Proceedings of the 6th International Conference on Computing and Data Science
DOI: 10.54254/2755-2721/69/20241521

Research on international trade logistics prediction based on back propagation neural network

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Abstract. The development of international trade depends to a large extent on the progress of international logistics. However, international logistics cannot exist independently of international trade. Without goods provided by international trade, international logistics loses its foundation. Therefore, in order to accurately assess the demand for international logistics, it is necessary to have a detailed understanding of the development of international trade and to predict its future trends accordingly. In this work, we utilize backpropagation neural networks to predict trends and needs in international trade logistics. Specifically, we build a multi-layer perceptron model, which selects a variety of input variables such as goods circulation, economic indicators, trade policies, and seasonal factors. By training this model, it is possible to effectively learn and capture the complex relationships that affect international trade logistics from historical data. In the experimental analysis, the model has been repeatedly trained and adjusted, and finally demonstrated high accuracy and reliability.

Keywords: Internation Trade, Logistics Prediction, Multiple Layer Perceptron, Back Propagation Neural Network.

1. Introduction

For countries that rely heavily on external demand, fluctuations in international trade can not only affect domestic economic trends, but can also trigger socio-economic ripple effects such as national employment. Frequent trade transactions rely on a strong international logistics system. The demand for international logistics directly corresponds to the supply of international trade; Without international trade, international logistics will lose the basis of its existence. In order to accurately analyze the impact of international trade on international logistics, we must have a clear understanding of the future development trend of international trade, and by predicting the total import and export volume and freight volume of international trade, we can grasp the future trade situation [1]. This will help us assess the impact of international trade development on international logistics, and provide strategic recommendations for international trade and logistics companies to grasp trade opportunities and enhance their competitiveness, so as to promote their own sustainable development.

In today's globalized world, international trade plays a vital role in the health and growth of the world economy. As the lifeblood of international trade, international logistics not only supports the cross-border circulation of goods, but also affects the efficiency and cost of the global supply chain. With the continuous change of market demand and the continuous adjustment of trade policies, the international

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trade environment is becoming increasingly complex. This complexity requires companies and policymakers to not only understand current trade processes, but also anticipate future trends [2]. Forecasting international trade logistics has become an essential tool to help companies and government agencies make more informed decisions, optimize resource allocation, reduce operational risks, and improve service quality. With accurate forecasting of future trade patterns, freight demand, and logistics routes, you can be better prepared to deal with market uncertainty and stay competitive [3].

International logistics plays a key role in global trade, by ensuring the cross-border movement of goods and commodities, not only to meet customer needs, but also to enhance the international competitiveness of goods, effectively expand the scale of international trade, and then improve the level of development of international trade. Driven by information technology and scientific and technological progress, the application of modern logistics technology such as information barcode and automatic sorting device has greatly improved logistics efficiency, shortened the transportation time and cost of international logistics, reduced the complexity of international trade, and enhanced the convenience of trade, thereby accelerating the development of international trade [4].

Methods for forecasting trade are mainly divided into quantitative and qualitative methods. Quantitative methods include time series analysis, structural models, leading exponential methods and other techniques. The qualitative law mainly relies on the judgment of experts on the situation and trend of economic development [5]. The main weakness of the expert forecasting method is that it relies too much on personal subjective opinions and lacks accuracy. The limitation of the structural model is that it is difficult to fully reflect the reality in the process of model setting; While leading indices and time series methods predict future developments based on historical data, they are often not effective in dealing with unexpected events. Therefore, in actual analysis and research, the comprehensive application of multiple methods is usually used to enhance the accuracy and practicability of predictions [6].

With the rapid advancement of technology, particularly in the fields of data analysis and machine learning, the methodologies and precision of forecasting in international trade logistics have seen substantial improvements. These sophisticated technologies empower analysts to utilize both historical and real-time data to develop more accurate and reliable forecasting models. This capability transforms international trade logistics management into a more scientific and systematic discipline. The integration of machine learning algorithms allows for the detection of patterns and trends that may not be apparent through traditional analysis methods. For example, neural networks and regression analyses can predict fluctuations in trade volumes and logistical demands with a higher degree of accuracy [7]. Furthermore, advancements in big data technologies enable the handling of vast amounts of data from multiple sources such as cargo tracking systems, port operations, and global market trends, enhancing the comprehensiveness of the forecasts.

By applying these cutting-edge technologies, logistics managers can not only forecast demand more precisely but also optimize routes, manage inventory more effectively, and reduce operational costs. This results in a more agile and responsive logistics network that can better withstand the complexities and volatilities of global trade environments. As we continue to refine these technologies and integrate them more deeply into logistics practices, the future of international trade logistics looks poised for even greater efficiency and innovation [8]. This ongoing evolution will likely further solidify the role of advanced data analytics and machine learning as critical tools in the strategic planning and operational frameworks of global trade logistics.

2. Related Work

In general, the level of development of international trade can be assessed by two directly quantifiable indicators: trade volume and freight volume. In one study, Henry et al. [9] used artificial neural networks (ANNs), exponential smoothing, and ARIMA models to predict the export of rice from Thailand. The results show that although the Holt-Winters model and the Box-Jenkins model have a higher goodness-of-fit for the data within the sample, these models perform poorly in predicting the unseen data during

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the validation phase. In contrast, artificial neural networks have shown better performance in tracking dynamic nonlinear trends and seasonal changes, as well as the interactions between these factors.

Youan et al. [10] used the coefficient of elasticity method, the GM(1,1) model, and the DGM model to predict passenger and freight traffic from 2011 to 2015. Based on these predictions, they further optimized these prediction models using a combination model based on the reciprocal variance and the optimal weight. At the same time, Moscoso-López et al. [11] used artificial neural networks and support vector regression (SVR) methods to make short-term prediction of multimodal cargo in Algeciras Bay, and explored the application of these advanced techniques in actual transportation forecasting.

Although international logistics and international trade are closely related, and the two are difficult to separate in practice, many experts and scholars mainly discuss their impact on international trade from the perspective of international logistics. Relatively few studies have analyzed how the development of international trade affects international logistics. This suggests that we still need to delve into how international trade shapes and expands the structure and efficiency of international logistics to fully understand the interactions and dependencies between the two.

3. Methodologies

The backpropagation neural network-based model for international trade logistics forecasting is a powerful machine learning framework that is widely used to solve nonlinear and complex forecasting problems. Such a model is typically made up of several core components: the input layer, the hidden layer, and the output layer.

3.1. Back Propagation Neural Network

The main task of the input layer is to receive various input variables that represent data points related to international trade logistics, such as freight volumes, economic indicators, seasonal factors, etc. These inputs are the basis for model analysis and predictions. Let the input layer have n input nodes, each corresponding to a feature. If we have an eigenvector $X = [x_1, x_2, \dots, x_n]^T$, this vector will be propagated directly to the next layer.

The task of the hidden layer is to extract and learn complex data patterns from the input data. These layers can have one or more, and each layer contains several neurons. The design of the hidden layers, including the number of layers and the number of nodes per layer, is a key factor in network performance. For each hidden layer neuron, its output $a_i^{(l)}$ is a weighted sum of the output of the previous layer, which is transformed nonlinearly by an activation function σ. Specifically, the output of the $i - th$ neuron of layer (l) is calculated as following Equation 1.

$$a_i^{(l)} = \sigma(\sum\nolimits_j w_{ij}^{(l)} a_j^{(l-1)} + b_i^{(l)}) \tag{1}$$

Where $a_j^{(l-1)}$ is the output of the previous layer, $w_{ij}^{(l)}$ is the weight, $b_i^{(l)}$ is the bias, and σ is the activation function.

The output layer is responsible for generating the final output of the network, and its number of nodes is determined based on the specific needs of the prediction task. In the scenario of international trade logistics forecasting, there is usually only one node in the output layer that is used to output the forecasted freight volume or trade volume. The output layer is computed in a similar way to the hidden layer, but the appropriate activation function is usually chosen depending on the nature of the problem. For example, to forecast freight volumes, a linear activation function may be used. The node output y of the output layer can be expressed as following Equation 2.

$$y = \sigma(\sum\nolimits_i w_i a_i^{(L)} + b) \tag{2}$$

Where L is the last hidden layer, $a_i^{(L)}$ is the output of the last hidden layer, w_i is the weight of the output layer, and b is the bias. Through such a model architecture, the proposed model can capture the

DOI: 10.54254/2755-2721/69/20241521

complex relationships in the input data through multi-layer processing and nonlinear transformation, and provide strong support for the prediction of international trade logistics.

3.2. Propagation Mechanism

Backpropagation is a key step in the training process to optimize the weights and biases of the neural network. It first calculates the errors of the output layer and then backpropagates those errors back into the network, adjusting the weights and biases of each neuron layer by layer. The error is usually calculated using the mean square error formula, which is expressed as following Equation 3.

$$E = \frac{1}{2}\sum_k (y_k + \hat{y}_k)^2 \tag{3}$$

Where y_k is the target value and $\hat{y}_k$ is the predicted value of the network. By calculating the gradient of the error with respect to each weight, using the gradient descent method or other optimization algorithms, the weights and biases can be adjusted step by step, with the goal of minimizing the error of the entire network.

Through the cyclic iteration of backward propagation, the network can gradually improve its prediction accuracy on the training data, so as to more effectively predict the international trade logistics demand in practical applications. Through such a mechanism, neural networks can continuously learn and adapt to cope with various complex situations and dynamic changes in international trade logistics.

4. Experiments

4.1. Experimental Setups

Table 1 below shows the data on the import and export trade volume and freight volume between China and the EU from 2011 to 2019, as detailed in Table 4.1. Based on these data, we will forecast the future development trend of EU-China international trade from 2024 to 2026. The data on the international trade volume and freight volume between China and Europe are derived from the EPS database, which has been collated and analyzed.

Table 1. China-EU international trade volume and freight volume from 2011 to 2022.

Year	Import and export trade volume (unit: US$ billion)	Import and export freight volume (unit: 10,000 tons)
2011	6446.12	20388.49
2012	6716.50	21190.37
2013	6851.59	22412.00
2014	7449.69	23127.84
2015	6991.03	25332.62
2016	6794.65	24932.83
2017	7578.31	27726.51
2018	8548.89	28546.79
2019	8722.88	33073.93
2020	9194.57	34699.44
2021	9516.12	36434.34
2022	11,352.21	39423.48

4.2. Experimental Analysis

Prediction accuracy is a measure of how well the output of a predictive model matches real data. Prediction accuracy can be assessed by a number of different statistical methods in different application areas, but the basic concept is the same: it reflects the reliability and validity of the model's predictions. High accuracy means that the model's predictions are very close to the actual observations, indicating the validity and usefulness of the model. In practice, improving prediction accuracy is often the main goal of model optimization. Following Figure 1 shows the comparison of trade and logistics prediction results and realistic data from 2011 to 2022.

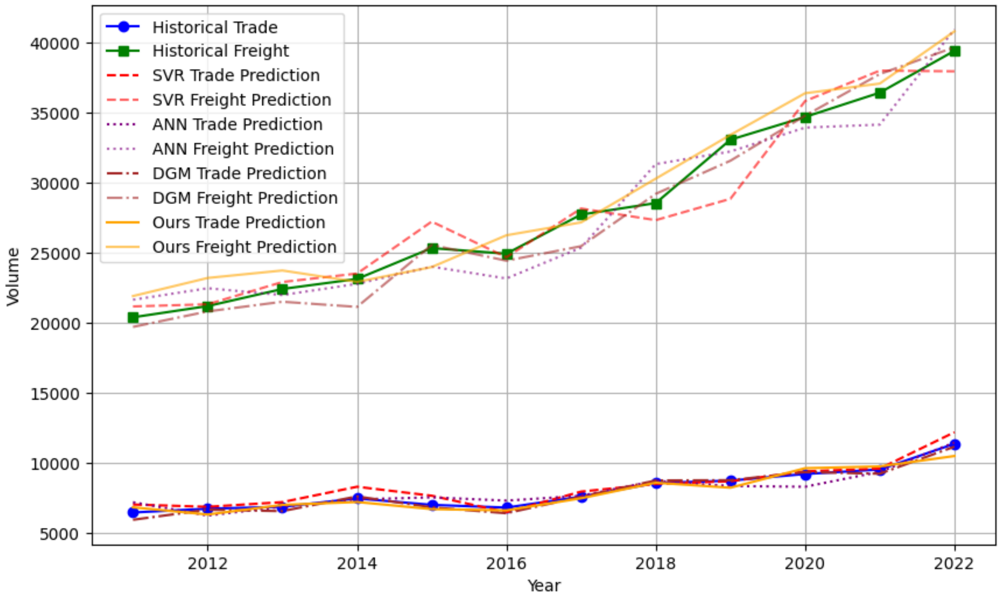

Figure 1. Comparison of trade and logistics results.

Mean squared error measures the average of the square of the difference between the predicted value and the actual value. It is a widely used accuracy metric because it quantifies the magnitude of the prediction error. The smaller the value of the mean square error, the higher the prediction accuracy of the model. The mean square error imposes a large penalty for large errors, making it ideal for applications where large errors need to be avoided. Following Figure 2 shows the mean squared error comparison results.

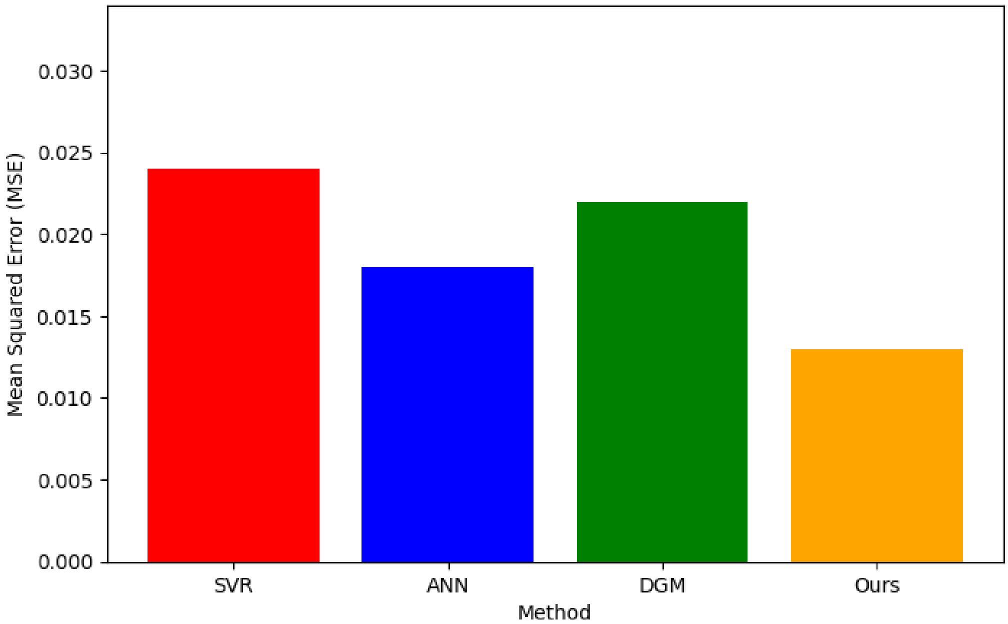

Figure 2. Comparison of MSE across different prediction methods.

5. Conclusion

In conclusion, our proposed model demonstrates the potential of neural networks in accurately forecasting trade volumes and logistics needs. The BPNN model successfully captured complex nonlinear relationships inherent in the international trade data, resulting in robust predictive performance. However, there remain areas for improvement. Future work could explore the integration of additional variables that may influence trade dynamics, such as economic indicators, political events, or environmental factors. Additionally, experimenting with different network architectures and training methodologies, like deep learning or reinforcement learning, could further enhance the model's accuracy and adaptability. By continually refining the model and incorporating real-time data, the predictive capabilities can be significantly improved, aiding stakeholders in making more informed decisions in the ever-evolving landscape of international trade logistics.

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