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Research Article

Evaluation and Analysis of an Industrial Cluster Based on the BP Neural Network and LM Algorithm

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With the development of global economy, the evaluation of industrial clusters has become an important method to scientifically analyze the advantages and disadvantages of industrial development. The current research model uses the traditional evaluation method, which leads to the problem of unsatisfactory evaluation results and low effect. This paper proposes an evaluation model based on the BP neural network combined with the LM algorithm, which has the advantages of fast convergence speed and strong application ability. The comprehensive evaluation model of industrial clusters is put forward from the comprehensive application of the scale, benefit, and 27 related evaluation indexes of industrial clusters. This paper takes Beijing, Tianjin, and Hebei industrial clusters for BP-LM evaluation and analysis, which fully illustrates the advantages of this method. The evaluation results show that the evaluation target value and the average error of the overall parity have obvious advantages compared with those of other models, which provides application guidance for local economic development and policy formulation.

1. Introduction

An industrial cluster is the product of industrial economic development, which is composed of related enterprises, suppliers, and related institutions in a specific region, reflecting the competitiveness level of industries. Scientific positioning of industrial clusters is beneficial to stimulate industrial development and play a guiding role in the further development of industrial economy. At present, there are many researches on the development of industrial clusters. For example, Literature [1] used factor analysis to evaluate the representatives of 56 high-tech zones in China and found that the development of industrial clusters is unbalanced. Literature [2] analyzed the development and innovation capability of equipment manufacturing industry based on the industry's own innovation capability and internal coordination. Literature [3] takes Guangxi regional economy as an example to explore the relationship between high-quality development of industrial clusters and regional economic development. Although the above methods have studied the development of industrial clusters to a certain extent, they lack a feasible scientific evaluation system for

the development of industrial clusters. Considering that an industrial cluster is a complex organizational network, the rapid development of the machine learning method BP neural network in recent years can effectively solve the problem of information data processing of a complex organizational network. Therefore, the BP neural network is used to evaluate the development of industrial clusters, and an evaluation model of industrial cluster development based on the improved BP neural network is constructed. Finally, the effectiveness and feasibility of the model is proven by evaluating the development of high-tech industrial clusters in 28 regions such as Beijing, Tianjin, and Hebei. Literature [4] analyzes the fresh grapes in the supply chain risk from the perspective of economic development and improves its supply chain risk evaluation and management. We use a neural network to evaluate its supply chain risk. Firstly, the possible risks are identified, and the evaluation index system is put forward. Then, the risk assessment models of a single BP neural network and optimized BP neural network (GABP and PSO-BP) are established. Finally, using the collected data to test and evaluate, the results show that the biggest risk is the risk between the links in the chain (R0), and the

high risk dimension is reflected from three aspects, such as economy, society, and cooperation. Literature [5] establishes a combined performance evaluation model based on the BP neural network and rough set, which can improve the performance evaluation of manufacturing collaborative logistics. The attribute reduction theory of rough set can select and optimize the evaluation indexes to obtain the set of key performance indicators. The function of the BP neural network is to predict and evaluate the data of key performance indicators, which can shorten the time and reduce the number of times. Experiments show that this method has certain effect. Literature [6] puts forward that a scientific talent evaluation system is the primary condition for the evaluation of talent work and the effective development of talent resources, and it is also the foundation of personnel work. Using a comprehensive evaluation method of talent training performance in integrated circuit industry based on the BP neural network based on the premise of determining the number of BP network layers, the sample and original value are selected in combination with talent training performance data, and then, the evaluation model is established by means of data processing. With the rapid development of catering O2O take-out industry, various platforms pay more attention to customer experience, such as distribution service and timeliness. The BP neural network model evaluates the customer experience of online-to-offline (O2O) take-out [7]. The model of the MATLAB neural network toolbox is used to simulate and train the buyer experience data, and then, the principal components are extracted as the input of the BP neural network model. Experiments show that the BP neural network model can evaluate the customer experience of O2O take-out. Reference [8] puts forward the evaluation model of a military bridge blasting scheme based on the BP neural network, constructs the evaluation index system of a bridge blasting scheme, and studies the evaluation method of a military bridge blasting scheme. Taking a practical task as an example, the effectiveness of the model is verified. Literature [9] is aimed at the particle swarm optimization BP neural network algorithm which can analyze teaching evaluation data, which is mainly used to improve the quality of teaching management, which is reflected in two aspects, namely, effectiveness and intelligence. Firstly, the BP neural network is used to model the evaluation index of teaching management, and then, the particle swarm optimization algorithm is used to optimize the weight and threshold of the function, which can ensure that the output of the BP neural network can get the most optimized and comprehensive solution. After verification, the algorithm is worth popularizing and can combine the predicted value with the actual value well. Literature [10] reports that phishing often induces people to open some illegal websites, so as to obtain users' personal privacy. The BP neural network will be limited. This paper presents a phishing website detection model DF. A grey wolf algorithm and backpropagation neural network (GWO-BPNN) are based on the improved BP neural network and double feature evaluation mechanism. Aiming at the problem of slow learning convergence caused by improper selection of weights and thresholds, it uses the gray wolf algorithm to optimize the

BP neural network and can reasonably select initial parameters. Literature [11] put forward the analytic hierarchy process (AHP), aimed at the subjective problem of man-post matching in decision-making, and determined the weight of each index in the evaluation index system of manager-post matching. The BP neural network is used to evaluate the matching of college administrators, and the basic evaluation model is constructed. If the error of the model is less than 5%, it is a better evaluation result. The model absorbs the expert's judgment experience and can adapt to the brain thinking to process sample data and effectively evaluate the matching between managers and personnel. The BP neural network algorithm and Radial Basis Function (RBF) neural network algorithm proposed in Reference [12] are used to evaluate the seismic performance of buildings and bridges and to analyze and control the collision response of adjacent beams and piers of bridges under strong earthquakes. Through experiments, the prediction effect of the RBF network is much better than that of the BP network. It is a method with high precision, which is used to calculate reinforced concrete columns under axial load and horizon action. Literature [13] reported that the evaluation model of sports training effect based on the genetic algorithm-improved BP neural network algorithm (GABP) has an obvious effect on improving sports training effect. The GABP neural network algorithm is constructed by using the idea of artificial intelligence. The code is vectorized on the basis of a sample matrix, and two neural networks are tested and evaluated to improve the simplicity and efficiency of the code, and the properties, topology, and parameter updating methods of the networks are analyzed and compared. Experiments show that the trained GABP neural network occupies less memory and can achieve ideal high fitting accuracy of training samples and high generalization ability of test samples.

2. Basic Algorithm

2.1. Brief Introduction of the BP Algorithm. The BP neural network [14] is one of the most widely used neural networks, including three basic network structures: input layer, output layer, and hidden layer, as shown in Figure 1.

For a typical three-layer BP neural network, it is assumed that the number of nodes in the input layer, hidden layer, and output layer is m, s, and n, respectively, and the outputs are u_l, y_j, and Z_i, respectively. The connection weights of neurons in the input layer and hidden layer and hidden layer and output layer are w_{ij} and v_{jl}, and neuron thresholds are random values θ_j and $B\gamma_i$ between $(-1, 1)$. If the learning coefficients are α and β, the specific steps of the BP algorithm are as follows.

Step 1. Initialize w_{ij}, v_{jl}, θ_j, and γ_i, and set the input vector as $X_i = (X_1, X_2, \cdots, X_m)$ and the output vector as $\widehat{Z}_i = (\widehat{Z}_1, \widehat{Z}_2, \cdots, \widehat{Z}_n)$.

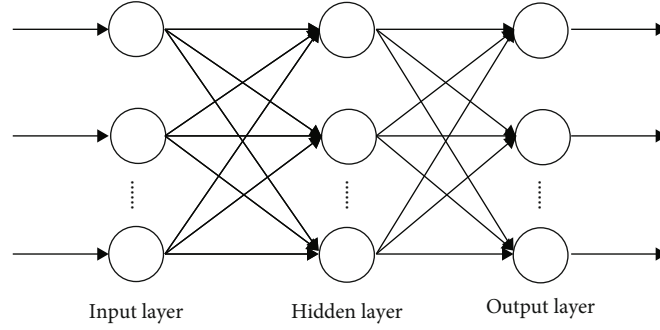*Step 2.* Calculate the hidden layer neuron output y_j and the output layer neuron output C_l according to

FIGURE 1: Basic structure of the BP neural network.

$$\begin{cases} s_j = \sum_{i=1}^{m} w_{ij} x_i - \theta_j, \\ y_j = f(s_j), \end{cases} \tag{1}$$

$$\begin{cases} u_l = \sum_{j=1}^{p} v_{ij} y_i - \gamma_l, \\ C_l = f(u_l). \end{cases} \tag{2}$$

Step 3. Calculate an output layer neuron error d_l^k and a hidden layer neuron error e_j^k:

$$\begin{aligned} d_l^k &= \left(z_l^k - C_l^k\right) f'(u_l), \\ e_j^k &= \left[\sum_{l=1}^{q} v_{jl} d_l^k\right] f\left(s_j^k\right). \end{aligned} \tag{3}$$

Step 4. Correct v_{ij} and γ_l according to d_l^k and y_j; modify w_{ij} and θ_j according to e_j^k and x_k:

$$\begin{cases} \Delta v_{jt} = a d_l^k y_j^k \quad (0 < a < 1), \\ \Delta \gamma_l = -a d_l^k, \end{cases}$$
$$\begin{cases} \Delta w_{ij} = \beta e_j^k x_i^k \quad (0 < \beta < 1), \\ \Delta \theta_j = -\beta e_j^k. \end{cases} \tag{4}$$

Step 5. Repeat the above steps until all samples complete one study.

Step 6. Calculate the global error function E according to

$$E(W) = \sum_{k=1}^{m} e(W_k) = \frac{1}{2} \sum_{k=1}^{m} \sum_{l=1}^{q} \left(Z_i^k - C_i^k\right)^2. \tag{5}$$

Step 7. Judge E and the size of the error set value; if E is less than the set value or reaches the maximum iteration times, the algorithm is terminated. If E is greater than the set value and the maximum number of iterations is not reached, the algorithm continues.

2.2. Improvement of the BP Algorithm. According to the above analysis, although the BP neural network has certain advantages in information data processing, it still has some shortcomings in practice, such as poor generalization ability [15] and slow convergence speed [16]. Therefore, aimed at the defects of the BP neural network mentioned above, the LM algorithm is used to improve it.

The LM algorithm is an algorithm to solve the extreme value of function through iteration. Its basic calculation method is as follows:

If the vector composed of the threshold value and weight value in the k-th iteration is x_k and the change amount is Δ_x, then the vector composed of the threshold value and weight value x_{k+1} in the $(k + 1)$-th iteration can be expressed as

$$x^{k+1} = x^k + \Delta x. \tag{6}$$

Newton's law formula is [17]

$$\Delta x = -\left[\nabla^2 E(x)\right]^{-1} \nabla E(x), \tag{7}$$

where $\nabla^2 E(x)$ represents the Hesse matrix of the error function $E(x)$; $\nabla E(x)$ denotes the gradient. Let $E(x) = 1/2 \sum_{p=1}^{n} e_p^2$, where e_p^2 represents the error term; then, there are

$$\begin{aligned} \nabla E(x) &= J^T e(x), \\ \nabla^2 E(x) &= J^T(x) J(x) + S(x). \end{aligned} \tag{8}$$

In

$$S(x) = \sum_{p=1}^{n} e_p(x) \nabla^2 e_p(x),$$

$$J(x) = \begin{vmatrix} \dfrac{\partial e_1(x)}{\partial x_1} & \dfrac{\partial e_1(x)}{\partial x_2} & \dfrac{\partial e_1(x)}{\partial x_3} & \cdots & \dfrac{\partial e_1(x)}{\partial x_n} \\ \dfrac{\partial e_2(x)}{\partial x_1} & \dfrac{\partial e_2(x)}{\partial x_2} & \dfrac{\partial e_2(x)}{\partial x_3} & \cdots & \dfrac{\partial e_2(x)}{\partial x_n} \\ . & . & . & . & . \\ . & . & . & . & . \\ \dfrac{\partial e_n(x)}{\partial x_1} & \dfrac{\partial e_n(x)}{\partial x_2} & \dfrac{\partial e_n(x)}{\partial x_3} & \cdots & \dfrac{\partial e_n(x)}{\partial x_n} \end{vmatrix}. \tag{9}$$

TABLE 1: Selection of indicators.

Indicators	Subindex	Variable
Cluster size	Total number of enterprises (units)	X1
	Average number of employees (persons)	X2
	Total assets (100 million yuan)	X3
	Main business income (100 million yuan)	X4
	Total profit (100 million yuan)	X5
Cluster benefit	Profits and taxes (100 million yuan)	X6
	Exit value (100 million yuan)	X7
	Number of R&B enterprises (number)	X8
	R&D member (person)	X9
	Full-time equivalent of R&D members (person-years)	X10
	New product development projects (pieces)	X11
	Expenditure on new product development (10,000 yuan)	X12
	Sales revenue of new products (10,000 yuan)	X13
	Patent application (piece)	X14
Technological innovation ability	Valid patent (piece)	X15
	Technical transformation funds (10,000 yuan)	X16
	Enterprises with R&D institutions (units)	X17
	Hair and hair institutions (units)	X18
	R&D personnel (person)	X19
Supporting mechanism	Expenditure of R&D institutions (10,000 yuan)	X20
	Construction projects (pieces)	X21
	Newly started projects (pieces)	X22
	Completed and put into operation projects (pieces)	X23
	Project completion and production rate (%)	X24
	Investment amount (100 million yuan)	X25
	New fixed assets (100 million yuan)	X26
	Delivery utilization rate of the same assets (%)	X27

When the algorithm is close to a solution, the calculation rule is

$$\Delta x = -\left[J^T(x)J(x)\right]^{-1}J(x)e(x). \tag{10}$$

The LM algorithm improves the above rules and can get

$$\Delta x = -\left[J^T(x)J(x) + \lambda I\right]^{-1}J(x)e(x). \tag{11}$$

In the formula, λ represents the proportional coefficient constant and λ decreases a little every iteration. When the value of T is large, the LM algorithm is close to the gradient descent method; I denotes the identity matrix.

3. Evaluation Model of Industrial Cluster Development Based on Improved BP

3.1. Indicator Selection.
In the process of industrial cluster development evaluation, the selection of the evaluation index has great influence on the model evaluation results. Therefore, before constructing the evaluation model of industrial cluster development, it is necessary to construct the evaluation index system of the model first. According

to the principles of objectivity, feasibility, scientificity, and importance, this study preliminarily selects the indicators from six aspects: infrastructure, supporting institutions, relationship among members, cluster scale, benefit, and innovation effect [18]. Then, considering that the characteristics of different industrial clusters are mostly dominated by high and new technology, this study screens the indicators again based on the characteristics of high and new technology and determines 27 important indicators in five aspects: cluster scale, benefit, technical energy creation ability, supporting institutions, and project construction, as shown in Table 1.

3.2. Modeling.
After the construction of the evaluation index system of industrial cluster development, the improved BP model can be used for training, which can realize the evaluation of industrial cluster development. The specific construction method of the industrial cluster development evaluation model based on improved BP is as follows:

(1) Determine the number of network layers

The more BP network layers, the longer the network training time and the more accurate the training results.
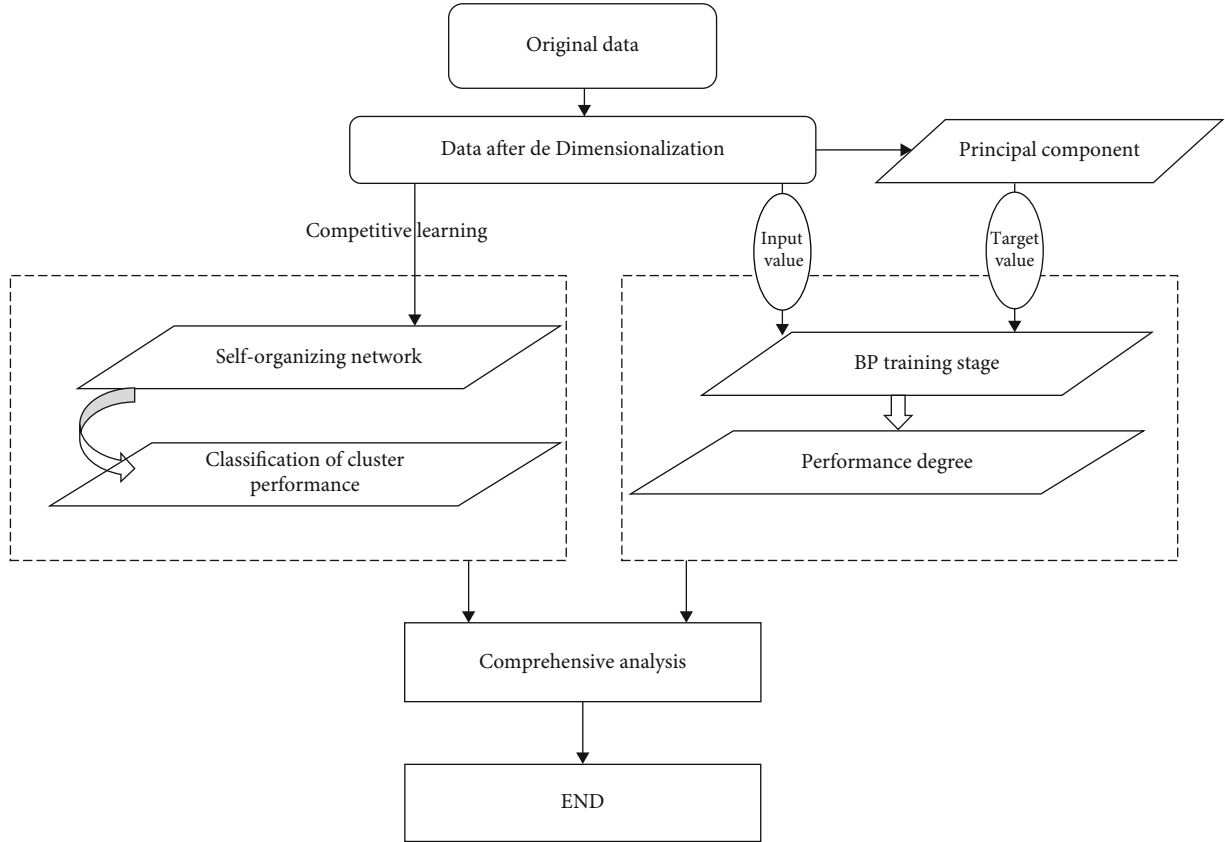
Figure 2: Construction of the industrial cluster development evaluation model based on improved BP (the BP network training stage is changed to the improved BP network training stage).

Therefore, the number of BP network layers directly affects the training efficiency and training effect of the model. In order to ensure the best training efficiency and training effect of the model at the same time, according to the evaluation index and the basic principles of the BP neural network, a three-layer BP neural network can map any m-dimensional to n-dimensional mapping [19], so the improved BP model network constructed in this study has three layers.

(2) Input layer determination

According to the 27 industrial cluster development evaluation indicators selected above, the number of neurons in the input layer of the improved BP network is 27.

(3) Hidden layer determination

The hidden layer is mainly responsible for extracting and saving the inherent laws of sample data information. If the number of neurons is too large, more information is extracted and saved, which will easily lead to irregular information being saved and affect the training results. On the contrary, the number of neurons is too small, which easily leads to the extracted information that cannot fully reflect the inherent laws of sample data information. Therefore, it is necessary to determine the number of neurons in the hidden layer. Generally, the number of neurons in the hidden layer can be determined by

$$N = \sqrt{m + n} + a, \tag{12}$$

where N represents the number of neurons in the hidden layer, n denotes the number of output nodes, m represents the number of input nodes, and a is a constant in the range of $(1, 10)$. Through many experiments, the best number of neurons in the hidden layer in this study is set to 27.

(4) Determination of the output layer

The output of the improved BP model is a qualitative evaluation of the training results. Therefore, for the needs of analysis and evaluation, the number of neurons in the output layer of the improved BP model is set to 1.

3.3. Evaluation Process. After the construction of the index system and improved BP network model, the index can be input into the model to evaluate the development power of industrial clusters. The evaluation process of the industrial cluster development evaluation model based on improved BP is as follows:

Step 1. Preprocessing the original index data of industrial cluster development evaluation by dedimensionalization

Step 2. Adopting principal component analysis to preprocess the data to obtain a target value

TABLE 2: LM algorithm parameter settings.

Parameter	Meaning	Parameter	Meaning
Mu	Initial value of parameter μ	Epochs	Maximum training times
Goal	Accuracy required by adjustment and training	mu_dec	Decrease factor
mu-inc	Increasing coefficient	mu_fal	Maximum number of failed steps
mem_reduc	Memory/speed parameters	min_grad	Minimum gradient
mu_max	Maximum value of mu		

Step 3. Inputting the pretreated data into an improved BP neural network model for training and taking the target value as an output

Step 4. Judge whether or not the network converges and the error reaches the set threshold range, output the result, and evaluate the development power of the industrial cluster according to the evaluation standard

The above flow can be illustrated by Figure 2 (principal component analysis).

4. Simulation Experiment

4.1. Experimental Environment and Data Sources. This experiment is simulated in MATLAB software and takes 28 regional high-tech industrial clusters such as Beijing-Tianjin-Hebei as research objects to evaluate their development. Considering that the 27 selected industrial cluster development evaluation indicators belong to different dimensions and cannot be directly calculated, the research carried out dedimensional pretreatment on the selected indicators. For the index where the required target value is larger, the dedimensionalization formula is better as shown in formula (13), and for the index where the required target value is smaller, the dedimensionalization formula is better as shown in formula (14) [20].

$$F_j = \frac{x_j - x_{j\,\min}}{x_{j\,\max} - x_{j\,\min}}, \tag{13}$$

$$F_j = 1 - \frac{x_j - x_{j\,\min}}{x_{j\,\max} - x_{j\,\min}}, \tag{14}$$

where F_j represents a standardized value and x_j represents a target value, $X_{j\,\max}$ represents the maximum value of the metric j, and $X_{j\,\min}$ represents the minimum value of the metric j.

The difference between formulas (12) and (13) is to design for different target values. Equation (12) sets the target value as large as possible, and equation (13) sets the target value as small as possible.

4.2. Parameter Settings. According to the evaluation index of industrial cluster development, this experiment adopts three-layer BP network structure to evaluate. The parameters of the BP network model are as follows: the number of neurons in the input layer and hidden layer is 27, and the number of neurons in the output layer is 1; the Tansig function is used as transfer function from the input layer to hid-

TABLE 3: Target value of the improved BP network.

Region	Principal component analysis score	Normalized processing target value
Guangdong	12.52	1
Jiangsu	10.74	0.75
Zhejiang	2.63	-0.33
Shandong	2.21	-0.39
Beijing	0.25	-0.65
Sichuan	0.14	-0.67
Shanghai	0.05	-0.68
River elucidation	-0.15	-0.71
Fujian	-0.37	-0.74
Hubei	-0.48	-0.75
Lake pottery	-0.51	-0.76
Safety sign	-0.58	-0.77
Canine fluid	-0.67	-0.78
Jiangxi	-0.89	-0.81
Liaoning	-1.08	-0.84
Shaanxi	-1.19	-0.85
Hebei	-1.25	-0.881
Jilin Province	-1.42	-0.883
Chongqing	-1.44	-0.885
Guangxi	-165	-0.91
Heilongjiang	-1.80	-0.93
Guizhou	-1.99	-0 .961
Shanxi	-2.01	-0.962
Yunnan	-2.11	-0 .97
Gansu Province	-2.13	-0 .98
Hainan	-2.21	-0 .992
Xinjiang	-2.26	-0 .995
Ningxia	-2.26	-1

den layer, and the purelin function is used as a transfer function from the hidden layer to output layer. The activation function adopts a bipolar S function, and its value range is $(-1, 1)$. The learning rate was 0.05.

LM algorithm parameters are automatically set by using the training function TRAINLM in MATLAB software. See Table 2 for specific parameter settings.
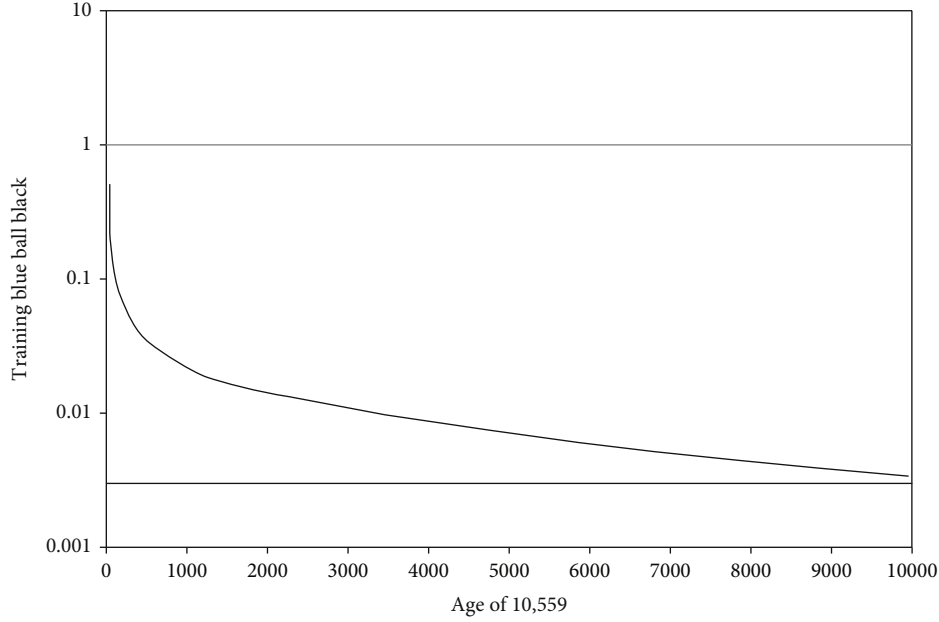
FIGURE 3: Improved training process of the BP network.

4.3. Target Value Acquisition.

The first three principal components Z_1, Z_2, and Z_3 were obtained by using 27 indexes of principal component analysis:

$$
\begin{aligned}
Z_1 = {} & 0.2181X_1 + 0.2112X_2 + 0.2133X_3 + 0.2149X_4 \\
& + 0.2162X_5 + 0.2157X_6 + 0.2066X_7 + 0.2094X_8 \\
& + 0.2069X_9 + 0.2043X_{10} + 0.2052X_{11} + 0.2049X_{12} \\
& + 0.2088X_{13} + 0.1972X_{14} + 0.1742X_{15} + 0.21X_{16} \\
& + 0.1887X_{17} + 0.1934X_{18} + 0.2177X_{19} + 0.2115X_{20} \\
& + 0.1728X_{21} + 0.1645X_{22} + 0.1667X_{23} + 0.0558X_{24} \\
& + 0.166X_{25} + 0.1735X_{26} + 0.0116X_{27},
\end{aligned}
$$

$$
\begin{aligned}
Z_2 = {} & 0.0304X_1 + 0.1194X_2 + 0.1068X_3 + 0.057X_4 - 0.018X_5 \\
& + 0.0217X_6 + 0.1183X_7 - 0.0607X_8 + 0.159X_9 \\
& + 0.1749X_{10} + 0.1379X_{11} + 0.1811X_{12} + 0.1311X_{13} \\
& + 0.217X_{14} + 0.2957X_{15} - 0.0949X_{16} - 0.2071X_{17} \\
& - 0.195X_{18} + 0.0341X_{19} + 0.1317X_{20} - 0.2938X_{21} \\
& - 0.3296X_{22} - 0.3343X_{23} - 0.3345X_{24} - 0.2861X_{25} \\
& - 0.2752X_{26} + 0.0869X_{27},
\end{aligned}
$$

$$
\begin{aligned}
Z_3 = {} & -0.0257X_1 - 0.0917X_2 - 0.033X_3 - 0.0241X_4 \\
& + 0.0461X_5 + 0.0079X_6 - 0.698X_7 + 0.1003X_8 \\
& - 0.0666X_9 - 0.776X_{10} + 0.0591X_{11} - 0.0107X_{12} \\
& + 0.0068X_{13} - 0.0353X_{14} - 0.089X_{15} - 0.0232X_{l6} \\
& + 0.1351X_{17} + 0.1251X_{18} + 0.0026X_{l9} - 0.0269X_{20} \\
& + 0.0157X_{21} + 0.0196X_{22} + 0.0385X_{23} - 0.2494X_{24} \\
& - 0.066X_{25} + 0.0902X_{26} + 0.9154_{27}.
\end{aligned}
$$

$$(15)$$

TABLE 4: Improved BP network simulation output value.

Region	Scoring result	Rank
Beijing	-0.75	9
Tianjin	-0.83	11
Hebei	-0.88	17

Among them, Z_1 contains 76.87% of information, and the main representative variables are X_1, X_{19}, and X_5. The amount of information contained in Z_2 is 13.59%, and the main representative variables are X_{22}, X_{23}, and X_{24}; Z_3 contains 3.95% information, and the main representative variable is X_{27}. Finally, according to the comprehensive score of principal components, the target value of BP network evaluation for industrial cluster development improvement can be obtained, as shown in Table 3.

4.4. Results and Analysis.

In order to verify the effectiveness of the proposed industrial development evaluation model based on improved BP, this paper uses this model to evaluate and analyze the high-tech industrial clusters in the Beijing-Tianjin-Hebei region. The training process is shown in Figure 3, and the training results are shown in Table 4. Comparing the output value and target value of the improved BP network in the table, it can be seen that the overall simulation effect of the improved BP network is good. There are local changes in the rankings of Beijing and Tianjin, but the evaluation results are consistent. The evaluation value of high-tech industrial clusters in Hebei is consistent with the target value, and the evaluation error is 2.5%.

In order to further analyze the relationship between the evaluation value and the target value of the improved BP network for high-tech industrial clusters in the Beijing-Tianjin-Hebei region, the evaluation value and the target
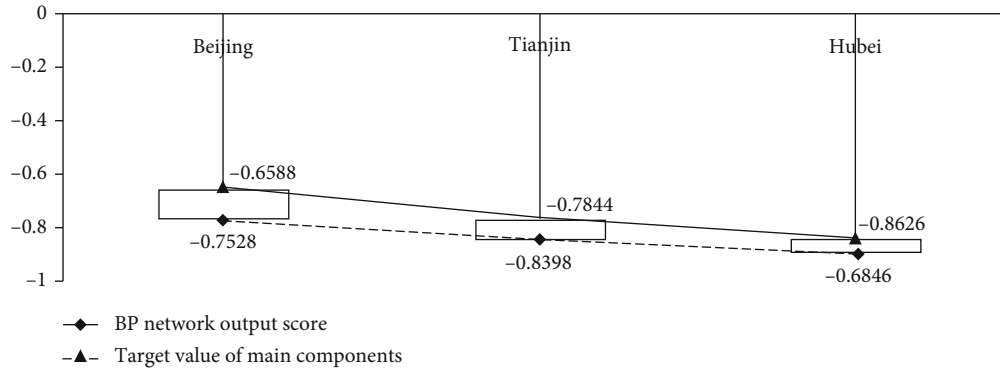
FIGURE 4: Comparison between the evaluation value and target value in the Beijing-Tianjin-Hebei region (the BP network output score is changed to the improved BP network output score).

TABLE 5: Evaluation and analysis of high-tech industrial cluster development based on improved BP.

	Province	Improving BP network scoring results
1	Guangdong	1
2	Jiangsu	0.75
3	Zhejiang	-0.33
4	Shandong	-0.39
5	Sichuan	-0.67
6	Shanghai	-0.68
7	Henan	-0.71
S	Fujian	-0.74
9	Beijing	-0.751
10	Hubei	-0.753
11	Hunan	-0.76
12	Anhui	-0.77
13	Jiangxi	-0.81
14	Tianjin	-0.83
15	Liaoning	-0.84
16	Shaanxi	-0.85
17	Hebei	-0.882
18	Jilin	-0.884
19	Chongqing	-0.89
20	Guangxi	-0.91
21	Heilongjiang	-0.93
22	Guizhou	-0.963
23	Shanxi	-0.965
24	Yunnan	-0.972
25	Gansu	-0 978
26	Hainan	-0.99
27	Xinjiang	-0.99
28	Ningxia	-1.00

value of the above three regions are compared, and the results are shown in Figure 4. It can be seen from the figure that the relative error of the Beijing high-tech industrial clus-

ter is 0.106; the relative error of the Hebei high-tech industrial cluster is small, which is 0.022. On the whole, it is feasible to use the improved BP neural network to evaluate the development of high-tech industrial clusters.

In order to analyze the wide practicability of improved BP, the improved BP network is used to evaluate and analyze the development of high-tech industrial clusters in 28 regions such as Beijing, Tianjin, and Hebei, and the development results of each enterprise are obtained, as shown in Table 5. Comparing the improved BP network evaluation value with the target value, we can see that the evaluation value in most areas is close to the target value, and the overall evaluation mean square error is 0.0041, which shows that the improved BP network has certain feasibility.

Comparing the output value of the improved BP network model with the target value, the overall prediction effect is better. In most areas, the evaluation value is close to the target value, which can be applied to experimental economic prediction. The BP neural network was used for the weight of all provinces in the country ranking better for the objective evaluation of industrial clusters.

5. Conclusion

The evaluation model of industrial cluster development based on the improved BP network is proposed in this study. It can effectively and accurately evaluate the development level of high-tech industrial clusters in Beijing, Tianjin, and Hebei. The evaluation value of high-tech industrial clusters in most areas obtained by improving the BP network is close to the target value of principal component analysis, and the relative error of the predicted value of Hebei high-tech industrial clusters is small, which is 0.022. The relative error of the predicted value of the Beijing high-tech industrial cluster is 0.106. The mean square error of the prediction of high-tech industrial clusters in various regions is 0.0041, which has strong feasibility and practicability. However, there are still some shortcomings in this study, such as limited space and conditions; the study did not put forward targeted policy recommendations for the evaluation results of industrial clusters and did not conduct in-depth discussion

on the applicability of improving the BP network model. In the next step, the research will improve these deficiencies in order to improve the applicability, scientificity, and practicability of the evaluation of industrial cluster development.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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