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Performance evaluation model of cross border e-commerce supply chain based on LMBP feedback neural network

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Abstract: In recent years, with the support of national policies, Cross Border E-Commerce (CBEC) has developed rapidly. This business model not only brings significant benefits to the national economy, but also has many unique challenges, especially at the level of supply chain management. Therefore, to enable CBEC enterprises to develop sustainable supply chain, this study discusses the performance evaluation model of supply chain and proposes a CBEC Supply Chain Performance Evaluation Model (CBECSC-EM) based on the Levenberg–Marquardt Backpropagation (LMBP) algorithm. This experiment constructs performance evaluation indicators for the supply chain of CBEC enterprises. On this basis, the LMBP algorithm is introduced, and improved in the experiment to make the overall performance of the evaluation model more scientific and reasonable. In the verification set, the maximum F1 values of LMBP, DEA, SBM, and BP are 98.46%, 93.78%, 87.29%, and 78.95%, respectively. The MAPE value of LMBP model is 0.102%, which is lower than the other three methods (0.282%, 0.343%, and 0.385%) selected in the experiment. The maximum standard deviation rates of importance and operability of the evaluation indexes are 0.1346 and 0.1405, respectively, and there is a significant consistency between the expert scores. Therefore, the LMBP algorithm has broad application prospects in supply chain performance evaluation of CBEC enterprises.

Key words: Levenberg–Marquardt Backpropagation (LMBP) algorithm; Cross Border E-Commerce (CBEC); supply chain performance evaluation; evaluation indicators; artificial fish swarm algorithm

1 Introduction

Cross-Border E-Commerce (CBEC) is constantly affected by the global supply and demand relationship, pushing the world into a new commercial era[1]. In recent years, China has attached more importance to the development of CBEC, which has also brought more favorable conditions for its development. With the rapid development of CBEC, there are many drawbacks such as small market capacity and slow logistics speed. CBEC involves different countries and regions, so its supply chain is more complex than normal e-commerce. It is not easy to evaluate the performance of CBEC Supply Chain (CBECSC) for every enterprise involved in the supply chain[2]. CBECSC can be evaluated according to the operating results of enterprises, so as to help enterprises to improve the supply chain and the economic benefits. However, the current CBECSC Performance Evaluation Model (CBECSC-EM) has many deficiencies[3]. First, the supply chain performance index system is not perfect. Due to the broad scope of supply chain management, it involves the whole process from raw materials to products. Therefore, it is necessary to screen indicators in a targeted way[4]. At present, there is no study to define it. Second, CBEC generates a lot of traceable data in its day-to-day operations. Therefore, how to construct a supply chain performance evaluation index and a model suitable for the enterprise itself is an urgent problem to be solved. In view of this, this study proposes a performance evaluation model of CBECSC based on Levenberg–Marquardt Backpropagation (LMBP)

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feedback neural network, so that CBEC enterprises can effectively measure the operation of supply chain. Relevant enterprises can use this model to conduct simulation analysis, so as to provide reasonable suggestions for the supply chain management of CBEC enterprises. Therefore, the main contributions of this study are as follows:

(1) Review the literature on performance evaluation methods of cross-border e-commerce supply chains and LMBP feedback neural networks, summarize their advantages, characteristics, and shortcomings, and lay a theoretical foundation for the content of this study.

(2) The performance evaluation model of cross-border e-commerce supply chain is elaborated, and combined with the characteristics of cross-border e-commerce industry, the performance evaluation index system of e-commerce supply chain is designed.

(3) The traditional Backpropagation (BP) algorithm is improved, that is, the LMBP performance intelligent evaluation model is built. In addition, artificial fish swarm algorithm is also introduced to improve the efficiency of LMBP model to obtain initial weight.

(4) Simulation experiments are carried out on the proposed model, and performance evaluation results are given. The final results show that the performance evaluation model of cross-border e-commerce supply chain based on LMBP has excellent application performance.

2 Related work

In recent years, researchers have attempted to explore the performance of CBECSC-EM and have achieved certain research results. Yu et al.[5] researched the impact of information technology on company performance from the upstream and downstream perspectives of the entire CBECSC. The experiment used the LISREL structural equation to model the collected data of 296 CBEC companies. And technical information affected the operational performance of enterprises, thereby affecting financial performance. This study provided important insights for the performance management of CBEC enterprises. This study provided important insights for the performance management of CBEC enterprises, but the overall method was complex and time-consuming, and there was still a great deal of room for improvement in intellectualization. From the perspective of China's digital trade, Yang et al.[6] researched the impact of digital platform's service capability and CBEC digital transformation capability on CBEC enterprises performance. The final empirical results showed that the cost control capability of CBECSC affected the service capabilities of digital platforms and ultimately had a significant impact on the performance of enterprise. This study provided a significant reference value for the performance of CBECSC-EM. Although this study had important reference value for improving the performance of CBECSC-EM, it lacked targeted research on cross-border e-commerce enterprises, and the overall applicability of this method needed further investigation. Cassia and Magno[7] explored the connection between enterprises' international marketing strategy, export operation capability, and financial performance from the perspective of resources. The experiment used partial least squares structural equations to model and analyze exporter data in the food and beverage industry. The comprehensive impact of export business capabilities and international marketing on the financial performance of the CBECSC was highlighted. This study had potential implications for the performance of CBECSC-EM. This study has a potential impact on the performance of CBECSC-EM, but no concrete empirical analysis has been conducted. Huang[8] explored the impact of real-time marketing profits on the SC performance of online cosmetics CBEC platforms. The SLS-SVM model was constructed in the experiment to conduct multi-level classification and statistical analysis of marketing profits. The experimental results indicated that this method could calculate the real-time profits of the CBECSC finance industry, which was conducive to observing the real-time fluctuations of its financial performance. Li et al.[9] proposed an RBF-DEMATEL model to explore the influencing factors between CBEC capabilities. The experiment selected relevant data from 249 enterprises for empirical analysis. E-commerce capability has a significant impact on CBECSC performance. The three most critical factors included the situation of international marketing, logistics technology, and electronic payments' supporting conditions. The experiment also verified the effectiveness of the constructed model. The model had certain inspirations for this research model, but its supply chain index system was not perfect and had certain limitations.

The LMBP algorithm is a commonly used neural network model that is widely used in multiple fields due to its practicality. Hao and Zhu[10] proposed a solution method for the optimal process parameter values of plastic gears. The proposed method used LMBP network as a fitness function. The experiment selected a small dataset for simulation, and the final results showed that this method can select the optimal process gear, improving the efficiency of traditional selection strategies. Xu et al.[11] chose to combine LMBP and SVM networks for deformation trend predictions to understand skin friendly deformation trends in hydropower stations. The actual data of hydropower stations' overturned deformation slopes were collected. Temperature, rainfall, etc., are regarded as parameters when inputting, and displacement was regarded as parameters when outputting. The final results showed that the LMBP-SVM method's highest error is 2.53%, with good practical value. Weera et al.[12] used LMBP networks to simulate the numerical behavior of computer viruses. The experiment selected 11%, 13%, and 76% of data to be tested, trained, and validated together with relevant neurons. The experimental analysis of regression actions, error histograms, and mean square error measurements showed that the LMBP model had high accuracy and superior simulation ability. From the perspective of data prediction, Jin and Zhang[13] proposed to introduce the idea of ecological niche into particle swarm optimization algorithm to improve its global search ability and convergence speed. Simultaneously, the LMBP network was used to continuously optimize parameters to improve the overall model's data prediction ability. The new model exhibited superior performance in data prediction. To accurately identify the important parameters of solid oxide fuel cells, Yang et al.[14] proposed to apply the LMBP network to the process of parameter identification. The LMBP network was mainly used to optimize the Artificial Neural Network (ANN) network to better assist it in identifying parameters in solid oxide fuel cells. The experiment compared the proposed model with the balance optimizer, grey wolf optimization, and moth flame optimization algorithms, and the final results showed that the LMBP algorithm showed good advantages in accuracy when estimating these unknown parameters, which had high speed and stability. All the above studies could show that LMBP algorithm had strong practical value in data prediction, but it failed to make innovations to further improve the performance of LMBP models.

In summary, both CBECSC-EM and LMBP algorithms have certain researches in their respective fields. However, the positive role of LMBP algorithms in the evaluation of supply chain performance of cross-border e-commerce enterprises has not been discussed by combining the two methods. Therefore, a CBECSC-EM model based on LMBP feedback neural network is proposed in this study, aiming to provide reference value for the supply chain management of cross-border e-commerce enterprises.

3 Construction of a CBECSC performance EM based on LMBP

3.1 Research on the performance EM of CBECSC

The prosperity of the Internet has led to the rapid development of CBEC in recent years. Compared to traditional international trade, CBEC also has its own unique characteristics. First, CBEC is more globalized and multilateral than traditional international trade. The buying and selling behavior of CBEC has broken the limitations of time and space. It is different from the linear trade structure of traditional foreign trade, with numerous participants and characteristic of multilateralism[15]. Second, CBEC has the characteristics of platforming and digitization. The buyers and sellers of the CBEC trade model are based on an open e-commerce platform, reducing the complex intermediate links in traditional trade models. Third, CBEC has the advantage of personalization and short cycles. CBEC has emerged based on the Internet, and therefore requires greater emphasis on the personalized needs of consumers[16]. The unique characteristics of CBEC itself pose challenges to its SC management. The globalization and diversification of CBEC have promoted more diversity and breadth of its participants. Its platformization and digitalization make relevant logistics, information flow, capital flow, and other data centralized; its personalized and short cycle characteristics makes it necessary for enterprises to prioritize customer needs and continuously improve their inventory management level, information sharing, and innovation. As a result, these factors have brought about SC challenges to CBEC.

Figure 1 shows the overall operational system of CBECSC. As shown in the figure, CBECSC can be divided into three parts: customer relationship management, integrated supply chain management, and supplier relationship management. These three parts are responsible for generating, responding to, and fulfilling customer needs, and also have a significant impact on the operational efficiency of supply chains. The supply chain systems in Fig. 1 need to coordinate with each other to make the entire system interconnected. Therefore, establishing an effective performance evaluation system for CBECSC is conducive to ensure the normal operation of CBECSC. Supply chain performance refers to ultimate goal achievement of the entire supply chain after various nodes integrate such as suppliers, agents, transporters,

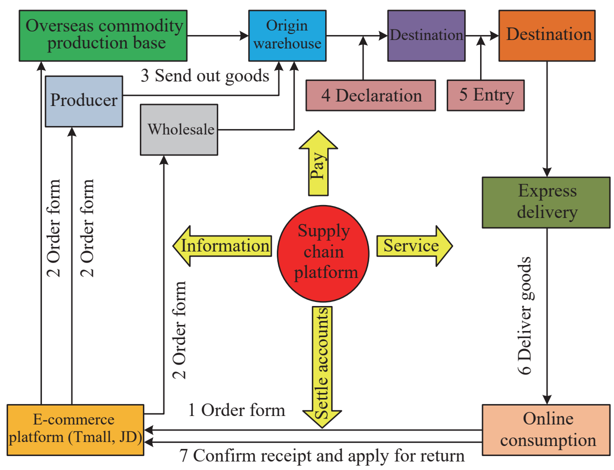


Fig. 1 CBECSC system.

and consumers. Evaluating supply chain performance levels can make reasonable judgment on operational effectiveness of enterprises during a certain period of time, to promote the growth and development of the enterprise[17]. The evaluation of supply chain performance needs to balance effectiveness and efficiency. This experiment focuses on CBEC enterprises as the main research object, attempting to evaluate the performance of the entire supply chain. CBECSC performance evaluation is different from traditional enterprises, and it is necessary to reconstruct a performance indicator evaluation system for them. After considering the relationship between the business process of the supply chain and each node of the supply chain, the performance evaluation index of cross-border e-commerce supply chain is designed, as shown in Table 1.

Table 1 shows the primary and secondary indicators included in CBECSC. With an understanding of their basic meanings and main functions, it is necessary to screen them to be more suitable for the performance evaluation of CBECSC for this study. The experimental selection uses expert scoring methods to score and evaluate the selected indicators[18]. The requirements for the selected experts are: experts, researchers, and senior experts with long-term theoretical and practical experience in the supply chain field. The authority coefficient is calculated, as shown in Eq. (1).

$$Q = (q_1 + q_2 + q_3)/3 \tag{1}$$

where q_1 represents the academic level of the expert, q_2 denotes the coefficient obtained jointly by the position and length of service of the expert, and q_3 indicates the expert's familiarity with the field. The mean of the above three values is the overall authority coefficient of the expert. The calculation of the experts invited in this article shows that 100% of the expert authority coefficients are above 0.7, and 46.89% of experts have an authority coefficient above 0.9. Therefore, the overall authority of experts can still meet the needs of this experiment, laying the foundation for obtaining reliable and effective experimental results. Figure 2 shows the performance

Table 1 CBECSC performance evaluation indicators.

Primary indicator	Secondary indictor		Indicator meaning
Customer (F_1)	Customer satisfaction	X_1	The degree of matching between customer expectations and actual experience
	Reliability	X_2	Product return rate
	Complaint rate	X_3	Customer dissatisfaction with the product
	Product quality	X_4	Product advantages
	Product price advantage	X_5	Product qualification rate
	Market share	X_6	The proportion of CBEC revenue of enterprises in total exports
Finance (F_2)	Profit	X_7	Operating profit
	Asset turnover	X_8	Asset turnover
	Stock	X_9	Inventory turnover rate
	Cost	X_{10}	SC operating costs
	Logistics	X_{11}	Delivery rate
Internal process (F_3)	Order completion rate	X_{12}	The rate of successful completion of orders
	Payment convenience	X_{13}	Payment methods are secure, stable, and convenient
	Convenient customs	X_{14}	The clearance process is simple
	Innovate	X_{15}	New product development cycle
	Market forecast accuracy	X_{16}	Is the prediction of future product and market development consistent with the actual development situation
Development (F_4)	Crisis response capability	X_{17}	SC response time
	Employee retention rate	X_{18}	Employee satisfaction
	Employee training	X_{19}	Employee improvement opportunities
	Sustainable development capability	X_{20}	Profit growth rate
	On time delivery rate	X_{21}	Supplier delivery status
Supplier (F_5)	SC flexibility	X_{22}	Suppliers' ability to adapt to unexpected situations and meet customer needs
Service capability (F_6)	Information sharingcapability	X_{23}	Ability to share information with SC enterprises: Ability to communicate information with customers in a timely manner
	Positive review rate	X_{24}	Positive review rate
	Turnover	X_{25}	Transaction quantity

evaluation indicator system for the final CBECSC obtained after three rounds of expert scoring. The overall system consists of 6 layers, representing the basic layer, associated layer, and ultimately achievable profit goals of the indicator system from the top to the bottom. Thus, for CBECSC, mutual cooperation is necessary to drive their performance to climb continuously.

3.2 Construction of performance intelligent EM based on improved LMBP

Back Propagation Neural Network (BPNN) is one of the most widely used and technologically mature ANNs, and is a common machine learning algorithm. BPNN generally uses the gradient descent method for learning, but this method can easily cause the BPNN model to fall into a local extremum during the iteration process, resulting in the output of the BPNN model not being the optimal solution[19]. In addition, the convergence of the BPNN model was poor, and there was a disconnection between the new and old samples. The traditional BPNN models have many defects, and this study proposes the use of the LM algorithm based on Newton's method to optimize the BPNN. As a result, the BPNN model exhibited convergence rate. Under the Newtons method, the weight update of the BPNN model is performed according to Formula (2).

$$w_{k+1} - w_k - H_k^{-1} g_k \tag{2}$$

where w_k represents the network weight of the BPNN model at the k-th iteration; g_k represents the gradient of the mean square error function, that is, the first

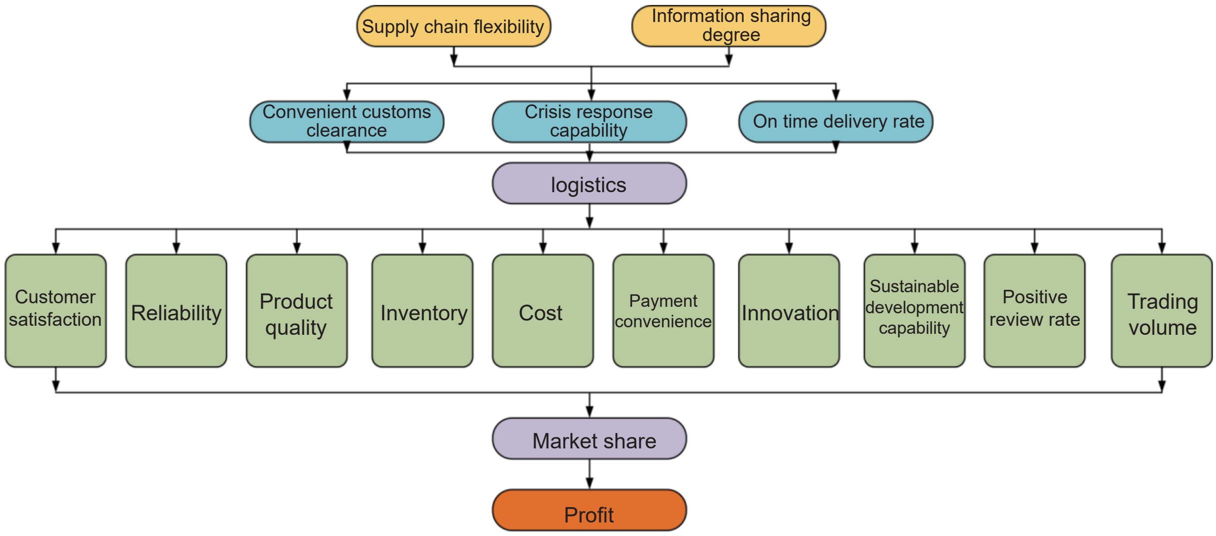


Fig. 2 Performance of CBECSC-EM.

derivative of $E(x,w)$, where x is the input of BPNN; H is the second-order derivative of $E(x,w)$ and an approximate matrix of a Hessian matrix. By using the Hessian matrix to solve H, the learning rate of BPNN can be obtained. Different from the fixed learning rate of the traditional BPNN model, the Heisenberg matrix also includes changes in the error function, so in the process of convergence, the BPNN will not have a Z-shaped convergence trajectory to avoid falling into local extremum[20]. However, this method can also cause the network weight correction process of the BPNN model to be complex, increasing its computational complexity and affecting its efficiency. Therefore, Gaussian Newton method is used to update BPNN model's weights, as shown in Eq. (3).

$$w_{k+1} = w_k - \left(J_k^{\mathrm{T}} J_k\right)^{-1} J_k e_k \tag{3}$$

In Eq. (3), J is obtained from Formula (4), and e_k is an error vector.

$$JJ^{\mathrm{T}} \approx H \tag{4}$$

In the LMBP network, if N is represented as node number when inputting; M is the node number when outputting, j is a hidden layer unit, i is an input layer unit, net_{pi} is the input for hidden layers, x_{pi} is the input layer value, w_{ji} is the weight, w_{jo} is the threshold, $g\left(net_{pi}\right)$ is the hidden layer's excitation function, W_{ko} is k layer network's threshold, y is the output value for the target, $\hat{y}$ is the actual output value, and η is the number of studies[21]. The LMBP's solution and mean square error can be calculated using Eq. (5).

$$E = \frac{1}{2}\sum_{p-1}^{N}\sum_{k=0}^{N}\left(y_{pk} - \hat{y}_{pk}\right) \tag{5}$$

The input value of the network hidden layer can be calculated using Eq. (6).

$$net_{pi} = \sum_{j=0}^{N} w_{jt} x_{pi} + w_{jo} \tag{6}$$

The excitation function of the hidden layer is represented by Eq. (7).

$$g\left(net_{pi}\right) = \frac{1}{1+\mathrm{e}^{-net_{pj}}} \tag{7}$$

The weight update of the model is represented by Eq. (8).

$$W_{kj} = -[H + uI]^{-1} J^{\mathrm{T}} e \tag{8}$$

where I is the identity matrix, u is a variable typically set to 0.01. Therefore, in Fig. 3, CBECSC-EM based on the LMBP is obtained.

In Fig. 3, the intelligent evaluation of CBECSC performance is mainly divided into three stages. First, data is collected based on the indicator system constructed through research, and this data is organized and calculated to achieve normalization processing, avoiding the increase in model calculation volume caused by differences in data format, magnitude, and so on, which affects the accuracy of the model[22]. The second stage involves training and learning the input data using the LMBP Neural Network (LMBPNN).

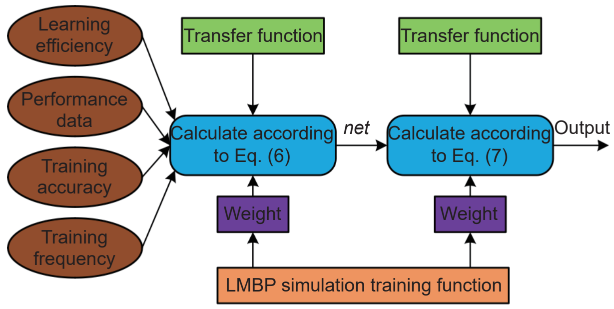


Fig. 3 CBECSC-EM based on LMBP.

The third stage analyzes the training results and the performance improvement path based on the output results of the model, and develops corresponding plans. The above steps are presented in Fig. 4.

In Fig. 4, the initialization weight value of the LMBPNN is generally determined through manual experiments based on the experimental results to determine the optimal initial weight value. This method has low efficiency and is time consuming, and the initial weight value obtained is often only a suboptimal value, which affects the performance of the model. Therefore, this study introduces the Artificial Fish School (AFS) algorithm to obtain the optimal initial parameters of the LMBPNN model, to improve the LMBP performance by obtaining initial the parameter efficiency[23]. Although there are too many iterations in AFS, it easily falls into the local extremum, which affects its optimization performance[24]. Therefore, this study proposes a strategy of introducing the attenuation factor α and cut-off factor γ to improve it and to accelerate algorithm's convergence speed, as shown in Formula (9).

$$\begin{cases} \alpha = \alpha_0^k, & 0 < \alpha_0 < 1; \\ Visual_k = \alpha \times Visual_0, & \alpha > \gamma; \\ Visual_k = \gamma \times Visual_0, & \alpha \leqslant \gamma \end{cases} \tag{9}$$

where α_0 is the attenuation base; k is the number of iterations; $Visual_0$ and $Visual_k$ represent the initial field of view and the field of view after iteration k, respectively. In the clustering stage, tail chasing stage, and foraging stage of AFS, a random behavior is added to enhance population diversity, avoid the algorithm falling into local extremum during iteration process, and improve algorithm performance[25]. The Improved AFS (IAFS) process is shown in Fig. 5.

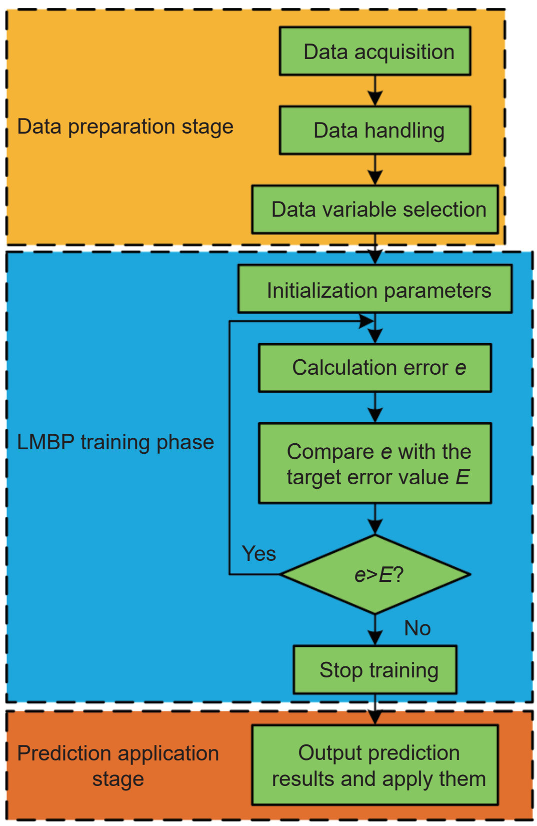


Fig. 4 Basic steps of CBECSC performance EM.

Based on the above content, the optimization of LMBPNN is completed, and an intelligent CBECSC-EM performance based on IAFS-LMBPNN is constructed to achieve an efficient and accurate evaluation of CBECSC performance, thereby improving the data and theoretical basis for performance improvements[26].

4 Performance analysis of CBECSC based on LMBP feedback neural network

4.1 Performance analysis of LMBP feedback neural network

To verify the performance of the LMBP model proposed in this study, an experimental environment was established and control experiments were conducted. Taking 5000 entries of performance evaluation data from a database for the sample, we randomly selected 40% as the test set and 60% as the validation set. This research compares the commonly used CBEC performance evaluation model, including the measurement model based on Slack-Based

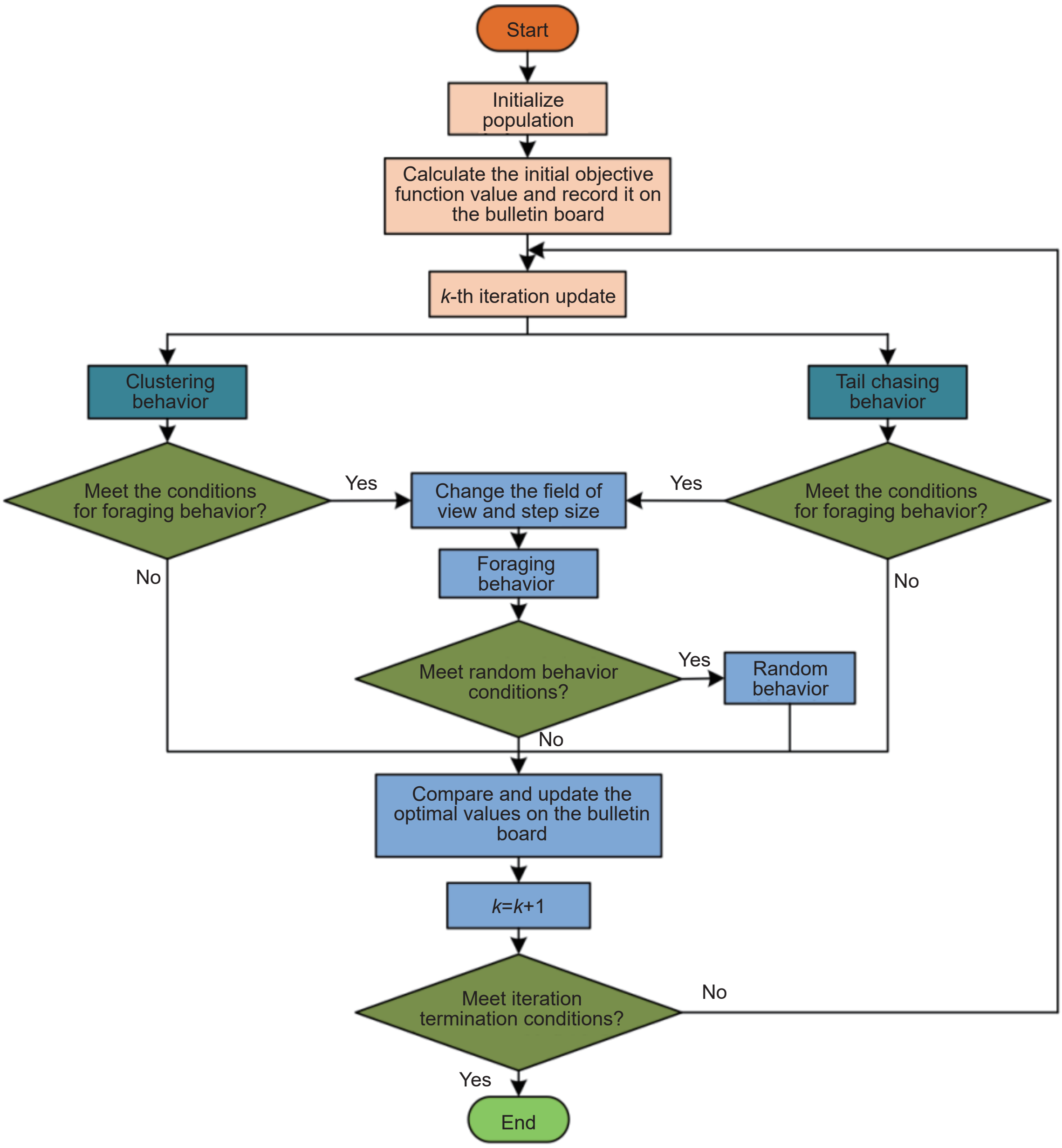


Fig. 5 Improved AFS process.

Measurement (SBM) and Data Envelopment Analysis (DEA). Applying each algorithm to two different datasets for training, the F1 result values obtained are shown in Fig. 6. As shown in Fig. 6, as the number of iterations increased, the F1 value of LMBP remained significantly higher than the other three algorithms. When the iterations reached 50, all algorithms in the test and validation sets obtained the maximum value of F1. In the test set, after 50 iterations, the maximum F1 values of the LMBP, DEA, SBM, and BP are 96.01%, 92.18%, 85.49%, and 76.97%, respectively. On the validation set, the maximum F1 values of LMBP, DEA, SBM, and BP are 98.46%, 93.78%, 87.29%, and 78.95%, respectively. The F1 value of LMBP is significantly higher than the other three algorithms, indicating that LMBP's comprehensive performance is better than the comparison method, and it is not prone to the phenomenon of inconsistent recall and accuracy.

The Mean Absolute Percentage Error (MAPE) results obtained by testing the two datasets are shown in Fig. 7. As the number of iterations increased, the overall MAPE values of the four algorithms exhibited a

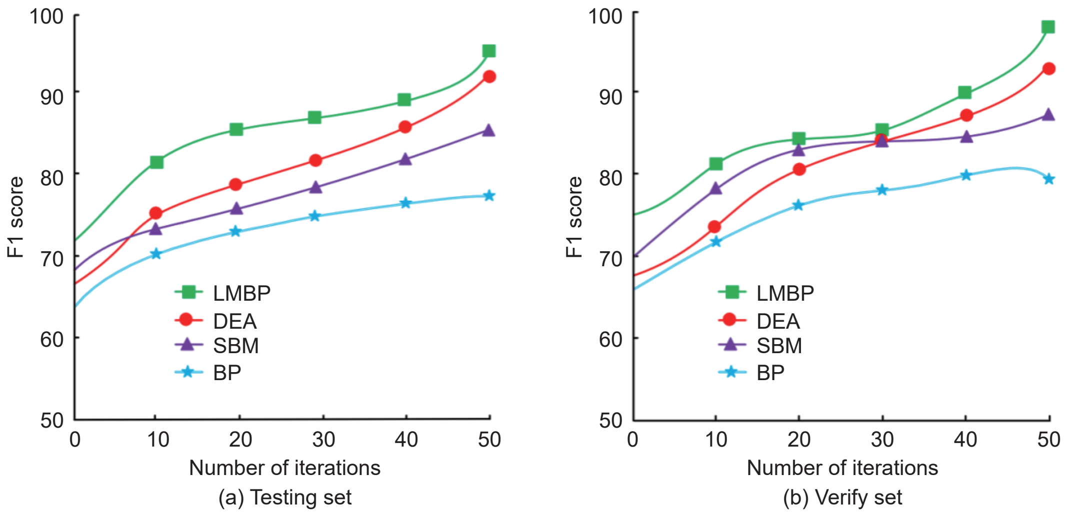


Fig. 6 F1 scores of the two datasets.

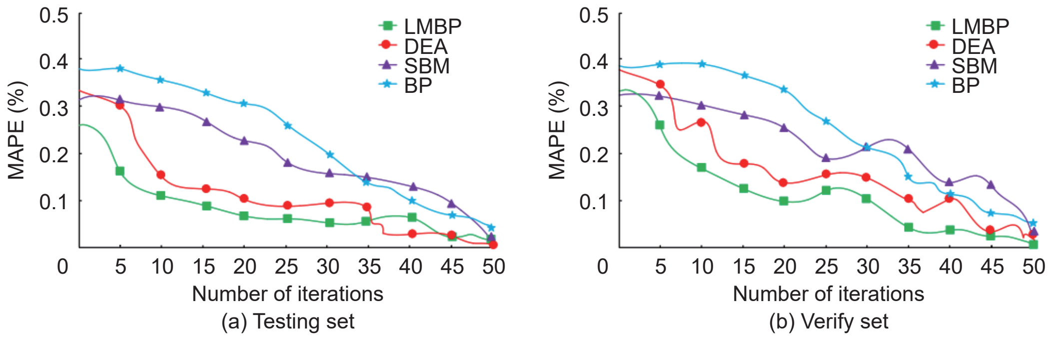


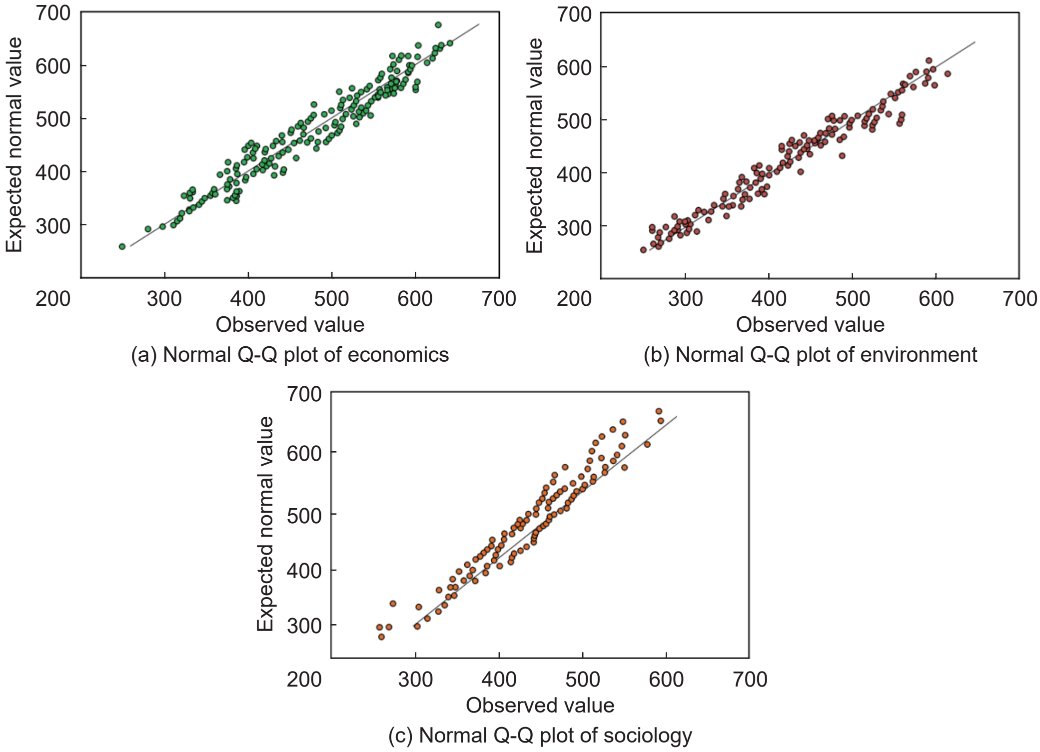
Fig. 7 MAPE of two datasets.

significant downward trend on different datasets. The MAPE value of the LMBP algorithm is significantly lower than other CBEC evaluation models' performance. From two datasets' average results, the MAPE values of the LMBP, DEA, SBM, and BP algorithms are 0.102%, 0.384%, 0.445%, and 0.487%, respectively. The average MAPE of the LMBP model is 0.082%, 0.149%, and 0.04% lower than the other three methods with the same order as above, respectively. Based on the analysis of significance results, significant difference exists in MAPE values between LMBP and the other three algorithms, indicating that LMBP has a smaller error and better performance in evaluating CBECSC performance.

Figure 8 shows the normal distribution test results of each indicator. The experiment was tested from three aspects: economy, environment, and society. The results show that it is not difficult to find that all indicators included in the CBECSC obey the Gaussian normal distribution.

4.2 Performance analysis of CBECSC based on LMBP feedback neural network

The expert rating of CBECSC performance evaluation indicators was constructed through research. The study invited 10 evaluation experts (all from the CBEC industry, responsible for performance audit work) to rank and score the importance of indicators with their subjective experience. The scoring results were based on a 5-point system, and the statistical results of scores obtained are shown in Table 2. For importance, the standard deviation between the customs clearance convenience ratio and product quality indicators is relatively large. In terms of operability, the standard deviation between logistics and payment convenience indicators is also relatively large. Overall, the scoring results of the indicators by scoring experts were relatively stable, indicating a high degree of



(a) Normal Q-Q plot of economics
(b) Normal Q-Q plot of environment
(c) Normal Q-Q plot of sociology

Fig. 8 Results of normality distribution test of all indicators.

Table 2 Performance indicator scoring results.

Measurement index	Importance			Operability	
	Mean value	Standard deviation	Full score rate (%)	Mean value	Standard deviation
Customer satisfaction	4.58	0.335	89.5	4.73	0.424
Reliability	4.97	0.451	84.3	4.79	0.391
Market share	4.26	0.189	87.2	4.25	0.457
Product quality	4.59	0.753	89.1	4.19	0.406
Prime cost	4.31	0.401	96.3	4.64	0.431
Logistics	4.09	0.492	76.8	4.38	0.695
Inventory possession	4.74	0.513	74.1	4.76	0.242
Profit	4.59	0.424	59.8	4.41	0.471
Order completion rate	4.37	0.409	66.9	4.50	0.492
Payment convenience	4.97	0.245	67.8	4.76	0.781
Convenient customs clearance	4.56	0.961	87.3	4.95	0.419
Crisis response capability	4.80	0.573	66.2	4.73	0.442
On time delivery rate	4.92	0.294	69.7	4.80	0.396
SC flexibility	4.81	0.510	88.4	4.36	0.407
Turnover	4.75	0.598	55.6	4.94	0.568

coordination in the evaluation opinions of experts on CBEC evaluation indicators.

We conducted consistency testing on the expert evaluation results mentioned above, and evaluated the volatility of the data by calculating the standard deviation rate of the evaluation results. The standard deviation rate is generally between 0 and 1, and the smaller the value, the less volatile the data. The scoring results' standard deviation rate is shown in Table 3. The maximum standard deviations of the evaluation indicators in terms of importance and operability are 0.1346 and 0.1405, respectively, indicating that the

Table 3 Standard deviation rate of scoring results.

Measurement index	Standard deviation rate	
	Importance	Operability
Customer satisfaction	0.0512	0.0943
Reliability	0.0734	0.0789
Market share	0.1206	0.0832
Product quality	0.0397	0.1009
Prime cost	0.1209	0.0643
Logistics	0.1346	0.1405
Inventory possession	0.0694	0.0633
Profit	0.0678	0.1327
Order completion rate	0.0963	0.1195
Payment convenience	0.0933	0.0908
Convenient customs clearance	0.0945	0.0642
Crisis response capability	0.0852	0.0915
On time delivery rate	0.1109	0.0199
SC flexibility	0.0968	0.0644
Turnover	0.1047	0.0791

standard deviations of all performance evaluation indicators are within 0.15, indicating significant consistency between the expert scoring results.

To test the trade-off effect of each indicator, this study also analyzed the sensitivity of the weight values of each indicator. The sensitivity of the weights of each index is shown in Fig. 9. The higher the weight of the index, the higher its sensitivity. The results showed that the sensitivity of each indicator to various factors ranged from 0.14 to 0.20, and the sensitivity of each factor to each other factor was within 0.05. The exponential distribution was within the range of 0.20 to 0.24. The highest sensitivity index was 0.09. From this, it can be seen that the indicator weight will affect the sensitivity of the indicator, thereby affecting the CBECSC performance.

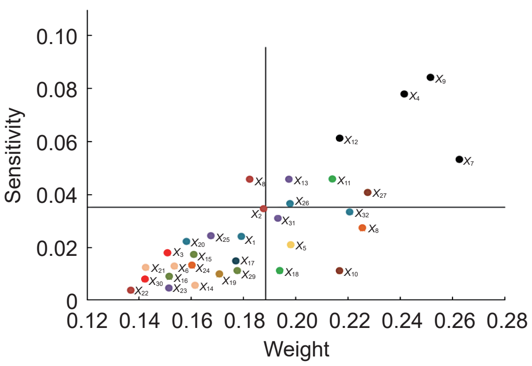


Fig. 9 Sensitivity distribution of indicators.

5 Conclusion

To enable CBEC entities to execute the sustainable development of their own SC, this study discusses the performance evaluation model of supply chain and proposes CBECSC-EM method with the LMBP algorithm. To verify the performance of the LMBP model proposed in this study, DEA, SBM, and BP algorithms are adopted for comparison. The training results on the training set show that when the iterations reached 50, all algorithms in the test set and validation set obtained the maximum F1 value. During this period, the F1 value of LMBP is significantly higher than the other three algorithms. This indicates that the LMBP algorithm proposed in this experiment was not prone to the phenomenon of inconsistent recall and accuracy, and its overall performance is superior. The MAPE values of the four models are 0.102%, 0.384%, 0.445%, and 0.487%, respectively. The average MAPE of the LMBP model is 0.282%, 0.343%, and 0.385% lower than the other three methods, respectively. Therefore, LMBP had smaller errors and better performance. The expert scoring results show that the standard deviation between the convenience ratio of customs clearance and product quality indicators is relatively large and that between logistics and payment convenience is relatively large as well. We conduct consistency checks on the expert evaluation results. The results show that the maximum standard deviation rates of the evaluation indicators in terms of importance and operability are 0.1346 and 0.1405, respectively, indicating that the standard deviation rates of all the performance evaluation indicators are within 0.15. There is a significant consistency between the expert scoring results. Cross-border e-commerce enterprises involve a large number of node enterprises with a wide range of data. In future studies, more enterprises should be investigated to enrich experimental data and further verify the performance of the proposed model.

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