Research on the operation and management mechanism of cross-border e-commerce shared practice training base

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Abstract

For the third-party cross-border e-commerce sharing platform, due to the lack of management and operation mechanism, the current sharing platform has relatively high fees, insufficient publicity, and consumption methods are not conducive to Chinese consumers. There are obvious problems such as insufficient personnel training. In this article, we use the CGA-LSO-BP network to solve the problems of various systems disjoint, complicated department settings, confusing distribution of powers and responsibilities in the training base, as well as unclear division of team functions, technology mismatch, and the training base itself. The scale, social reputation and other factors lead to the difficulty of reducing financing channels and other related operation and management issues to study and analyze. The results show that the minimum error can reach 0.5% for CGA-LSO-BP, which is much smaller than the traditional algorithm. It is proved that the algorithm can help the BP neural network to jump out of the local optimal value to a certain extent, and play an active role in the regression task. In addition, the improved CGA-LSO-BP neural network based on this can provide a good reference for various problems in cross-border e-commerce, such as disjointed systems, complicated department settings, and chaotic distribution of rights and responsibilities, and propose optimal solutions.

Keywords: CGA-LSO-BP network, Cross-border e-commerce, Sharing platform

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1 Introduction

In recent years, cross-border e-commerce has accounted for an increasing proportion of the market in international trade. The amount of cross-border e-commerce transactions has reached a trillion level, and the number of graduates engaged in related fields has exceeded 10 million [1-3]. At present, China's cross-border e-commerce still maintains a rapid growth. With the development of the global network, the popularization of express delivery, and the fast online payment, cross-border e-commerce has ushered in new vitality [4-6]. At present, my country's cross-border e-commerce is mainly divided into three categories. The first is the enterprises with their own platforms, such as JD.com, etc.; the second is the third-party platforms that provide platforms and services for enterprises, such as Alibaba; the third is mainly to use third-party platforms for import and export trade of SMEs [7-9]. Third-party cross-border e-commerce platforms mainly provide services such as transaction channels, logistics and distribution, electronic payment and professional management [10-12]. Cross-border e-commerce logistics provides a strong guarantee for the development of e-commerce, mainly including international small packages, international express delivery, cross-border logistics and other modes. Each model has its own advantages and disadvantages, and can meet different customer needs. At this stage, my country's cross-border e-commerce is in its infancy, with huge development potential and rapid development. However, while the cross-border e-commerce is developing rapidly, the small enterprises under the platform are facing more and more serious confusion in the operation and management mechanism. And other issues. The risks of e-commerce platforms are huge. When foreign customers communicate, business negotiation, final payment, after-sales, etc., there are often great risks. In addition, cross-border e-commerce will also encounter risk factors such as unqualified goods quality, foreign customer credit risk, and low taxation efficiency [13, 14]. First, due to the lack of long-term development strategic goals for small and medium-sized enterprises, low management level, financial chaos, and insufficient funds; secondly, small and medium-sized enterprises do not have their own training bases, so it is difficult to cultivate their own exclusive talents, and the talent system is completely lacking; therefore, it is easy to fall into Difficulties, it is difficult to become bigger and stronger.

Although the rapid development of e-commerce has achieved good results, there are still great deficiencies in the international trading platform and personnel training. At present, for some small and medium-sized enterprises, they do not have their own platforms and can only rely on third-party platforms to provide a series of services such as related information acquisition, order payment, logistics and distribution, so how to obtain the corresponding space on the shared platform limits them development [15-17]. How to effectively manage the practice and training of the cross-border e-commerce sharing platform has attracted widespread attention. In the CNKI database, the number of articles related to cross-border e-commerce and platforms has reached 10,000+ in the past 10 years. As can be seen from Figure 1(a), the related articles have shown a substantial growth trend. Since 2018, articles have been published every year. In addition, through the distribution of related topics, we can see that e-commerce platforms, talent training, and e-commerce logistics are the three research directions with the largest proportions, accounting for 30.87%, 26.89%, and 20.27% respectively. %. Huang Yuwen [18] analyzed the characteristics of consumers and cross-border e-commerce, constructed an evaluation index system of consumer perception trust from three aspects, and applied the AHP to determine the final index system. They proposed that in the current online shopping environment, the virtuality of transactions and the characteristics of cross-time and space transactions make them face certain uncertainties and risks. NanChen [19] studied the intermediary effect of network structure embedded in customer experience and consumers' purchase intention in the context of cross-border e-commerce relationship, not just marketing. Ying Wang [20] focuses on analyzing and describing how cross-border e-commerce companies generate supply chain service capabilities, thereby improving the quality of supply chain relationships for users of electronic platforms and other
platforms. The findings provide important insights into how to best manage the supply chain resources associated with the three flows of cross-border e-commerce firms to promote relationship quality, an attribute that is now a key factor in competitive differentiation. Yu-Hsiang Hsiao [21] proposed a process to integrate text mining into perceptual engineering (KE), and studied the perceptual design of cross-border logistics services (CBLS). In order to improve the management and operation of the cross-border e-commerce sharing platform, Xijin He [22] and others proposed a model based on the combination of embedded and genetic algorithms. The improved genetic algorithm can play a certain role in the distribution process of e-commerce, improve transportation efficiency, meet realistic requirements, improve genetic computing and data preparation innovation for massive information, coordinate the dissemination channels of cross-border Internet business, and strengthen coordination of appropriation and financial event Internet business docking. Shuyun Ren [23] proposed an e-commerce coordination management scheme based on deep learning to optimize the configuration of 3PFL operational capabilities related to cross-border e-commerce. Based on the Seq2Seq prediction architecture, it integrates CNN and LSTM networks, and can build e-commerce platform management mold. In addition to generating point forecast results, the method can quantify demand uncertainty through dynamic distribution and make optimal decisions for capacity allocation. On the optimization aspects of cross-border e-commerce platforms, Mian Wu [24] developed a process model to visualize the time and modularization process of the cross-border digital payment ecosystem. The findings suggest that the modular pattern of digital platform-based ecosystems dominated by complementers is attributable to the transaction costs and network effects of complementers. Their research proves that the introduction of deep learning to optimize the platform can improve the efficiency of platform operation and management.

Cross-border e-commerce platforms have strong information communication and matching capabilities [25, 26]. With the continuous innovation of cross-border commerce, the current cross-border information service platforms, cross-border e-commerce trading platforms, and third-party open platforms, these Platforms often have insufficient platform usage, and the management and operation of related shared platforms are more confusing. This phenomenon is more prominent on third-party open platforms, which can provide cross-border e-commerce services for small and medium-sized enterprises and individual businesses. At the same time, it helps merchants to provide effective assistance in payment, logistics, risk management, etc. Third-party platforms can provide relevant enterprises with various services such as transaction certification, business consulting, platform training, and personnel training [27-29]. However, on shared platforms, due to the lack of management and operation mechanisms, the current shared platform charges are relatively high, and
the publicity is insufficient, the consumption method is not conducive to Chinese consumers, and there are obvious deficiencies in the use of relevant training bases for relevant personnel training. Therefore, in this paper, we use the CGA-LSO-BP network to solve the problems of various systems disjoint, complicated department settings, chaotic distribution of rights and responsibilities in the training base, as well as unclear division of team functions and technology mismatch. The scale of the training base itself, social reputation and other factors make it more difficult to reduce financing channels and other related operation and management issues to conduct research and analysis.

2 The feasibility of neural network in cross-border e-commerce

With the development of e-commerce informatization, various problems such as disjointed systems, complicated departmental settings, and chaotic distribution of rights and responsibilities have emerged within the training base. So that the division of functions of the team is not clear. In addition, the Internet and technology applications in the training base continue to merge with the increasing flow of information, so that many team members cannot adapt to the status quo, and there is a problem of technology mismatch. The training base will reduce the financing channels due to its own scale, social reputation and other factors, which will increase the difficulty of the base's project management. In order to efficiently improve the training base, it summarizes the inflow of a large number of information flows, and filters out unnecessary junk information. Therefore, this paper proposes to use the CGA-LSO-BP network to optimize this kind of problem.

2.1 BP neural network theory

BP neural network, because its data processing and calculation distribution are stored on different nodes, can process input information at the same time, can avoid poor node performance caused by abnormal parameters in the calculation process, and greatly enhance the robustness of the neural network; in addition, each The connection of neurons through weights can strengthen each other's quantification, making them self-adaptive; the BP network can learn to capture the relationship between the input and output data. The specific training process is shown in the Figure:

![BP neural network training flow chart](image)
However, the BP neural network follows the global approximation method. When the gradient calculation method determines an extreme point, the gradient will drop to zero. At this time, it falls into the local optimum point and cannot search for the global optimum solution, as shown in the figure. In addition, when the gradient is updated to a minimum value, the calculation speed of the algorithm drops sharply, which greatly increases the number of training times.

![Figure 3. Schematic diagram of the error curve](image)

### 2.2 Overview of Chaos Search (CGA) Strategy

Aiming at the defects and deficiencies of BP algorithm, this paper introduces the chaotic search strategy to optimize the genetic algorithm. Chaos search is used for random search to generate chaotic solutions within nonlinear chaotic time series systems. It can be divided into four categories:

1) **Boundedness.** The chaotic time series is fixed in a certain area during the iterative process, and will not exceed this area during the iterative process.

2) **Initial value sensitivity.** A chaotic time series is very sensitive to initial conditions and can produce greatly different values due to small changes.

3) **Pseudo-randomness.** The chaotic time series is affected by the previous iterative value in the iterative process. It has randomness and can follow the iterative rules. It is used in combination with the BP algorithm population initialization.

4) **Ergodic.** The trajectory generated by the chaotic time series in the iterative process will not stay at a certain point, which can improve the diversity of the algorithm.

Using CGA to improve the BP neural network:

1) **Population initialization based on chaotic time series.** The iterative values of different initial values under the Logisti map can be well distributed in the solution space, replacing the process of randomly generating populations of the standard genetic algorithm, and improving the initial population state of the BP algorithm.

2) **Western search based on chaotic search strategy.** After each round of genetic operation, the fitness value of all individuals is calculated, and then the optimal solution with a better fitness of 15% is selected, and the chaotic disturbance of the Logisti map is introduced to conduct a detailed search and expand the search range of the solution.
2.3 Lions Algorithm (LSO)

The lion colony algorithm is a new type of swarm intelligence algorithm. By simulating the behavior of the lions as a whole and individuals, a group intelligence algorithm is formed. The positions of the three lions can be regarded as point sets in the hyperspace, and their respective update positions are exchanged as point sets.

The LSO is made up of three male lions, female lions and cubs. Patrol in a small area by male lions (update iterations in a small area); male lions and female lions cooperate with each other to pull nets to hunt (the mutual pulling nets update iterations between two individuals); lion cubs approach male lions to get food and approach lionesses to learn hunting skills. And then independently replace the leadership position. (Each lion represents a feasible solution to the problem)

First initialize the LSO: N is the total number of lions; the maximum number of iterations of the prey position of an individual lion is T; the proportion of male lions and female lions is β ∈ (0, 1); The numbers are 1, N*β-1, and N-N*β, respectively, the specific steps are as follows:

1) According to different types of lions, use different iterative formulas to search for the prey and obtain its position;

2) Calculate the fitness of each lion, and judge whether to update the optimal prey position of the individual lion and the whole lion group according to the fitness value;

3) When the number of iterations reaches a certain level, the fitness of all lions is recalculated, and new lion types are reclassified;

4) When the number of iterations reaches a certain level, output the male lion at this time as the optimal solution of the objective function, and return to the first step for a new round of calculation.

The specific algorithm of LSO is as follows:

1) How the lion updates its position

\[ x^{k+1} = \gamma (1 + \gamma \| p_i^k - g^k \|) \]

Among them, \( \gamma \) is a random value with a normal distribution \( N(0,1) \); \( p_i^k \) it is the historical best position of the i-th lion in the k-th generation of the lion pride; \( g^k \) it is the best position for all lions in the k-th generation.

2) How lionesses update their positions

\[ x^{k+1} = (1 + \alpha_f \gamma) \frac{p_i^k + p_c^k}{2} \]

\[ \alpha_f = step \times \exp\left(-\frac{30t}{T}\right)^{10} \]
Among them, $p_c^k$ represents a random selection of the historical best position of the lioness in the k-generation lion group; $\alpha_t$ represents the disturbance factor when the lioness is looking for the optimal solution; $T$ represents the maximum number of iterations; $t$ is the current number of iterations.

3) The way the lioness updates its position.

Equations (5)-(7) are feeding, learning, and expulsion of the lion cubs, respectively.

$$
\begin{align*}
\text{step} &= 0.1 \left( \bar{h} - \hat{i} \right) \\
\end{align*}
$$

Among them, $p_c^k$ represents the disturbance factor in the process of finding the optimal solution for the lion cub; $p_m^k$ it is the historical optimal position for the cubs to follow and learn the k-th generation of male lions; $\bar{g}^k$ the position of the lion cub; $\bar{h}$ represents the upper mean of each dimension; $\hat{i}$ represents the lower mean of each dimension; $q$ is a random value that obeys the uniform distribution U(0,1).

2.4 CGA-LSO-BP model design

This section summarizes the above algorithms, and the process is described as follows:

1) Genetic coding. By encoding the weights and biases of the BP neural network with floating-point numbers, the traditional problem of low precision of binary bias codes is abandoned, and the computational efficiency of the algorithm is enhanced.

2) Fitness function. Through the fitness function, individuals are naturally selected to judge the pros and cons of individuals. The specific calculation process is as follows:

$$
F = \frac{1}{N_f} \sum_{i=1}^{N_f} \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right|
$$
Among them, $N_f$ is the total number of training samples; $y_l$ is the predicted value corresponding to the $l$th sample; $\hat{y}_l$ is the actual value corresponding to the $l$th sample.

3) Population chaos initialization.

Randomly generate random vectors with dimensions equal to the control variable:

$$\lambda_0 = (s_1, s_2, s_3 \ldots s_n) \quad (0 \ll s_j \ll 1), j = 1, 2, 3 \ldots n$$

(9)

And get $m$ chaotic vectors from all the elements in the vector according to the Logisti map:

$$(s_{l1}, s_{l2}, s_{l3} \ldots s_{ln}), (s_{l_{21}}, s_{l_{22}}, s_{l_{23}} \ldots s_{ln}), \ldots (s_{l_{m1}}, s_{l_{m2}}, s_{l_{m3}} \ldots s_{ln})$$

(10)

Mapped to the solution space by certain rules:

$$v_{ij} = d_j + s_{ij} (u_j - d_j)$$

(11)

4) Select an operation. The selection operation follows the principle of proportional fitness distribution. The specific calculation process is as follows:

$$P_i = \frac{1/F_i}{\sum_{i=1}^{m} 1/F_i}$$

(12)

Among them, $F_i$ is the fitness value of the $i$th node; $m$ is the total number of nodes in the population.

5) Crossover operation. Since this paper uses floating-point encoding, the arithmetic crossover method is adopted.

$$\begin{align*}
  v_{ij} &= \hat{v}_{ij} (1 - r) + \hat{v}_{jk} r \\
  v_{kj} &= \hat{v}_{kj} (1 - r) + \hat{v}_{ij} r
\end{align*}$$

(13)

Among them, $\hat{v}_{ij}$ is the $j$th gene of the $i$th chromosome, $\hat{v}_{kj}$ is the $j$th gene of the $k$th chromosome; $v_{ij}$, $v_{kj}$ for the offspring generated by the incidental crossover, $r$ is a random value in (0-1).

6) Mutation operation. In this paper, non-uniform mutation is used to adaptively adjust the search area. The calculation process is as follows:

$$v_{ij} = \begin{cases} 
  v_{ij} = v_{ij} + (v_{ij} - v_{\text{max}}) \left[ r \left( 1 - \frac{\hat{v}_{ij}}{e_{ij}} \right) \right]^2 & r > 0.5 \\
  v_{ij} = v_{ij} + (v_{\text{min}} - v_{ij}) \left[ r \left( 1 - \frac{\hat{v}_{ij}}{e_{ij}} \right) \right]^2 & r \leq 0.5
\end{cases}$$

(14)
Among them, \( v_{ij} \) is the jth gene of the ith chromosome, \( y_{ij}^{\text{max}}, y_{ij}^{\text{min}} \) respectively represent the upper and lower limits of, \( r \) is a random value in [0-1], \( e_{g} \) is the current iteration step of the algorithm, \( e_{g}^{\text{max}} \) is the maximum number of iterations of the genetic algorithm.

7) A chaotic perturbation that approximates the optimal solution. Select the approximate optimal chromosome, and use the Logisty sequence to perform chaotic perturbation optimization. The specific calculation process is as follows:

\[
c_{t} = (v_{i1}, v_{i2}, v_{i3}...v_{in})
\]  
(15)

\[
V_{ij} = (1 - \theta)v_{ij} + \theta v_{ij}^k
\]
(16)

\[
\theta = 1 - \left( \frac{k - 1}{k} \right)^\hat{n}_t
\]
(17)

Among them, \( V_{ij} \) gene value optimized for chaotic disturbance; \( v_{ij} \) is the jth gene of the ith chromosome of the population; \( v_{ij}^k \) is the gene value iterated k times using the Logisty sequence; \( \theta \) is a random number in the interval [0-1]; \( \hat{n}_t \) is an integer tailored to the optimization goal.

Therefore, the genetic coded BP neural network in the CGA-LSO-BP model can effectively distinguish the floating point codes of departments in the management mechanism of cross-border e-commerce training bases through the weight and bias of the analysis, so as to reduce the complexity of setting up e-commerce management departments; At the same time, through the fitness function, the rights and responsibilities of the management mechanism are naturally selected and allocated to judge the advantages and disadvantages of the management mechanism, so as to achieve the optimal allocation of rights and responsibilities in the management mechanism. Through the chaos initialization of the population, random vectors of the team's function dimensions are generated randomly, and chaos vectors are obtained by mapping the team's functions to the solution space according to the Logisti map. After the chaos vectors are mapped to the solution space, it can be clearer to analyze whether the division of functions in the management mechanism of e-commerce training base is reasonable; Under the selection operation, the number of management mechanism departments shall be determined according to the proportional fitness distribution principle. Under the influence of non-uniform variation, the management mechanism of e-commerce training base is divided into multiple regions. In order to improve the matching degree of technology, multiple iterations are required for multiple regions to achieve adaptive adjustment, so as to improve the matching degree of technology; In order to ensure the optimal management mechanism of cross-border e-commerce training base in this paper, chaos perturbation of the optimal solution is required. In this process, by selecting the approximate optimal chromosome in the system and using the Logisti sequence, chaos perturbation optimization is carried out to determine whether the cross-border e-commerce management mechanism in this paper is the most reasonable mechanism.

3 Model fitness analysis of experiments

Affected by the global new crown pneumonia epidemic, the international situation is tense, the situation has changed dramatically, the difficulty of international trade has increased, and the difficulty of cross-border e-commerce has also increased. As a result, the CGA-LSO-BP model was
born to predict and adapt to the operation and management mechanism of international cross-border e-commerce.

80% of the samples were randomly selected from 300 sets of cross-border e-commerce data samples for the neural network to learn and train. From the perspective of control variables, the parameters are determined as follows: the learning rate of the neural network is 0.002; the maximum training step is 200; the target accuracy is 0.002.

The optimal individual fitness value change curve of the CGA-LSO-BP neural network is shown in Figure 4. Since the fitness function defined by the text is related to the error MSE of the neural network, the smaller the fitness value, the smaller the error of the neural network, and the better the quality of the solution.

![Figure 4. Optimal individual fitness curve](image)

When the evolutionary algebra iterates for the 22nd generation, the fitness value of the optimal individual drops sharply from the initial 3.4832 to the next 0.2341. When the evolutionary iteration reached the 33rd generation, the fitness value of the best individual was 0.1999. When the algorithm iterates to 55 generations, the fitness value is 0.1555. When the algorithm iterates to 65 generations, the value is 0.1519. When reaching 100 generations, the algorithm ends, and the best individual fitness value at this time is 0.1512. It can be seen from the change trend of the above fitness value that the CGA-LSO-BP model algorithm can quickly find the best individual in the early iteration, and basically the fluctuation range is not large within 20 generations, and in the later stage Continue to steadily search for the global optimal individual. At this time, the change of fitness value tends to be stable, and the algorithm has produced individuals with better fitness. When the evolutionary algebra reaches 100, the algorithm stops and the best individual is obtained, which is decoded as the best weight and threshold of the neural network.

Under the influence of non-uniform variation, the management mechanism of e-commerce training base is divided into multiple regions. In order to improve the matching degree of technology, multiple iterations are required for multiple regions to achieve adaptive adjustment, so as to improve the matching degree of technology; In order to ensure the optimal management mechanism of cross-border e-commerce training base in this paper, chaos perturbation of the optimal solution is required. In this process, by selecting the approximate optimal chromosome in the system and using the Logisti sequence, chaos perturbation optimization is carried out to determine whether the cross-border e-commerce management mechanism in this paper is the most reasonable mechanism.
3.1 Comparative analysis of forecast results

In order to verify the superiority of the CGA-LSO-BP neural network, this chapter selects the same data set. Under the condition that the network parameters are basically the same, the traditional BP neural network and the improved BP neural network are used to share the cross-border e-commerce. The operation and management mechanism of the practice and training base are predicted, and the predictions of the two are compared. The following data were obtained from the experimental analysis, and the statistical analysis of the predicted values is presented in Table 1.

<table>
<thead>
<tr>
<th>Actual value</th>
<th>Predictive value</th>
<th>Relative error</th>
<th>Predictive value</th>
<th>Relative error</th>
</tr>
</thead>
<tbody>
<tr>
<td>90.2</td>
<td>85.3</td>
<td>4.9%</td>
<td>88.2</td>
<td>2%</td>
</tr>
<tr>
<td>88.3</td>
<td>84.3</td>
<td>4%</td>
<td>85.9</td>
<td>2.4%</td>
</tr>
<tr>
<td>85.3</td>
<td>80.3</td>
<td>5%</td>
<td>82.3</td>
<td>3%</td>
</tr>
<tr>
<td>78.2</td>
<td>75.2</td>
<td>3%</td>
<td>77.2</td>
<td>1%</td>
</tr>
<tr>
<td>76.3</td>
<td>70.3</td>
<td>6%</td>
<td>75.3</td>
<td>1%</td>
</tr>
<tr>
<td>74.3</td>
<td>69.3</td>
<td>5%</td>
<td>73.4</td>
<td>1%</td>
</tr>
<tr>
<td>69.4</td>
<td>65.2</td>
<td>4.2%</td>
<td>67.5</td>
<td>1.9%</td>
</tr>
<tr>
<td>60.4</td>
<td>55.3</td>
<td>5.1%</td>
<td>58.3</td>
<td>2.1%</td>
</tr>
<tr>
<td>57.3</td>
<td>50.3</td>
<td>7%</td>
<td>56.3</td>
<td>1%</td>
</tr>
<tr>
<td>68.3</td>
<td>66.3</td>
<td>2%</td>
<td>67.3</td>
<td>1%</td>
</tr>
<tr>
<td>45.3</td>
<td>43.2</td>
<td>2.1%</td>
<td>44.8</td>
<td>0.5%</td>
</tr>
</tbody>
</table>

It can be seen from the above statistical analysis table that ten groups of data are taken, and the actual values among them are compared with the model predicted values, and the specific numerical values and relative error analysis are presented in the table. From the results of the above two models, it is clear that the prediction effect of the CGA-LSO-BP model is much better than that of the traditional model. The maximum error rate of the traditional single prediction model can reach 7%, which is very difficult in prediction. To be precise, it is very unfavorable for the operation mechanism and management mode of cross-border e-commerce. Most of the errors are greater than 2%, and the smallest error is 2%. The maximum error of the operation mode of cross-border e-commerce predicted based on the CGA-LSO-BP neural network model is 3%, and the minimum error is only 0.5%. Most of the error control rate is controlled within 2%, and the accuracy of each time the prediction rate is higher than that of the traditional model, and the relative error is smaller than that of the traditional model, which means that the prediction effect of this model is much better than that of the traditional model. The effect is better than that of the traditional BP neural network in terms of prediction accuracy and generalization performance. The network is better. It shows that the algorithm has a positive effect on improving the prediction performance of BP neural network.

The genetic coded BP neural network in the CGA-LSO-BP model can effectively distinguish the floating point codes of departments in the management mechanism of cross-border e-commerce training bases by analyzing the weights and offsets, so as to reduce the complexity of setting up e-commerce management departments; At the same time, through the fitness function, the rights and responsibilities of the management mechanism are naturally selected and allocated to judge the advantages and disadvantages of the management mechanism, so as to achieve the optimal allocation of rights and responsibilities in the management mechanism.
4 Conclusion

In this study, a neural network prediction model was used to conduct multi-agent-based dynamic simulations to effectively evaluate different prediction models. The main conclusions of this study are as follows:

1) The error performance and prediction effect of the CGA-LSO-BP prediction model and the traditional neural network prediction model are compared and analyzed. The results show that the prediction accuracy and adaptability of the former are better than those of the latter. The minimum error can reach 0.5%, which is far smaller than the traditional algorithm. The error rate of the traditional algorithm is generally greater than 2%.

2) It is proved that the genetic algorithm can help the BP neural network to jump out of the local optimal value to a certain extent, and play an active role in the regression task. In addition, the improved CGA-LSO-BP neural network based on this can provide a good reference for various problems in cross-border e-commerce, such as disjointed systems, complicated department settings, and chaotic distribution of rights and responsibilities, and propose optimal solutions.

3) The innovative model of introducing cross-border e-commerce shared training bases is to promote the co-construction and sharing of logistics training bases, and maximize the function and efficiency of logistics training bases, thereby making the competition in international trade more harmonious and conducive to the realization of healthy competition. Under the prediction of the CGA-LSO-BP algorithm model, the practice base of the sharing economy can be predicted in advance. Solve the problem that many team members cannot adapt to the status quo and the technology does not match with the increasing information flow of the Internet and technology applications in the training base.

4) The CGA-LSO-BP algorithm model can accurately screen out unnecessary junk information, improve the input of a large amount of information flow in the training base, and make a summary.

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