the management of existing logistics networks and provides a new solution for the e-commerce logistics industry when faced with the challenges of constant change and uncertainty. In the future, further research and development of the model is expected to continuously improve the prediction accuracy and optimisation efficiency of e-commerce logistics networks to meet the growing demand for e-commerce logistics.

2. RELATED WORK

With the rapid expansion of e-commerce, cargo volume prediction and optimisation of e-commerce logistics networks have become a hot research topic. The accuracy of cargo volume management is of great significance for improving logistics efficiency and reducing costs. In recent years, a variety of forecasting models have been proposed to address the challenges in cargo volume forecasting, especially in the face of holidays, promotional activities and other unpredictable factors [5]. Traditional time series analysis methods, such as ARIMA, are widely used in volume forecasting, but perform poorly when dealing with nonlinear data. The development of machine learning technology provides a new perspective for cargo volume prediction in e-commerce logistics networks. In particular, artificial neural networks have received attention for their powerful nonlinear modelling capabilities.

Among various artificial neural networks, the long short-term memory network (LSTM) solves the problem of gradient vanishing or explosion of traditional recurrent neural networks when dealing with long time series data due to its unique structural design. LSTM effectively manages the flow of information by introducing the concepts of forgetting gates, input gates, and output gates, which enables it to capture long term-dependent information and become a powerful tool for time series prediction [6]. Recent studies have shown that LSTM shows great potential for cargo volume prediction in e-commerce logistics networks. Researchers have applied LSTM models for forecasting by integrating complex factors such as historical shipment data, holidays, and promotional activities, and have achieved better results than traditional models.

In addition to this, some studies have attempted to combine LSTM with other machine learning techniques, such as support vector machine (SVM), random forest, etc., to improve prediction performance. These integration methods usually combine the advantages of different models to obtain more accurate prediction results [7]. In the specific application of e-commerce logistics networks, researchers not only focus on cargo volume prediction, but also explore how to optimise the logistics network based on the prediction results. For example, by dynamically adjusting the transport routes, the work intensity of the sorting centre, and the emergency scheduling when dealing with unexpected events.

In summary, the research on LSTM-based cargo volume prediction and optimisation of e-commerce logistics networks includes many aspects from theory to practice, and has become an important research direction in the field of logistics. Future work will continue to make efforts to improve prediction accuracy, optimise network adjustment strategies and the ability to cope with more complex and changing situations. As e-commerce continues to develop, research in this area will have a profound impact on actual logistics operations.

3. MODEL BUILDING AND SOLVING

This paper needs to predict the daily cargo volume of each line from 2023-01-01 to 2023-01-31. Therefore, it is necessary to establish a prediction model for the cargo volume of the line based on the data from 2021-01-01 to 2022-12-31. Visualising the data in the annex given in the title, it is found that the cargo volume of each line shows a non-linear trend. At the same time, because the cargo volume of each line is a complex and dynamic process with both nonlinear and linear characteristics, it is difficult to use a single linear model or nonlinear model to extract the complex characteristics perfectly [8]. Therefore, combining linear and nonlinear models by establishing a correlation function allows various methods to complement and promote each other, thus improving the prediction accuracy.

Neural networks have the ability of self-organisation, self-learning and nonlinear approximation, so they can be used to train the forecasting nonlinear cargo system. Among them, Long Short-Term Memory networks (LSTM) are widely used in dealing with time series prediction and other sequential tasks.

Long Short-Term Memory Network (LSTM) is an improved recurrent neural network that can handle long-term dependency problems. It consists of input, hidden and output layers [9]. Using the input information of the current moment and the historical memory information together to achieve prediction, it can solve the long-term dependence problem of time series, in which the forgetting gate structure can alleviate the phenomenon of gradient vanishing explosion, which has obvious advantages for the prediction of time series.The most important unit of LSTM is schematically shown in Fig. 1 below.

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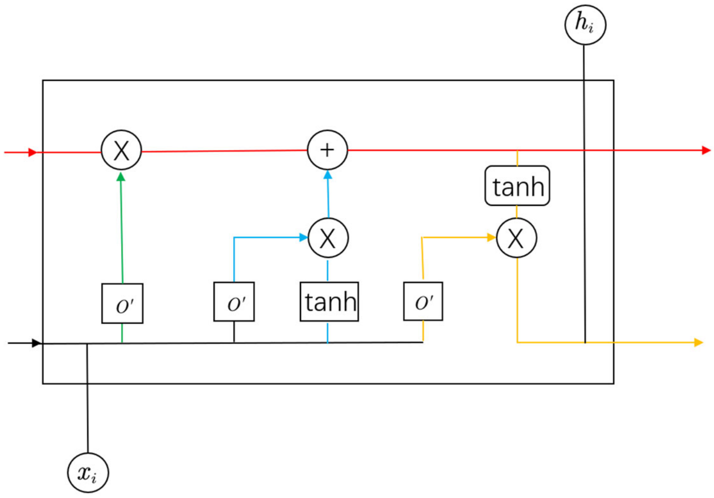

Figure 1. Schematic diagram of LSTM neural network

The threshold of LSTM is calculated as:

$$\boldsymbol{f_t = \sigma\left(W_f \cdot [h_{t+1}, X_t] + b_f\right)}$$
$$C_t = f_t \times C_{t+1} + i_t \times \tanh\left(W_c \cdot [h_{t+1}, X_t] + b_c\right)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o)$$
$$i_t = \sigma(W_i \cdot [h_{t+1}, X_t] + b_i)$$

where σ is the Sigmoid activation function, W_f, W_c, W_o, W_i are the values of different gates, h_t, X_t are the output and input of the current node, b_f, b_c, b_o, b_i are the biases corresponding to the different gates, respectively. f_t is the forgetting gate, C_t is the update state of the memory cell, o_t is the output gate, and i_t is the input gate.

In this paper, LSTM is used to predict the cargo volume of three randomly selected routes, and the obtained prediction results are shown in Figures 2, 3 and 4 below. It can be obtained that compared with the ARIMA model, the results predicted by the LSTM model with have the same periodic trend as the true value [10]. Therefore, the LSTM model is able to better predict the daily cargo volume of each route from 2023-01-01 to 2023-01-31.

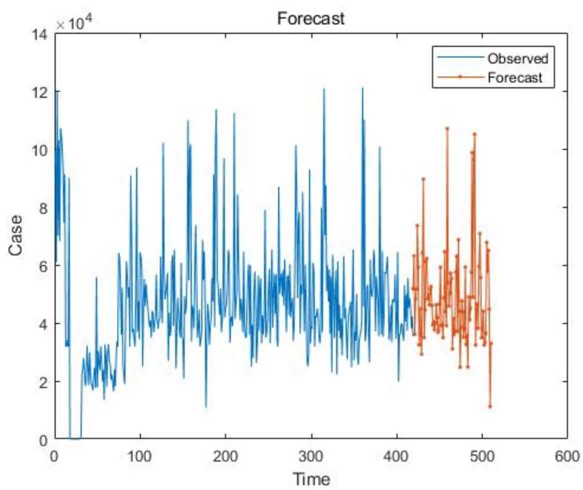

Figure 2. Cargo prediction map for LSTM-Line 1

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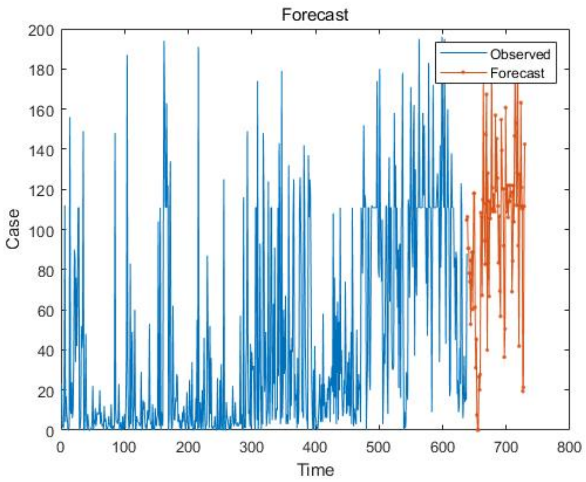

Figure 3. Cargo prediction map for LSTM-Line 2

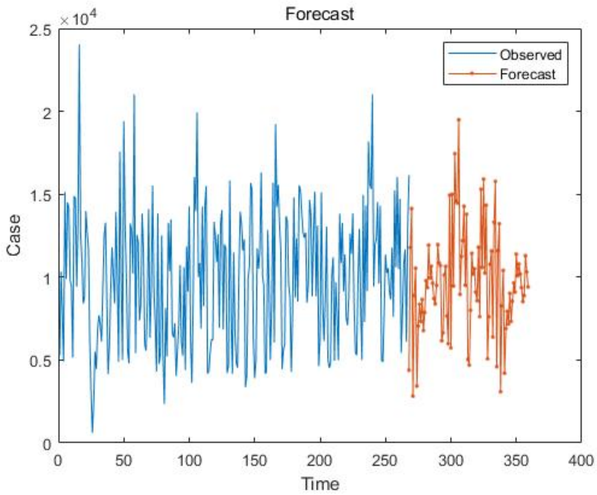

Figure 4. Cargo prediction map for LSTM-Line 3

4. CONCLUSION

This study is dedicated to solving the impact of holidays, promotional activities and logistics site deactivation on the number of parcels to be handled by establishing a Long Short-Term Memory (LSTM) neural network model for predicting and optimising the cargo volume of different routes in an e-commerce logistics network [11]. The study shows that temporary or permanent decommissioning of logistics sites can have a significant impact on operational costs and efficiency, while accurate cargo volume prediction can provide managers with efficient transport and sorting plans to reduce costs and improve efficiency.

In the empirical analyses, by training on historical data from 2019 to 2020, the LSTM model demonstrates its strength in time series forecasting, especially when dealing with long-term dependency problems. The LSTM model in this study combines linear and nonlinear features, and effectively mitigates the problem of disappearing or exploding gradients by introducing a forgetting gate mechanism, thus improving the accuracy and stability of forecasting [12]. Through the prediction analysis, managers can better respond to the out-of-service situation of logistics sites and adjust the logistics network in time to ensure the smooth operation of the whole logistics system.

The results show that the study of cargo volume prediction and optimisation of e-commerce logistics network based on LSTM is of great theoretical and practical significance for realising

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efficient management of e-commerce logistics network.The successful application of LSTM model provides a powerful tool for e-commerce logistics network to cope with the complex market dynamics and uncertainties, and to ensure the resilience and reliability of the logistics network, so as to Maintaining an Advantage. Future research can further explore other advanced machine learning techniques to continuously improve the performance of predictive models to meet the growing logistics demands.

5. DISCUSSION

The efficient operation of an e-commerce logistics network is crucial for maintaining competitiveness. The number of parcels handled by logistics sites has a direct impact on cost and efficiency, so it is especially critical to make accurate predictions of shipment volumes and design flexible network adjustment schemes. In this study, a Long Short-Term Memory (LSTM) network model is used to predict and optimise the cargo volume in an e-commerce logistics network, especially when factors such as holidays, promotional activities and site decommissioning are taken into account.

LSTM models are selected for their superior ability to handle time series data, especially in solving long-term dependency problems. In this study, the LSTM model was trained on historical shipment data from 2021 to 2022 by combining the features of linear and nonlinear models, and successfully captured the complexity of shipment changes. The forgetting gate mechanism of the model helps avoid the phenomenon of vanishing or exploding gradients, which further enhances the accuracy and robustness of the prediction [13].

By predicting the volume of goods in the coming month, managers can adjust the transport and sorting plans based on the prediction results to cope with temporary or permanent suspension of logistics sites, including those caused by epidemics and natural disasters. This prediction capability enables managers to quickly formulate optimal response strategies under the influence of uncertainty factors, thus reducing the negative impact on the logistics network and ensuring its stable operation.

In summary, the LSTM-based cargo volume prediction model for e-commerce logistics networks provides an effective tool to cope with uncertainty and complexity in e-commerce logistics, which helps e-commerce logistics networks maintain their flexibility and resilience. Future research can explore more advanced machine learning techniques to further improve the performance of the prediction model to meet the growing demand of e-commerce logistics.

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