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A study of deep learning-based algorithms for supply chain logistics demand forecasting

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Abstract: To accurately capture the dynamic changes and patterns of supply chain logistics demand, a prediction algorithm based on BiLSTM-AM is proposed. After collecting relevant data on supply chain logistics demand, outliers were removed using the Local Outlier Factor (LOF) to enhance data quality. From the cleaned dataset, features such as the supply chain logistics demand growth rate, inventory turnover rate, seasonal index, customer order volume, supplier delivery cycle, and transportation efficiency were extracted to construct a time series feature set for supply chain logistics demand. Based on the Long Short-Term Memory (LSTM) neural network model, a bidirectional structure was introduced, combined with an Attention Mechanism (AM), to establish a BiLSTM-AM-based supply chain logistics demand forecasting model, which was then trained using the gradient descent method. The obtained time series of supply chain logistics demand features were input into the trained forecasting model, and its output represented the forecasted supply chain logistics demand results. The experiment shows that the algorithm can accurately predict the demand for supply chain logistics. After applying this algorithm, the on-time delivery rate for each month is above 95%, and the decrease in logistics costs ranges from 0.3 to 0.5, indicating strong application value.
Keywords: *BiLSTM, Deep learning, Feature items, Logistics demand forecasting, Local outliers, Supply chain.*

1. Introduction

Supply chain management refers to the effective organization of product manufacturing, transshipment, distribution, and sales management to meet certain customer service conditions while minimizing the cost of the entire supply chain system. This includes suppliers, manufacturers, warehouses, distribution centers, and channels [1]. Its core lies in the integration and optimization of various links in the supply chain to improve overall efficiency and responsiveness, reduce costs, and enhance customer satisfaction [2]. In today's complex, dynamic, and competitive business environment, supply chain management has emerged as a critical factor for the survival and development of enterprises [3]. Supply chain logistics demand forecasting, as a complex system in the "navigator," its importance is self-evident [4]. It is a crucial decision-making analysis tool in the logistics and warehousing system. By accurately forecasting future trends in supply chain logistics demand, enterprises can plan logistics needs, enhance efficiency, better meet customer demands, significantly reduce operating costs, ensure smooth supply chain operations, and improve market competitiveness and profitability.

In recent years, many scholars have conducted a lot of research on logistics demand forecasting and achieved certain research results. Based on logistics demand data from the Chengdu-Chongqing Dual-City Economic Circle (CC-DEC), a comprehensive logistics demand forecasting indicator system was constructed using Fuzzy Support Vector Regression combined with the Adam optimization algorithm (FSVR-AD). The accuracy of three forecasting models was validated through historical data, with

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FSVR-AD exhibiting superior performance and providing a reliable reference for strategic planning in logistics management [5]. The decision support model in humanitarian logistics considers potential vehicle routes, demand at each node under probabilistic disaster scenarios, the probability of road openness, and incorporates heterogeneous fleet factors in terms of vehicle size. A case study and numerical analysis of a potential earthquake in Kartal, Istanbul, demonstrated the model's effectiveness in minimizing total costs and total travel time. Additionally, a heuristic method based on clustering algorithms was proposed to address larger problem instances. This model and its heuristic method can provide support for pre-disaster preparations by decision-makers [6]. By integrating historical transportation data from TMS systems (historical sales data, market activity data, transportation costs, time factors, etc.) and utilizing the learning capabilities of ANN models, trend analysis is conducted on these data to predict future logistics and distribution demand [7]. However, while the ANN model in this method can identify patterns and trends in historical data, its prediction capabilities are limited for sudden market demand changes or abnormal fluctuations, making it difficult for enterprises to make effective responses and adjustments in the face of market changes in a timely manner. By comprehensively considering product-related factors such as sales data and inventory status, as well as trip-related factors such as transportation routes, transportation time, and transportation costs, a logistics demand forecasting model based on Support Vector Machines (SVM) is established to accurately predict future logistics demand [8]. However, this method has weak generalization ability and cannot well adapt to the diversity and uncertainty of logistics information, leading to inaccurate prediction results. By collecting annual sales data for products, the ABC-FSN classification method is applied to categorize products into different classes based on factors such as importance, outbound amount, outbound variety, and consumption speed. Then, according to the characteristics of different product categories, the exponential smoothing method and multiple regression model are selected for logistics demand forecasting [9]. However, this method mainly relies on internal corporate data for prediction and lacks a collaborative forecasting mechanism with upstream and downstream enterprises in the supply chain, which may result in the prediction results failing to fully consider the overall demand and changes of the supply chain, affecting the accuracy of the prediction results. By collecting and analyzing multi-source big data information such as historical sales data, market trends, consumer behavior, and supply chain dynamics, a prediction model based on linear regression is established to capture the correlations and trends among the data, thereby achieving predictions of supply chain logistics demand [10]. However, in actual supply chain logistics demand, the relationships among various data often exhibit nonlinearity and complexity, and the linear regression model cannot accurately capture all correlations and trends among the data, leading to deviations in prediction results.

Deep learning is a form of machine learning that enables computers to learn from experience and understand the world in a conceptual hierarchy [11]. It simulates the human brain's neural network and extracts features from large datasets through deep neural network models for automated processing and decision-making of complex tasks [12]. Deep learning is powerful in data processing, automatic feature extraction, nonlinear relationship modeling, generalization, and handling large-scale data, and has been widely used in fields like natural language processing, predictive analytics, classification, and recognition [13]. This paper explores the deep learning-based supply chain logistics demand forecasting algorithm, aiming to utilize deep learning technology to improve the accuracy, timeliness, and robustness of supply chain logistics demand forecasting and enhance the responsiveness and flexibility of the supply chain to cope with rapid market changes.

2. Supply Chain Logistics Demand Forecasting

2.1. Outlier Removal in Supply Chain Logistics Demand Data Based on Local Outlier Factor

Due to wrong inputs, transmission errors, equipment failures, and other reasons, there are often a certain number of outliers in the raw supply chain logistics demand data collected in the previous subsection [14]. These outliers deviate from the normal distribution range of the data, which will adversely affect the subsequent model training, prediction analysis, and decision-making, leading to inaccurate or misleading results [15]. Therefore, in order to ensure the quality and reliability of supply chain logistics data, outlier removal is required. Local outlier factor (LOF), as a density-based unsupervised anomaly detection method [16] can identify and quantify the local outlier degree of each data point in the supply chain logistics demand data set. The method calculates the LOF score of a supply chain logistics demand data point by analyzing the density difference between the data point and its neighboring points, and determines whether it is an outlier according to the LOF score. The LOF algorithm is highly adaptable, does not require predefining the number of outliers, and is sensitive to local anomalies, making it particularly suitable for detecting outliers in raw supply chain logistics demand data.

Outlier removal in supply chain logistics demand data based on local outlier factor, the specific steps are as follows:

(1) Define the distance of k .

Define a data point in the raw data set of supply chain logistics demand, the distance $L_k(o)$ from a certain data point o to the k -th neighbor point g , described as:

$$L_k(o) = L(o,g) \quad (1)$$

(2) Calculate the reachable distance.

Calculate the k -th reachable distance $L_{R_k}(o,g)$ for g and o , described as:

$$L_{R_k}(o,g) = \max\left\{D_k(o), L(o,g)\right\} \quad (2)$$

In the formula, the k -th distance neighborhood data point set of o is described by $D_k(o)$.

(3) Calculate the local reachable density.

The locally accessible density represents the number of data points around the data point o , the higher the density, the closer the point is to the normal area. Local attainable densities $\eta_k(o)$ of o is described as:

$$\eta_k(o) = \frac{\left|D_k(o)\right|}{\sum_{g \in L_k(o)} L_{R_k}(o,g)} \quad (3)$$

(4) Calculate the outlier factor LOF.

Perform outlier diagnosis based on the size of the LOF to the data in the raw supply chain logistics demand data o . The formula for LOF is:

$$LOF_k(o) = \frac{\sum\limits_{g \in D_k(o)} \eta_k(g)/\eta_k(o)}{\left|L_k(o)\right|} \quad (4)$$

According to the actual situation of supply chain logistics demand forecast, set the corresponding critical value. If $LOF_k(o)$ is greater than this threshold, then represents that data point o is an outlier; conversely, if $LOF_k(o)$ is less than or equal to this threshold, then represents that the data point o is a normal value.

Using the above method, we can accurately identify the outliers in the raw data of supply chain logistics demand, and after removing them, we can achieve the purpose of data cleansing and effectively improve the quality of the data set.

2.2. Supply Chain Logistics Demand Forecasting Feature Term Selection

Since the supply chain logistics demand dataset contains a large amount of multi-dimensional and complex data, to extract useful information for prediction and reduce data dimensionality, we select indicators that intuitively reflect the changes in supply chain logistics demand as feature items. Mainly include:

(1) Supply chain logistics demand growth rate

The growth rate of supply chain logistics demand reflects the trend and speed of continuous change in supply chain logistics demand over time, and is an important basis for predicting future changes in logistics demand, which is described by the following formula:

$$p_q = \frac{Q_b - Q_s}{Q_s} \times 100\% \quad (5)$$

In the formula, p_q represents the growth rate of supply chain logistics demand, Q_b represents the supply chain logistics demand in the current period, Q_s represents the supply chain logistics demand in the previous period.

(2) Inventory turnover ratio

Inventory turnover reflects the speed and liquidity of inventory. By monitoring and analyzing this indicator, supply chains can more accurately predict future logistics requirements. If inventory turnover is high, it means that inventory can be quickly converted into sales, which usually means that market demand is stronger and thus requires more frequent logistics support. On the other hand, if inventory turnover is low, it means that market demand is weak or there is a backlog of inventory, and logistics needs will be reduced accordingly. Inventory turnover is calculated as follows:

$$p_z = \frac{C}{J} \quad (6)$$

In the formula, p_z represents the inventory turnover rate. C represents cost of goods sold. J represents average inventory.

(3) Seasonality index

The seasonal index measures fluctuations in supply chain logistics demand during specific seasons relative to the annual average demand level. According to the change of seasonal demand, the layout of logistics network and transportation mode can be adjusted to better meet customer demand and reduce logistics costs, which is a new indicator for supply chain logistics demand forecasting. The formula of seasonal index is as follows:

$$\ell = \frac{Q_d}{Q_e} \quad (7)$$

In the formula, ℓ represents the seasonal index, Q_d represents the actual logistics demand in a given season. Q_e represents the average logistics demand for the year.

(4) Volume of customer orders

Customer order quantity refers to the customer in a certain period of time to the enterprise issued by the number of products or services ordered, reflecting the market demand for products, is the supply chain logistics demand forecasting one of the important reference indicators.

(5) Supplier delivery lead time

Vendor lead time is the time it takes from the time an order is placed to the time the goods are received, which affects inventory requirements and logistics planning. For supply chain logistics demand forecasting, supplier lead time is a crucial factor. It directly affects the enterprise for inventory demand planning, logistics planning and the entire supply chain response speed. Specifically, the length of the supplier's delivery cycle will determine when the enterprise needs to place an order to ensure that the inventory is sufficient, but also affects the deployment of logistics resources and transportation time arrangements.

(6) Transportation efficiency

Transportation efficiency is an important factor affecting supply chain logistics requirements. Improvement of transportation efficiency can shorten the delivery cycle and reduce the inventory backlog. Therefore, it is necessary to refer to the trend of transportation efficiency to forecast supply chain logistics demand. The formula for calculating transportation efficiency is:

$$p_a = \frac{S_z}{T} \quad (8)$$

In the formula, p_a represents transportation efficiency. S_z represents the total weight of goods successfully delivered. T represents the total time spent on transportation.

Each of the above features corresponds to a specific time point or time period, thus forming a time series set that includes the characteristics of supply chain logistics demand. This time series set is the basis for training and prediction of the subsequent deep learning model. The values of the feature items at each time point constitute a multi-dimensional input vector, and the model learns the relationship between these input vectors and the output of the time series (logistics demand) to predict the future logistics demand of the supply chain.

2.3. The Realization of Supply Chain Logistics Demand Forecasting

2.3.1. BiLSTM-AM Based Supply Chain Logistics Demand Forecasting Model Construction

Given the complexity of supply chain logistics demand forecasting and its reliance on time series data, this paper employs the Long Short-Term Memory (LSTM) neural network for forecasting. The LSTM model, with its unique gating mechanism, performs well in dealing with time series data with long-term dependence relationships [11, 17, 18]. In the field of supply chain logistics, logistics demand is affected by multiple factors such as market demand, inventory, delivery lead time and transportation efficiency, which show complex dynamic relationships in time. LSTM is able to learn and memorize these intrinsic patterns and potential trends to provide decision-making support for supply chain managers, and has the ability of self-adaptation and generalization to adapt to data changes.

However, LSTM has limitations in capturing sequence context information and focusing on important information. Therefore, this paper introduces bi-directional LSTM (Bi-LSTM) to capture the contextual information and combines with the attention mechanism (AM) to enhance the attention to the key information, to construct a prediction model based on Bi-LSTM-AM to improve the robustness of supply chain logistics demand prediction. The structure of supply chain logistics demand prediction model based on BiLSTM-AM is shown in Figure 1.

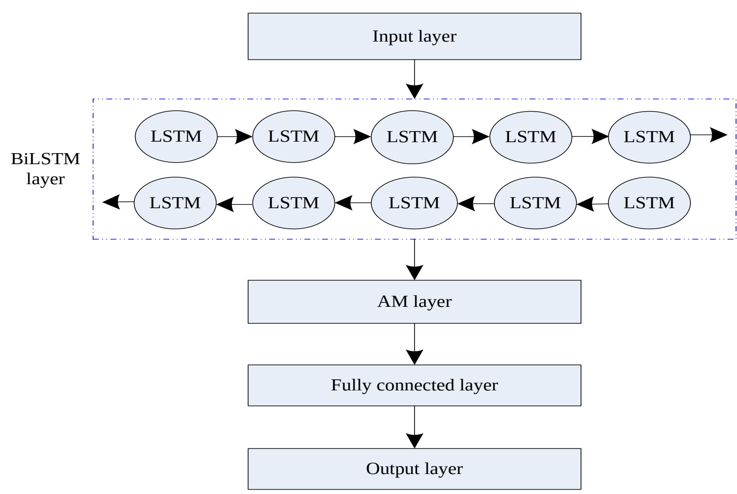

Figure 1.
Supply chain logistics demand prediction model based on BiLSTM-AM

As can be seen from Fig. 1, the BiLSTM-AM based supply chain logistics demand prediction model consists of input layer, BiLSTM layer, AM layer, fully connected layer and output layer. Among where: the input layer is responsible for receiving supply chain logistics demand data; the BiLSTM layer is used to capture the long-term dependencies in the input data; the AM layer allows the prediction model to focus on the important information in the input data to improve the accuracy of the model prediction; the full connectivity layer integrates the information from the attention layer and maps it to the prediction feature space for further processing and extraction of the key features to prepare for the final prediction results; the output layer is responsible for transforming the processing results of the full connectivity layer into the final prediction information, i.e. the predicted value of supply chain logistics demand.

The specific description of each layer in the BiLSTM-AM based supply chain logistics demand forecasting model is as follows:

(1) Input layer

The input layer is responsible for receiving the time-series information of supply chain logistics demand characteristics obtained from subsection 2.2, converting these data information into the applicable format of the model, and passing them to the next layer for processing.

(2) BiLSTM layer

The BiLSTM layer is the core component of the supply chain logistics demand prediction model. It captures temporal dependencies in the input data through gating mechanisms, including the forget gate, input gate, and output gate. In addition, BiLSTM consists of two independent LSTMs, which are responsible for processing the input sequences from two directions (forward and reverse), so that the information before and after the current time step can be acquired simultaneously, and the contextual information in the sequences can be captured more comprehensively. Specifically, the forward LSTM is used to process the time series information of supply chain logistics demand characteristics passed from the input layer from left to right, and then the backward LSTM is used to process it from right to left. Then, the outputs of the forward LSTM and the backward LSTM are spliced together to obtain the feature representation after deep learning integration, which covers the key information used for predicting the logistics demand of the supply chain.

A unidirectional an LSTM network consists of a combination of three parts: the input layer, the output layer and the implicit layer [19]. Its implicit layer uses gated memory modules to replace the conventional neurons. The LSTM memory module structure,as shown in Figure 2.

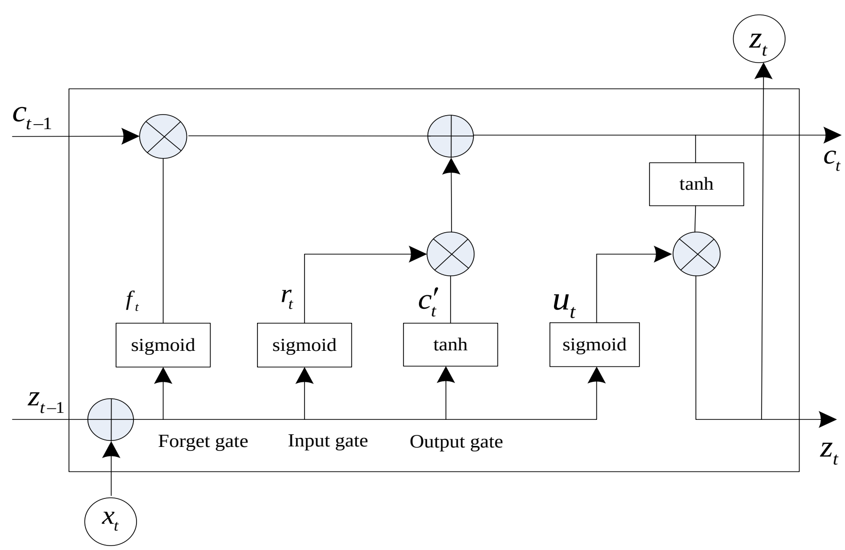

Figure 2.
LSTM memory module structure

As can be seen from Figure 2, at the t moment, the input of a memory cell module in LSTM mainly consists of: input data x_t (i.e., supply chain logistics demand characterization time series data), the state z_{t-1} of the implicit layer at the previous moment (i.e., the representation of the internal characteristics of the supply chain logistics demand at the previous moment, reflecting the model's understanding and analysis of the previous supply chain logistics demand) and the state c_{t-1} of the memory cell at the previous moment (i.e., the model's memory of the supply chain logistics demand at the previous moment); the outputs of the memory unit module mainly include: the state z_t of the implicit layer at the moment t (i.e., a representation of the internal characteristics of the supply chain logistics demand at the current moment) and the state c_t of the memory cell (i.e., the model's memory of the supply chain logistics demand at the current moment). Input gate control the degree of influence for x_t to c_t; output gate control the degree of influence for c_t to z_t; the forgetting gate controls and processes the historical supply chain logistics data information in the memory unit. The main formulas involved are described as follows:

$$r_t = sigmoid(w_r \bullet [z_{t-1}, x_t] + b_r) \quad (9)$$

$$u_t = sigmoid(w_u \bullet [z_{t-1}, x_t] + b_u) \quad (10)$$

$$f_t = sigmoid(w_f \bullet [z_{t-1}, x_t] + b_f) \quad (11)$$

In the formula, r_t, w_r, b_r represent the output result of the input gate, the weight matrix and the bias, respectively. u_t, w_u, b_u represent the output of the output gate, the weight matrix and the bias, respectively. f_t, w_f, b_f represent the output of the forgetting gate, the weight matrix and the bias, respectively.

The output results at the memory module t are shown by c_t and z_t, the expression for c_t is:

$$c_t = f_t \bullet c_{t-1} + r_t \bullet c_t' \quad (12)$$

In the formula, c_t' represents the memory unit candidate status at the moment t. The expression for c_t' is:

$$c_t' = \tanh(w_c \bullet [z_{t-1}, x_t] + b_c) \quad (13)$$

In the formula, w_c and b_c represent the input cell weight matrix and the state bias term, respectively.

Based on c_t can then calculate z_t, expressed as:

$$z_t = u_t \bullet \tanh(c_t) \quad (14)$$

Since the BiLSTM layer is composed of multiple LSTM units with opposite directions, when the input layer passes the supply chain logistics demand feature data into the BiLSTM layer, all the feature data will be processed by the bi-directional LSTM units, and as a result, we can get the two hidden states $\vec{z}_t$ and $\bar{z}_t$, by fusing these two hidden states together, we can obtain the expression for a feature vectors $\tilde{z}_t$ and $\tilde{z}_t$ that combines the previous and subsequent information of the current input supply chain logistics demand characterization data:

$$\tilde{z}_t = \vec{z}_t \oplus \bar{z}_t \quad (15)$$

Through the above processing, we can obtain the sequence $\dot{z}_t = (\tilde{z}_1, \tilde{z}_2, \cdots, \tilde{z}_n)$ of feature vectors corresponding to the current input data of supply chain logistics demand characteristics, of which n represents the number of characteristic vectors. These vectors have continuity in time, which can reflect the long-term dependence and dynamic changes in supply chain logistics demand.

(3) Attention layer (AM layer)

By introducing the attention mechanism, the AM layer enables the supply chain logistics demand forecasting model to dynamically focus on different parts of the input sequence and give these parts different weights according to the context. Thus, it pays more attention to the information that is closely related to the current supply chain logistics demand forecasting task and ignores the unimportant information, which improves the accuracy of the model prediction.

First, the attention weights are derived. That is, a nonlinear transformation operation is implemented on the feature vector $\tilde{z}_t$ output by the BiLSTM layer, mapping it into a new vector space, and thus obtaining the attention weight values ϖ_i, which is expressed as:

$$\varpi_i = \tanh(\tilde{z}_t) \quad (16)$$

Then, the AM layer will apply these weights to the feature vectors output from the BiLSTM layer and perform the weighted sum operation. In this way, the prediction model can pay more attention to the information that has an important impact on the supply chain logistics demand prediction, which is described by the formula as follows:

$$v_i = \sum \varpi_i \tilde{z}_t \quad (17)$$

In the formula, v_i represents the weighted context vector, which contains important information about the hidden states of all time steps.

v_i is the output of the AM layer, which will be used as the input of the fully connected layer for the subsequent prediction task.

(4) Fully connected layers

The fully connected layer maps the output of the AM layer to the output space through a linear transformation. In this layer, each neuron is associated with the output v_i of the AM layer, using the weight matrix and bias matrix can realize the linear combination of the two to generate a linear transformation result, which is given by:

$$H = W \bullet v_i + \vartheta \quad (18)$$

In the formula, H represents the fully connected layer output vector, W represents the weight matrix, ϑ represents the bias matrix.

(5) Output layer

The output layer, as the terminal of the prediction model, is responsible for converting the vectors passed by the fully connected layer into the form of probability distribution through the softmax function, in which each probability value corresponds to a different possibility of supply chain logistics demand prediction, according to which the final prediction result can be determined. The formula for the softmax function converting the element in H to the predicted probability value ρ_i is:

$$\rho_i = \frac{e^{h_i}}{\sum_{j=1} e^{h_j}} \quad (19)$$

In the formula, e represents the exponential function, d_i and d_j denote the elements in the fully-connected layer output vector H.

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In the supply chain logistics demand forecasting model, the probability value ρ_i corresponding to different supply chain logistics demand prediction probabilities. In the end, the model selects the category with the highest probability as the prediction result Y , i.e:

$$Y = \arg\max_i \rho_i \quad (20)$$

In summary, the supply chain logistics demand prediction model based on BiLSTM-AM is able to capture the dependencies and dynamically focus the important information in the sequence data of supply chain logistics demand characteristics and output the final prediction results through the collaborative work of each layer.

2.3.2. Supply Chain Logistics Demand Forecasting Model Training

Model training is a crucial step in developing the supply chain logistics demand forecasting model. This paper uses the gradient descent method as the optimization algorithm and calculates the logarithmic loss between the predicted and actual results using the cross-entropy loss function. Through iterative training, the gradient descent method continuously adjusts the parameters of each layer of the prediction model to minimize the cross-entropy loss function. In each iteration, the model updates the parameters according to the gradient of the current parameters (i.e., the partial derivatives of the loss function to the parameters). This process continues until the number of iterations reaches a preset upper limit.

Through such iterative training, the parameters of the supply chain logistics demand prediction model will be gradually adjusted to the optimal state, so that the model's performance (i.e., prediction accuracy) on the test set reaches the best. In this way, the model can better capture the dynamic changes of supply chain logistics demand and provide powerful support for the logistics decision-making of enterprises.

The cross-entropy loss function F is described as:

$$F = \sum_{i=1}^{M} Y_i \lg \tilde{Y}_i + (1 - Y_i) \lg(1 - \tilde{Y}_i) \quad (21)$$

In the formula, Y_i represents the output of the prediction model in this paper, $\tilde{Y}_i$ represents the actual result. M represents the number of training samples.

The time series information of supply chain logistics demand characteristics obtained through subsection 2.2 is inputted into the trained supply chain logistics demand prediction model, and the output of the model is the result of supply chain logistics demand prediction, i.e., in the future period of time (e.g., weekly, monthly, quarterly, etc.), the supply chain parties' logistics prediction of the demand for transportation, warehousing and other logistics demand values.

3. Experimental Analysis

The supply chain of an office furniture manufacturer is the experimental object, and the application effect of the deep learning-based supply chain logistics demand forecasting algorithm proposed in this paper is experimented. The enterprise specializes in the design, manufacture and sale of office furniture, and has a perfect production process and quality control system. Upstream are raw material suppliers and component manufacturers, which provide raw materials and components such as wood, metal, hardware and accessories required for the production of office furniture. Downstream are the sellers and final consumers, who are responsible for bringing office furniture products to the market to meet the office needs of enterprises and individuals.

The main experimental parameters of this experiment are shown in Table 1. The experimental platform is shown in Figure 3.

Table 1.
Main parameters of the experiment

Parameter name	Selection/value
Server	NC-R620 G40
Gateway	H3C-F1000-C-G5-LI
LOF critical value	1
LSTM unit hidden layer	4
Number of hidden layer neurons	50
Maximum number of iterations	100
Time step	8
Batch size	72
Initial learning rate	0.1
Attenuation learning rate	0.95

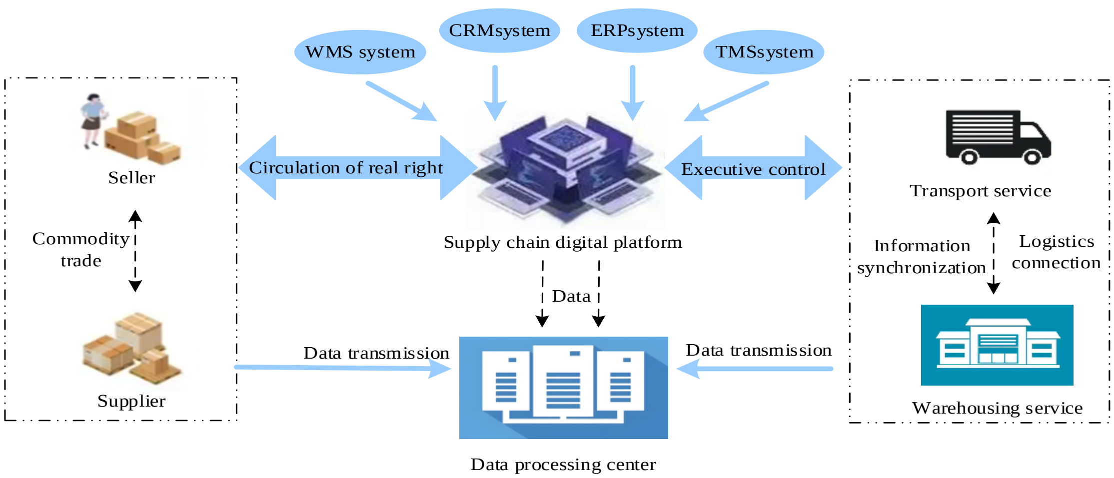


Figure 3.
Experimental platform built.

Utilizing the built experimental platform, collect data related to supply chain logistics demand, construct the original data set of supply chain logistics demand, and the distribution of part of the original data is shown in Fig. 4. Using the local outlier factor to remove the outliers in the data set, the outlier removal effect is shown in Figure 5. From the supply chain logistics demand dataset after removing the outliers, extract the feature items that have a close relationship with the supply chain logistics demand, and construct the time series collection of supply chain logistics demand features. A supply chain logistics demand prediction model based on BiLSTM-AM is established, and the model is used to realize the prediction of supply chain logistics demand, and the results are shown in Figure 6.

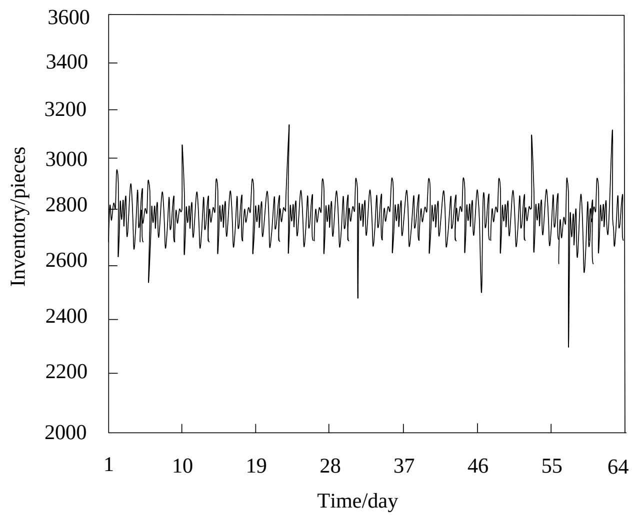


Figure 4.
Distribution of original inventory data (Partial data)

As can be seen from Figure 4, due to the influence of various factors such as equipment precision and human error, the original inventory data collected obviously contain abnormal values. These anomalies significantly deviate from the normal data distribution range, presenting anomalous prominent or extreme value characteristics, compared with normal data, the difference is more obvious. The existence of these outliers will mislead the subsequent data analysis, model training and data-based decision making, and affect the accuracy and reliability of the analysis results. Therefore, in order to ensure the effectiveness of data analysis, we need to take appropriate measures to identify and remove these outliers to eliminate their potential interference with data analysis results.

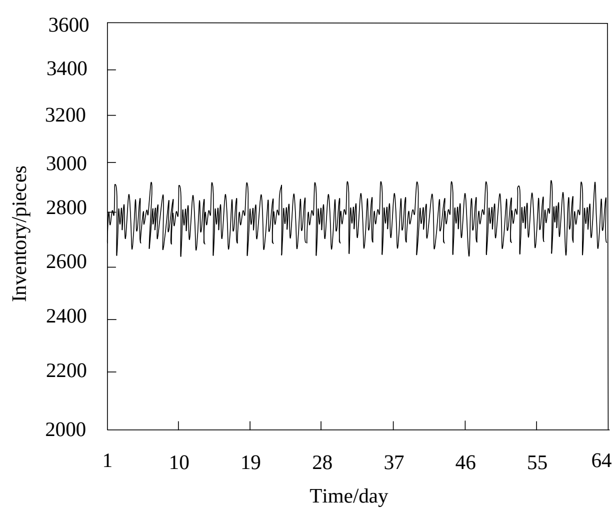
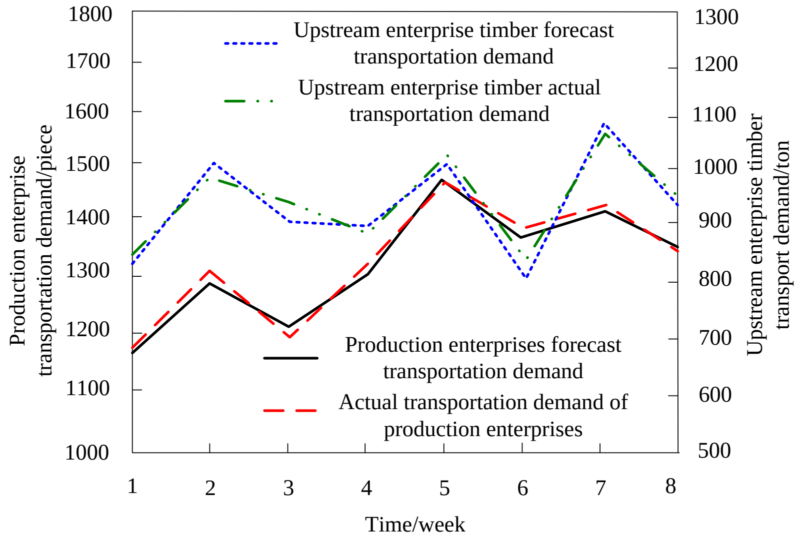
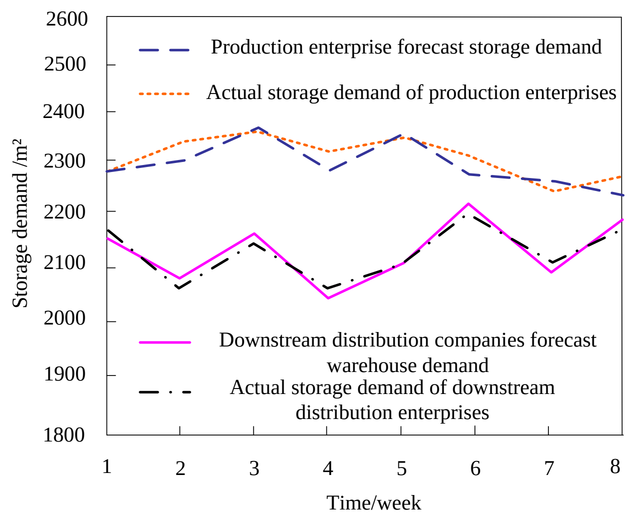


Figure 5.
Distribution of inventory data after the removal of outliers (part of the data)

As can be seen in Figure 5, after applying the local outlier factor proposed in this paper to remove the outliers in the original data set, the inventory data become smoother and more stable, the outliers are effectively identified and eliminated, and the overall trend and characteristics of the data are better preserved and reflected. The processed data are more in line with the actual business scenarios and expectations, providing a more accurate and reliable basis for the subsequent data analysis. This shows that the local outlier factor proposed in this paper can efficiently identify and remove the outliers, improve the data quality and analysis effect, and lay a foundation for the subsequent data application.



(a) Supply chain transportation demand forecast results



(b) Supply chain warehousing demand forecast results

Figure 6.
Forecast results of supply chain logistics demand

Transportation demand mainly refers to the demand of goods moving between different geographical locations, which is an important part of supply chain logistics demand, covering the transportation demand of raw materials, work-in-progress and final products. Warehousing demand refers to the storage space required for storing and managing inventory in supply chain logistics, which is an important indicator for supply chain logistics demand forecasting. As shown in Fig. 6(a) and (b), the proposed algorithm accurately predicts supply chain transportation and warehousing demands. The

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predicted results are highly consistent with actual demands, with only minor deviations, demonstrating strong accuracy and reliability. This shows that the supply chain logistics demand prediction algorithm proposed in this paper can effectively predict the logistics demand in the supply chain, provide a scientific basis for enterprise logistics planning and resource allocation, and help enterprises optimize the supply chain operation, improve logistics efficiency and economic benefits.

In order to further verify the application effect of the deep learning-based supply chain logistics demand forecasting algorithm proposed in this paper, the logistics efficiency and logistics cost control of the office furniture manufacturer after applying the method of this paper were analyzed, and the on-time delivery rate and the magnitude of logistics cost reduction were evaluated. Among them, the on-time delivery rate reflects the reliability of logistics services and the ability to meet customer demand, while the logistics cost reduction margin directly reflects the contribution of the algorithm in economic efficiency. After testing, the results are shown in Figure 7.

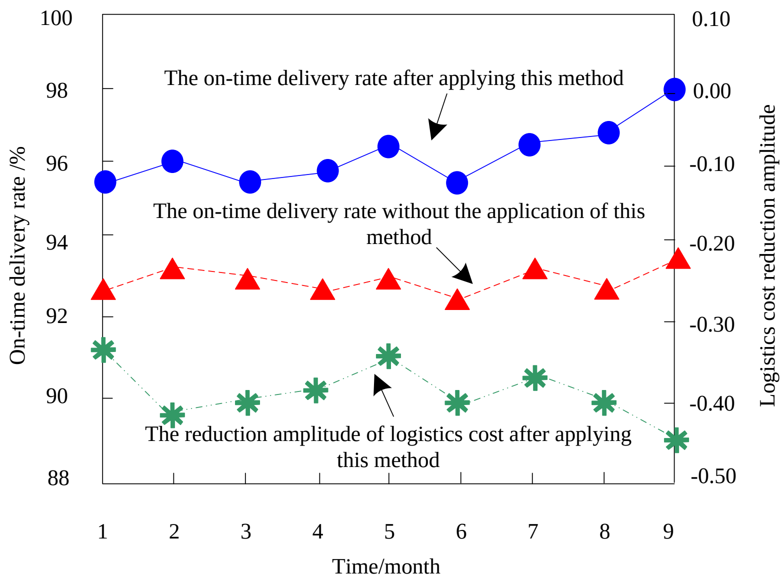

Figure 7.
The on-time delivery rate and the reduction amplitude of logistics cost after the application of this algorithm

As can be seen in Fig. 7, after implementing the proposed deep learning-based supply chain logistics demand forecasting algorithm, the on-time delivery rate of the office furniture enterprise significantly improved, exceeding 95% each month, a marked increase compared to the period before the algorithm was applied. In addition, the logistics cost has also realized a large reduction, the lower value is between 0.3 and 0.5. This shows that the algorithm in this paper is effective in improving the reliability of logistics services and the ability to meet customer demand, and also has a positive impact on the economic benefits, effectively reducing the logistics costs of enterprises, and enhancing the competitiveness of enterprises in the market.

4. Conclusion

With the rapid advancement of information technology and the increasing globalization of trade, supply chains have grown increasingly complex and dynamic. Accurate logistics demand forecasting has become crucial for improving operational efficiency and enhancing market competitiveness. To this end, this paper studies the deep learning-based supply chain logistics demand prediction algorithm, which mines and analyzes the historical data through deep neural network model, automatically extracts the key features in the data, captures the subtle changes in the market demand, and takes into account the interactions of a variety of influencing factors, so as to realize the high-precision prediction of the logistics demand of the supply chain. Experimental results demonstrate that the algorithm performs well in terms of accuracy and stability in logistics demand forecasting, providing reliable decision-making support for enterprises.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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