

Retraction

Retracted: Supply Capability Evaluation of Intelligent Manufacturing Enterprises Based on Improved BP Neural Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Q. Quan and Z. Zhang, "Supply Capability Evaluation of Intelligent Manufacturing Enterprises Based on Improved BP Neural Network," *Journal of Mathematics*, vol. 2022, Article ID 8572424, 8 pages, 2022.

Research Article

Supply Capability Evaluation of Intelligent Manufacturing Enterprises Based on Improved BP Neural Network

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With the rapid development of economy and information technology, traditional manufacturing industry is facing severe challenges. Enterprises need to rectify the traditional manufacturing industry and realize the transformation from traditional manufacturing industry to intelligent manufacturing industry. In order to adapt to market demand, enterprises need to constantly integrate resources to improve the competitiveness of enterprise supply chain. Based on the background of suppliers in intelligent manufacturing enterprises, the evaluation method of supplier efficiency was studied by using machine learning. In this paper, based on the traditional backpropagation (BP) neural network, combined with the improved particle swarm optimization (PSO) algorithm, and on the basis of the supplier evaluation index system, the supplier efficiency evaluation model of intelligent manufacturing enterprises based on DPMPPO-BP neural network is constructed. Through the collected sample data, the network is trained and simulated, and the results are analyzed. Finally, the designed model is applied to a large battery manufacturing enterprise, and the supplier efficiency evaluation method based on DPMPPO-BP neural network is validated and analyzed. Compared with the traditional BP neural network method, the supplier efficiency evaluation method is effective and feasible.

1. Introduction

Manufacturing plays a key role in the economic development of a country or region and reflects the comprehensive strength of a country or region. After the outbreak of the global financial crisis in 2008, the economic growth of all countries in the world is weak, and all developed countries have moved their traditional manufacturing industry closer to the intelligent manufacturing industry, among which the intelligent manufacturing enterprises led by the United States and Germany are developing most rapidly [1, 2].

With the rapid development of intelligent manufacturing, the supply chain of some large manufacturing industries has undergone great changes, and the relationship between enterprises and suppliers has changed from simple “buyer-seller relationship” to “partnership relationship.” With the transformation of the relationship between enterprises and suppliers, enterprises

have higher and higher requirements on suppliers. How to dig out important value from massive supplier information and apply it to supply chain management is an urgent problem for enterprises. In the supply chain, supplier is the source of supply chain, and the evaluation of supplier is the key problem [3]. Supplier efficiency evaluation is very important in supplier evaluation. Supplier efficiency is an indicator of the rationality of the resources and output value of efficient supplier manufacturing enterprises. Its quality can reflect the carrier of suppliers. Through the study of supplier efficiency hierarchy, on the one hand, it can be used to monitor supplier status and performance. Recognition and translation are related, and it is also the decision basis for selecting supplier incentive strategies. Supplier efficiency evaluation is aimed at efficiency-oriented suppliers, which measures the product quality, cost, and service of such suppliers by establishing appropriate evaluation index system and classifies the efficiency of suppliers by using certain

evaluation criteria. Supplier efficiency evaluation is a key step in the construction of supply chain, which has great influence on the smooth operation of efficient supply chain [4].

Supplier evaluation methods have gone through a process from qualitative to quantitative, a combination of qualitative and quantitative, and a mixed use of qualitative and quantitative. Liu Xiufen adopted the intuitive judgment method in the method of selecting manufacturers, which can quickly and efficiently respond to the intuitive judgment method [5]. When Wang Hao talked about the supplier evaluation method and solution, this method requires both the supplier and the buyer to go through the process. Many times of negotiation to ensure the maximization of the interests of both supply and demand [6], Qiu Min said that in the procurement of materials, choosing the bidding method has a better competitive advantage, but it is cumbersome and unable to deal with emergency procurement [7].

In the quantitative supplier evaluation method, Wang proposed a number of supplier evaluation indicators in view of the characteristics of S Company's petrochemical equipment importing relatively high technology content and used the linear weight method to select appropriate suppliers [8]. Degraeve et al. used the real data generated by Belgian multinational steel companies to build a mathematical model and concluded that the multiobjective mathematical programming model method has great advantages in supplier evaluation and selection [9]. Among quantitative evaluation methods, cost-based methods are the most common, and cost is the easiest indicator to quantify. Taking the reduction of product cost as an example, Zhou Jianzhong proposed the basic ABC cost method and the Analytic Hierarchy Process (AHP) method in the supplier evaluation method for how to select supplier partners, such as the method of using the Analytic Hierarchy Process (AHP) combined with the genetic algorithm. To evaluate suppliers, first use the analytic hierarchy process to evaluate and score, then use genetic algorithm to optimize and sort, and finally use it to evaluate and select suppliers [11]. Dong Shengxu analyzed the characteristics of suppliers of telecom operators and constructed a supplier evaluation indicator system according to their characteristics. Then, he used the traditional BP neural network to train the indicator data collected and finally verified the practicality of BP neural network for supplier evaluation of telecom enterprises [12].

This paper summarizes the research studies of many researchers, who evaluated and selected suppliers in different ways from various angles. Among many evaluation methods, the qualitative method is relatively simple and convenient to operate, but its subjectivity is too strong, which has some hidden dangers for the development of enterprises. The single quantitative evaluation method has too high requirements for quantification of indicators and data collection, and it is rarely used in enterprises because of complicated calculation [13]. The more reasonable supplier evaluation method is the combination of qualitative and quantitative methods, which can not only make up for the strong subjectivity of qualitative evaluation method but also

simplify the complex quantitative evaluation. However, it also has limitations. If different evaluation methods are mixed together, problems such as accuracy can be well solved.

In the mixed evaluation method, the method combining BP neural network is more advanced and has the advantages of objective, scientific, easy operation, simple calculation, and so on. Supplier evaluation is a complex nonlinear mapping problem. However, the traditional BP neural network has many shortcomings. Therefore, this paper proposes an improved PSO-BP model by improving particle swarm optimization (PSO) and combining it with the traditional BP neural network and applies the model to the supplier evaluation of a large battery manufacturing enterprise. In Section 2, the discussion is carried out for the intelligent manufacturing enterprises' supplier evaluation index system. Moreover, the BP neural networks are explained with their drawbacks. Further, the improved BP neural networks are deliberated. Also, the steps of DPMPPO-BP algorithm are also given. In Section 3, the experiments are carried out and their outcomes are analyzed. Finally, the paper is concluded in Section 4.

2. Theoretical Basis and Methods

In this section, we propose the main methods. For that reason, first we discuss the intelligent manufacturing enterprises' supplier evaluation index system. Then, BP neural networks are explained with a list of their drawbacks. Further, the improved BP neural networks are deliberated. The steps of DPMPPO-BP algorithm are also given.

2.1. Supplier Evaluation Index System of Intelligent Manufacturing Enterprises. According to the definition of intelligent manufacturing and related documents of intelligent manufacturing enterprise suppliers, the characteristics of intelligent manufacturing enterprise suppliers are summarized as follows: high intelligence level, strong product competitiveness, and good personalized service. This paper collected a large number of domestic and foreign literatures on supplier evaluation and analyzed the quality, cost, delivery, service, and other important indicators in supplier evaluation. By summarizing the research results of domestic and foreign scholars on evaluation index system, analyzing the characteristics of suppliers of intelligent manufacturing enterprises, and constructing the principle of supplier efficiency evaluation index system, the basic indicators are reconstructed from the perspective of supplier efficiency and intelligent manufacturing, and the supplier evaluation index system of intelligent enterprises is formed. The index system consists of three dimensions: product dimension, intelligent dimension, and operation dimension. Each dimension is divided into different categories, and each category is subdivided into different factor domains. Indicators of supplier classification are divided as shown in Table 1.

2.2. BP Neural Network. The most basic component of neural network is neuron, which is connected with other

TABLE 1: Indicators of supplier classification.

First-level indicator	Secondary indicators	Third-level indicators	Fourth-level indicators
Performance	Quality of the product	Quantitative	Expert scoring
	Cooperation degree	Qualitative	The formula to calculate
	Service level	Quantitative	Expert scoring
	Credit	Qualitative	The formula to calculate
Strategic potential	Technology research and development ability	Quantitative	Expert scoring
	The management level	Quantitative	Expert scoring
	Collaborative innovation capability	Quantitative	Expert scoring
	Level of informatization	Quantitative	Expert scoring

neurons to complete the information transmission between neurons. At present, the neuron receives input signals with n weights. The total input received by the neuron is compared with threshold 0, and then the output value is calculated through activation function processing [14]. The description of the basic structure is shown in Figure 1.

The traditional BP neural network uses the error back-propagation algorithm to update the weights and thresholds of the network structure through error back-propagation to make the error smaller and iterate continuously until the error is smaller than the given expectation [15]. BP neural network also has certain drawbacks which are listed below:

- (i) Easy to fall into local minimum values: mathematically, the traditional BP neural network, as a local search optimization method, solves complex nonlinear problems, and the network weight is gradually adjusted through the local improvement direction, so the algorithm can become a local extreme value. Therefore, network training fails. In addition, the BP neural network is very sensitive to the initial weight of the network, and when the network is initialized with different weights, it tends to converge to different local minima, which is the fundamental reason why many scholars get different results every time they train.
- (ii) Slow convergence: since BP neural network algorithm is the gradient descent method in essence, the objective function it needs to optimize is very complex. Therefore, "saw-tooth phenomenon" is inevitable, which makes BP algorithm inefficient. In addition, since the optimized objective function is very complex, when the neuron output is close to 0 or 1, some flat areas will inevitably appear. In these regions, the weight error changes very little, making the training process almost stop. In the BP neural network model, in order to make the network perform THE BP algorithm, the step size of each iteration cannot be calculated by the traditional one-dimensional search method, but the step size update rule must be given to the network in advance, which will also cause the algorithm to be inefficient. All of the above result in slow convergence of BP neural network algorithm.
- (iii) Sample dependence: the training of BP neural network model requires a large number of training

samples, and the small sample data network cannot learn the rules therein, causing problems in accuracy.

Aiming at the disadvantage of the traditional BP neural network easily falling into local minimum, the improved particle swarm optimization algorithm was used to optimize the traditional BP neural network.

2.3. Improved PSO-BP Neural Network Model. The improved particle swarm optimization algorithm is stimulated by the following two operations.

2.3.1. Division Operation. Division operation is to do population division of particle swarm to prepare for mutation operation. In the process of particle optimization, the fitness value of particles is calculated, and the calculated results are divided into molecular populations. Let ε be a sufficiently small integer if the following is true:

$$\frac{\text{fit}(X_i^t)}{\text{fit}_{\text{avg}}^t} \leq \varepsilon, \quad (1)$$

In which, X_i^t represent particle, $\text{fit}_{\text{avg}}^t$ is the average value of the fitness of the first generation of particles, satisfying $\text{fit}_{\text{avg}}^t = (1/m) \sum_{i=1}^m \text{fit}(X_i^t)$. Among all outstanding subgroups (ESP), the particle swarm is represented as $X_{EP-\alpha}^t, \alpha \in (1, 2, \dots, \theta)$. Through the dynamic setting of values, the division of subpopulations is controlled, and the calculation formula is as follows:

$$\varepsilon = \varepsilon_2 - \frac{\text{MAXITER} - \text{iter}}{\text{MAXITER}} (\varepsilon_2 - \varepsilon_1), \quad (2)$$

where ε_1 and ε_2 are the initial and final values of $\varepsilon_2 > \varepsilon_1$, MAXITER is the maximum allowable iteration number, and iter is the current iteration number. At the beginning of iteration, the number of particles in ISP is large, that is, the number of mutated particles is large. We increase the diversity of particles. At the end of iteration, the number of variable particles decreases and the particles converge to the optimal solution.

2.3.2. Probability Mutation. The traditional adaptive mutation is to re-initialize some particles with a certain probability [16], but the mutation object and the probability of the mutation object are not reasonably defined, which has

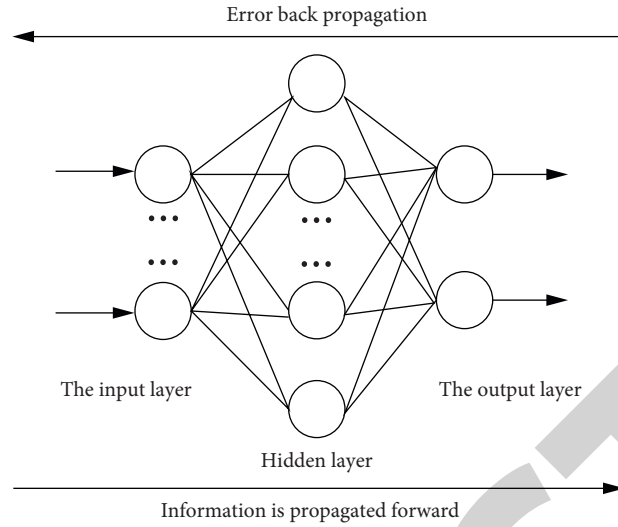


FIGURE 1: Basic structure of BP neural network.

a certain impact on the result of optimization. New position information will be generated after the particle is mutated, assuming that the position of the newly generated particle is $X_{\text{son-}\beta}^t$. The mutation operator of $X_{\text{son-}\beta}^t$ is designed as follows:

$$X_{\text{son-}\beta}^t = X_{IP-\beta}^t + P_v \sqrt{\sum_{d=1}^D (X_{\beta-d}^t - X_{P_{g-d}}^t)^2} \psi \circ V_{IP-\beta}^t, \quad (3)$$

where $P_v = \text{fit}(X_{IP-\beta}^t) / \sum_{\beta=1}^{\varphi} \text{fit}(X_{IP-\beta}^t)$, $\sqrt{\sum_{d=1}^D (X_{\beta-d}^t - X_{P_{g-d}}^t)^2}$ is the Euclidean distance of the β -th IP position from the global optimal value of the current iteration, and the direction coefficient is a 1xD matrix composed of random numbers within $[-1, 1]$. At early iterations, the IP and the global optimal solution of the Euclidean distance are large, and the particles will enhance the ability of searching global optimal values. In the iterative process, the particles are in the middle to near the global optimal value, and the optimal value gradually decreases, and the algorithm pays more attention to the search in the later development ability.

The Ackley nonlinear function [17] compares the performance of the original PSO algorithm and the improved PSO algorithm, and the Ackley function is shown as follows:

$$y = -c_1 \exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{j=1}^n x_j^2}\right) - \exp\left(\frac{1}{n} \sum_{j=1}^n \cos(2\pi x_j)\right) + c_1 + e. \quad (4)$$

Particle swarm optimization combined with BP neural network is mainly used to optimize the threshold and weight in the network structure, so that the prediction model can find the

optimal weight and threshold for network training and prediction. The steps of DPMPPO-BP algorithm are as follows:

Step 1: determine BP neural network structure parameters.

Step 2: initialize the particle information and the position and velocity of the particle. Parameters required by PSO algorithm include population size m , particle dimension d , maximum number of iterations MAX-ITERSIZE, inertial weight initial value and termination value ω_0 and ω_1 , learning factors c_1, c_2 , and particle maximum and minimum velocity.

Step 3: the synthetic error function of BP neural network was used as the particle swarm fitness function F :

$$F = \frac{1}{P} \sum_{p=1}^P \sum_{i=1}^l (\widehat{y}_i^p - y_i^p)^2. \quad (5)$$

Step 4: preliminarily determine the particle individual optimal solution and the population optimal solution.

Step 5: call partition algorithm to divide particle swarm into ESP and ISP. ESP enters the next iteration search, and ISP calls probabilistic mutation algorithm to generate new position and speed.

Step 6: search for individual and group extremes of particles. If the current fitness value is better than the individual extreme value, it is updated; if not, the particle speed and position are directly updated. If the particle fitness value is better than the group and volume extreme value, then update.

Step 7: update its speed and position.

Step 8: check whether the particle optimization conditions are met. If so, stop the iteration and map the global optimal value of the particle swarm to the initial

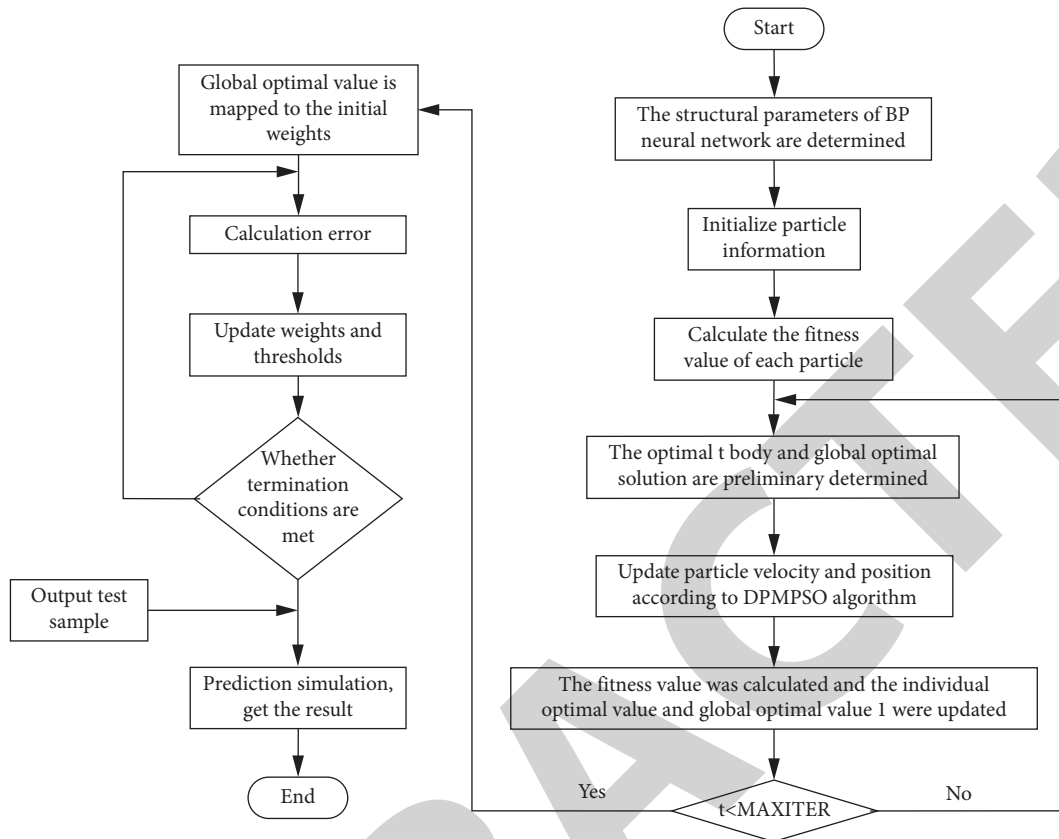


FIGURE 2: DPMSO-BP flowchart.

weight and threshold value of the BP neural network; otherwise, return to Step 4 and recalculate the fitness value of the particle.

Step 9: calculate the error of BP neural network, update the weights and thresholds in the network, and check whether the network termination conditions are met. If so, complete the network training and input test samples for prediction simulation. If not, the error is recalculated and the weight and threshold are updated. Figure 2 shows the flowchart.

2.4. General Steps of Supplier Efficiency Evaluation for Intelligent Manufacturing Enterprises

- (i) Data collection: the original supplier classification and evaluation datasets were collected by enterprise survey, system data export, and expert and relevant personnel scoring.
- (ii) Classification of suppliers: suppliers are classified by Naive Bayes algorithm, and efficient suppliers are output.
- (iii) Preprocessing of supplier evaluation data: due to the dimension difference of index data, the data cannot be directly substituted into the model for learning simulation, and the initial data should be standardized. There are positive indicators and negative indicators in the indicator set in this paper, which

need to be standardized in different ways according to different properties.

- (iv) Network training: with the secondary index in the evaluation index system as the input data and the comprehensive efficiency evaluation value of the supplier as the expected output value, the network is trained by the error backpropagation algorithm.
- (v) Result analysis: the results are obtained through experiments, and the results are analyzed. Finally, suggestions for improvement and incentive strategies are put forward for suppliers.

3. Experiments and Results

With the rapid development of the supply chain of intelligent manufacturing enterprises, the evaluation of supplier efficiency has been paid more and more attention by the enterprise management, and more and more researchers have joined in the research of supplier efficiency evaluation. On the basis of the research of experts and scholars, this paper constructed a set of intelligent manufacturing enterprise classification index system and evaluation index system, respectively, through the enterprise field investigation and relying on the school-enterprise cooperation project. The DPMSO-BP neural network model was used, and the enterprise example was used for simulation verification, and finally the supplier efficiency evaluation model was established.

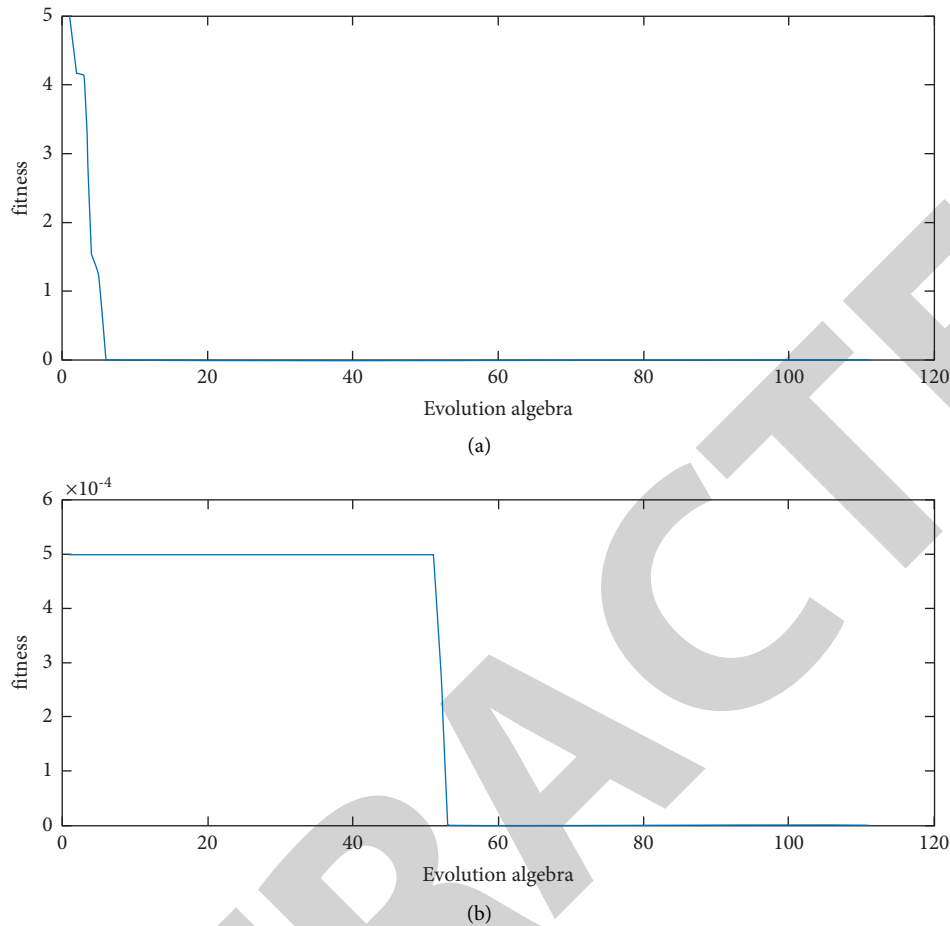


FIGURE 3: The experimental results of iteration. (a) PSO running effect. (b) DPMPPO running effect.

For a large battery manufacturing enterprise in China, 2,000 suppliers were selected for case analysis. As there are both qualitative and quantitative indicators in the established index system, the qualitative indicators are scored by enterprise managers and experts. For quantitative indicators, classification and evaluation data are collected through systematic data export and formula calculation. Firstly, traditional PSO and improved DPMPPO are compared, where $c_1 = 2$, $e = 2.71282$, and $n = 2$. The experimental results of iteration are shown in Figure 3.

The traditional PSO algorithm obtained the optimal individual fitness value of 0.0095 after 45 iterations, which was close to the actual optimal value of the function, indicating that the PSO algorithm has strong function optimization ability. However, DPMPPO algorithm gets the optimal individual fitness value 0 at iteration 106, which is consistent with the global optimal value of the Ackley function. The experimental results show that DPMPPO algorithm can jump out of the local minimum point and improve the premature convergence of traditional PSO algorithm.

This paper adopts a three-layer neural network structure. The hyperparameters of the BP neural network are set as follows: Inputnum = 25, Hiddennum = 20, Outputnum = 1, use the 'tansig' function from the input layer to the hidden layer, and use purelin activation from the hidden layer to the

output layer function, the rest use the trainingda training function, set the maximum number of training to 5000, the learning rate is 0.01, and the error is 0.000010. Parameters of PSO algorithm are set as follows: population size $m = 110$, particle degree $D = 341$, MAXITERSIZE = 100, $\omega_0 = 0.9$, $\omega_1 = 0.4$, $c_1 = c_2 = 1.49445$, $v_{\max} = 1$, and $v_{\min} = -1$. MATLAB R2015b was used to train and test BP, PSO-BP, and DPMPPO-BP models, respectively. The simulation result is shown in Figure 4.

According to the experimental results, the maximum error between the expected output value and predicted value of DPMPPO-BP model is 0.0015, which fully meets the needs of supplier efficiency evaluation of intelligent manufacturing enterprises. When the trained model is stored in the knowledge base, it only needs to input the attribute value matrix of each secondary indicator of the supplier to be evaluated in the supplier management system to obtain the comprehensive evaluation indicator data, which avoids the randomness and human factors in determining the index weight and improves the efficiency of evaluation decision making.

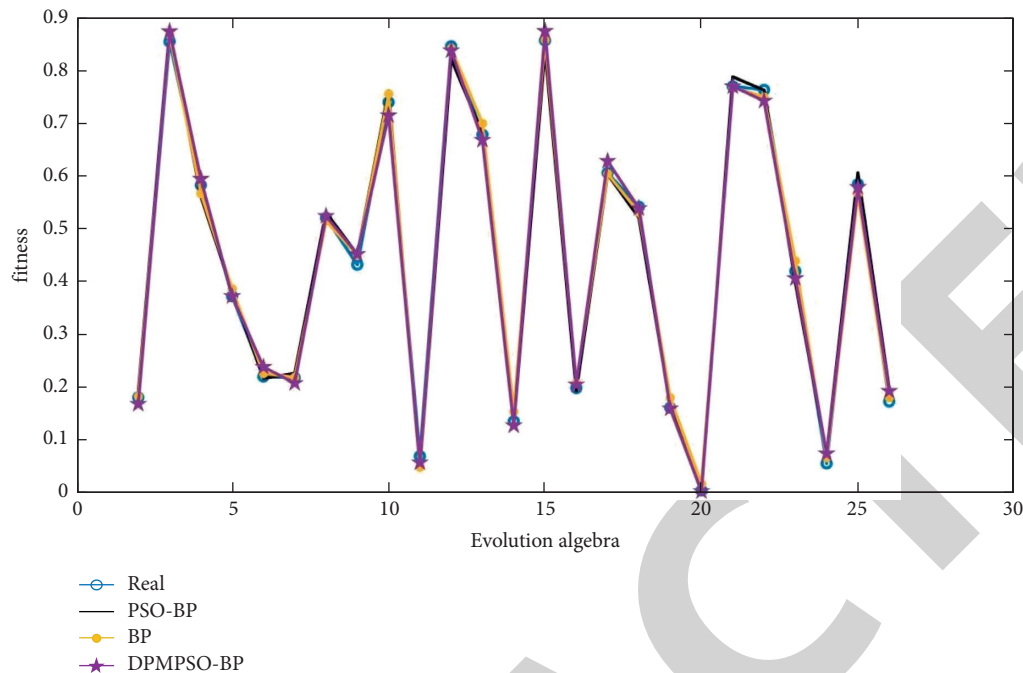


FIGURE 4: The experimental results of neural network.

4. Conclusion

This paper improved the traditional supplier evaluation method and existing supplier evaluation index system. To this end, the research carried out the analysis of supplier efficiency evaluation index system and supplier evaluation method of intelligent manufacturing enterprises. The current research has theoretical and practical research significances. Machine learning has gradually become a new direction of supplier management research methods, which has obvious value for information mining of massive data. This paper applied the improved PSO-BP neural network model to supplier efficiency evaluation. Use neural network to establish an evaluation model, collect relevant data for analysis and application, and make up for the subjectivity, randomness, and real-time problems of supplier evaluation. It has certain theoretical value for supplier management and supplier scientific innovation research.

Supplier evaluation is an important decision for the operation and production of intelligent manufacturing enterprises. In order to adapt to the development of the new round of industrial revolution, the intelligent reform of enterprises is imperative. The intelligent enterprises are achieved through providing the personalized and intelligent products and services. Based on the background of intelligent manufacturing, this paper puts forward the corresponding supplier evaluation index system and evaluation method, so as to improve the management mode of suppliers, improve production efficiency, point out the direction for the future development of suppliers, and further enhance the core competitiveness of enterprises.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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