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Research Article

Evaluation Method of Industrial Efficiency of Green Manufacturing Enterprises Based on Machine Learning

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The cultural construction in the process of industrialization is intertwined with the culture required by the development of green manufacturing industry, which has become the growth point of economic construction and the new trend of economic development. Efficiency is the basis for the development of various industries. If we do not improve efficiency, industrial development will cause waste of resources and environmental pollution. Therefore, this study proposes a new evaluation method of green industrial manufacturing efficiency. The proposed method suggests cultural enterprises. In addition, this study examines the cultural green manufacturing industry productivity of cultural enterprises and combines it with machine learning. The excellent performance of neural network in prediction makes it possible to predict the efficiency of green manufacturing industry of cultural enterprises. Genetic algorithm is also proposed to optimize BP network. This algorithm is easy to operate and requires few parameters. In the process of finding the optimal solution, the optimal individual in the group can be used to control the iterative process. The particle swarm optimization algorithm is improved and combined with genetic algorithm to get an improved hybrid algorithm. BP network is optimized, and an improved BP network prediction model is established to evaluate the efficiency of green manufacturing industry of cultural enterprises. A large number of experiments have proved the effectiveness and reliability of this method. Separate simulations and results are presented to verify the effectiveness of the proposed model.

1. Introduction

Culture not only symbolizes the notch of development of a nation but is also a sign of a nation's inclusive asset. Dynamically emerging the social industry can not only rapidly make up for the vast breach in a cultural mandate by firming the supply of cultural products, but also accelerate the transformation of the economic development model. In the context of economic globalization, culture is an evaluation index of a country's comprehensive competitiveness, and it also symbolizes the degree of civilization development of a country and nation. In recent years, the income level of residents has been continuously increasing in line with the pace of national economic development, and with it has come a strong demand for consumer goods including culture. Therefore, the cultural enterprise market urgently needs further prosperity, and the cultural enterprise industry is also facing unprecedented development prospects. Cultural construction is an effective measure to promote my country's economic growth and enhance the level of competition in the country's comprehensive national strength. It also plays a certain role in promoting overall progress. In recent years, the cultural industry has shown a strong growth trend and development potential, and the number of professional practitioners in the cultural industry has continued to increase. Compared with other industries, the number of people employed by the cultural industry is much higher than that of other industries.

On the one hand, the development of cultural industry contributes to the improvement of the regional economy, and on the other hand, it enriches the spiritual needs of the people. The cultural industry not only satisfies people in the spiritual realm, but also realizes its value on the economic stage [1–7]. With the continuous deepening of reform and development and opening to the world, the cultural enterprise industry has entered a period of fast development, and the development speed is significantly higher than that of other industries. In 2000, the added value of the cultural industry accounted for less than 1% of the country's total GDP. By 2012, this share jumped to 3.48%. After more than ten years of development, the average annual growth rate of the cultural industry has exceeded 25%. In 2014, the added value of the cultural industry exceeded 2 trillion yuan, achieving a high growth rate of 12% compared with the previous year. In 2015, the share of cultural industry added value in total GDP reached a new high, and the added value of this industry in some developed provinces contributed more than 5% to GDP.

Scholars have evaluated and calculated based on the evaluation growth rate of the cultural industry and believed that by 2016, the ratio of China's cultural industry's added value to GDP will hopefully exceed 5%. The cultural industry is just around the corner as the highlight of the economic structure blueprint. The state vigorously supports the development of the cultural industry, by supporting the creation of cultural products, focusing on the cultivation of cultural professionals, and improving the cultural service. The continued rapid development is the general trend and one of the new driving forces for long-term economic growth. With the advent of globalization, informatization, and the economy, the cultural enterprise industry has become an important force in promoting industrial restructuring and regional economic development. Although my country's cultural enterprise industry has achieved economic growth, it is small in scale and still has a big gap with Western developed countries. In addition, there are many issues in the development process of the cultural enterprise industry, like low marketization, serious waste of resources, and poor management, especially the unreasonable structure of the cultural industry, uneven regional development, and low overall efficiency of production and operation [8–15].

A series of problems have affected the improvement of the development level. The key to promoting cultural industries is to enhance the efficiency level of cultural industries in various regions and improve the level of production, operation, and management. Therefore, it is necessary to conduct a comprehensive and effective assessment of the efficiency level of the cultural industry. In this way, effective measures and industrial policies that are conducive to the healthy development of the cultural industry can be put forward based on research conclusions, and the efficiency of the cultural enterprise industry can be comprehensively improved. It is very necessary to study efficiency level and influencing factors for the cultural industry. Combining the hot machine learning technology in computers, this work proposes an evaluation method for the industrial efficiency of cultural enterprises.

This research presents a novel approach for industrial efficiency evaluation. The proposed method is suggested for cultural enterprises. In addition, the research examines the cultural industry productivity of cultural enterprises and integrates it with machine learning. Although the genetic algorithm has a global optimization, it needs to set many parameters, the operation is more complicated, and it does not have a memory function. Therefore, a particle swarm algorithm is proposed.

2. Related Work

There are relatively few researches on the evaluation for the efficiency of the cultural industry in foreign countries, and most of them focus on the micro-level research, such as public theaters, museums, and other specific units and enterprises. The British Government Sports Department published the report in 1999, which demonstrated the necessity of establishing efficiency measurement indicators and related models for cultural institutions. Literature [16] used the data envelopment method to analyze and research Spanish theaters in the Valencia region from 1995 to 1999. There is a clear correlation between the decline in total efficiency and the decline in technical efficiency, whereas the scale efficiency appears to be stable. Literature [17] found through research that the improvement of scale efficiency can further improve the operating efficiency of German public theaters. Literature [18] measured the development efficiency of cultural industries with cultural heritage institutions and museums in Tehran as representatives. It is expected to provide a reference for improving industrial operational efficiency and optimizing resource allocation. To better stimulate and support the growth of Korean culture industries, literature [19] employs the DEA model to evaluate the operational effectiveness of community cultural institutions in South Korea's main cities. To evaluate the efficiency of the public sector, literature [20] created the CCR model, which is the most traditional data envelopment method.

Literature [21] developed another BCC model that evaluates the relatively effective production technology in response to the fact that the cone hypothesis that production may be concentrated does not hold. Literature [22] uses DEA to analyze development and changes of European railway productivity from 1975 to 1999. Literature [23] first elaborated on the three-stage DEA method and conducted a performance evaluation of 990 nursing homes in 1993. Literature [24] combined the DEA with the Malmquist index model to track and measure the grain production efficiency. Literature [25] uses the input and output-oriented DEA to measure comprehensive technical efficiency. It then evaluates the resource utilization and output of each state in India from 2013 to 2014. Generally speaking, the original purpose of these models and methods is mostly to study the efficiency of the public domain, departmental institutions, or production enterprises. But it provides powerful method support for the current research in the cultural field. Domestic scholars' research on efficiency of cultural industry mostly focuses on macro as well as meso-levels. The status of the cultural industry in my country's economic life is also increasing day by day. Literature [26] constructs an indicator system from seven aspects.

It used the statistical normalization method to conduct empirical evaluation on competitiveness for the cultural industry in my country's 31 provinces in 2003. Literature

[27] uses the CCR model and super-efficiency model in DEA theory to analyze the efficiency performance of the cultural industry in my country's 24 provinces and cities in 2006. When constructing the efficiency evaluation index system, she used the number of employees, total asset value, and total fixed-asset investment as input indicators, and industrial added value, total industrial output, and paid profits. The literature [28], after excluding the influence for environmental factors and random factors, found that in 2004, the comprehensive technical efficiency of the cultural industry in my country's provinces and cities was generally at a low level, and the scale efficiency was relatively lower. Literature [29] considers the development level of the cultural industry in six provinces and cities in the central region from the perspective of input and output and uses the data analysis to comprehensively evaluate the efficiency of the cultural industry in this part of the region. Literature [30] uses DEA to conduct an empirical study of the efficiency of the cultural industry on the panel data. This study found the gap between the efficiency of cultural industry in the eastern region and the central and western regions is shrinking, but the pure technical efficiency of my country's cultural industry is still generally low [31].

3. Proposed Method

This paper presents a novel approach to industrial efficiency evaluation. The proposed method is suggested for cultural enterprises. The proposed method uses neural networks to evaluate the efficiency of cultural enterprises in cultural industries. The BP network is analyzed first, and then the GA-BP network is constructed by combining the genetic algorithm and the BP network. Because the genetic algorithm cannot memorize the performance of individuals in the population, this paper proposes an improved particle swarm algorithm to optimize the network and improves the particle swarm algorithm to obtain the IPSO-GA-BP hybrid algorithm [32].

3.1. BP Network. Figure 1 shows a typical BP structure; the general structure of BP can be seen from the figure: one input layer, several hidden layers, and one output layer.

BP is an application of multi-layer feedforward structure, which can propagate errors back from the output layer. BP network is a process of continuous learning internally, and the purpose of training is achieved by continuously adjusting the mapping relationship between input and output. But similarly, BP also has shortcomings such as long training time, weak global search ability, and easy to fall local minimums. The signal is attuned by the hidden layer neurons from the input layer the BP network and then to the output layer. At this time, if there is a certain gap between output value and ideal output, error signal is fed back to the front layer. The error signal is transferred backward step by step from output layer and finally returns to input layer through hidden layer. In the error backpropagation process, the ratio of the error generated by each layer to the total error is calculated, and then the value of the weight threshold of each layer is adjusted.

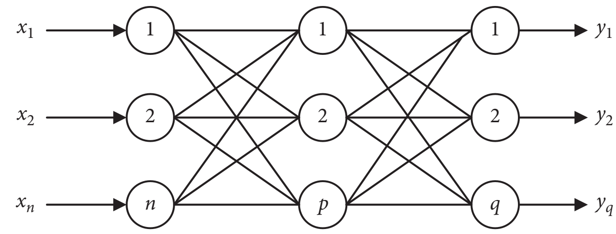

Figure 1: The structure of BP network.

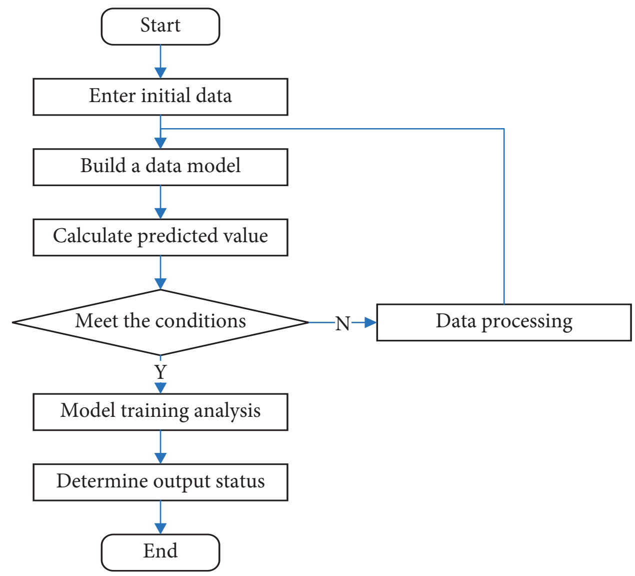

Figure 2: The process of BP network.

The process of realizing self-learning is the repeated process of the solid line and dotted line in the figure. When the final weight threshold is adjusted to the most appropriate value, the error between predicted value of BP network and actual output value reaches the specified preset value. Figure 2 shows a flowchart of the neural network, which assigns initial data to the network to establish a data model. By calculating the predicted value and comparing the predicted value with the actual value, it is judged whether the network accuracy meets the preset conditions. If it is satisfied, determine the output state and output the result. If it is not met, perform data processing and recalculate to give the predicted value until the output condition is met.

3.2. Improved BP Network Based on GA. The genetic algorithm operates on the samples in the entire interval and is not affected by the gradient, so it can realize global optimization. Because it can realize the full-area solution of nonlinear problems, genetic algorithms are chosen in many places in engineering. Examples include machine learning, image processing, economic analysis, pattern recognition, intelligent detection, big data analysis, and management science. The genetic algorithm can solve complex problems; at the same time, it can realize search and optimization in the whole domain. The workflow of the genetic algorithm is shown in Figure 3.

BP network is the most basic neural network model with a wide range of applications, but it still has defects when dealing with some specific problems in engineering. (1) The convergence speed is slow. When the error of the evaluation is relatively small or is close to the value of the objective function, the convergence speed of the neural network will be greatly reduced, and in some cases, the convergence will stop. (2) The global search ability is weak. The neural network can only solve the individuals in the local interval quickly. When training on the global scope, it often stagnates in the local extreme value, and the global search ability is poor. (3) The learning ability is weak. When processing fresh samples, the prediction of the result will have a large deviation, and the over-fitting will happen from time to time. With the development of intelligent algorithms, it has been added to the neural network to solve deficiencies of the BP network in processing data. The improved network can achieve very good results.

Optimization strategies based on genetic algorithms are divided into optimization steps and optimization processes. Before using genetic algorithm optimization, you need to encode the optimized object first. There are many coding schemes. After comprehensively considering factors such as operational difficulty, accuracy, and post-encoding effect, the scheme using real-number coding is determined. The selection of fitness function should be based on the solution of the objective function to be sought, and the relationship with multiple parameters can be considered comprehensively, such as the sample size, the number of training steps, the number of layers, and the number of neurons. When selecting genetic algorithm optimization, the fitness function value should be greater than or equal to zero. The core part of the genetic algorithm is to realize the selection, crossover, and mutation of the solution of the objective function. After the determination of each optimization scheme and the selection of optimization parameters is completed, the weights of the neural network are quickly optimized in the entire domain, which increases the solution speed and range of the original BP network. The optimization of the network mainly refers to the optimization of the connection weights between the neurons, and the process of optimization by the genetic algorithm can be expressed as follows. (1) Randomly generate n structures and encode each structure. (2) Each structure is assigned multiple initial weights. (3) Train the network to calculate fitness value for each time, and determine the best fitness value through comparison. (4) Excellent individuals show better adaptability during the solution process so that excellent individuals can be selected for the next step. (5) Perform genetic operations (crossover, mutation) on these selected individuals to generate new data groups. (6) Check whether the number of updates reaches the given value or whether the weight meets the accuracy requirements; if it is satisfied, output the result; if not, continue to return to the second step for iteration.

Since the neural network does not need to input the parameters of each layer for the first training sample, the model assigns its values, which will slow down the training speed. The input and output of neural networks are mostly nonlinear, so it is easy to fall to a local minimum during the training process and training is terminated early. The above-mentioned problems of the BP neural network can be improved by using the characteristics of a genetic algorithm to quickly optimize the whole domain. The specific operation process of the GA-BP network model is shown in Figure 4.

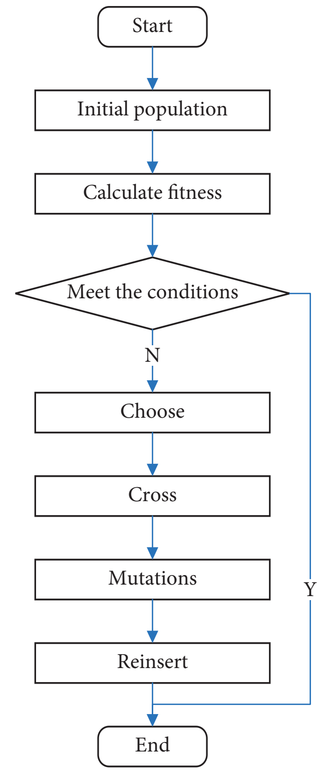

Figure 3: The workflow of genetic algorithm.

3.3. Improved BP Network Based on PSO. The particle swarm algorithm is proposed after being inspired by this group behavior of animals. Each individual in the population can be regarded as a candidate for the optimal solution. When the individual moves in a certain area of space, it can be regarded as the process of solving the objective function. Individuals feed back their own information to the surrounding group and then get optimized information from the group, gradually approaching the optimal search goal. In the process of optimization, the moving speed and position coordinates of each individual can represent the characteristics of the particles. The moving speed and position of the particles change with the optimal solution of the current group. After multiple information transmission and feedback, all particles gradually move closer to the optimal solution area, thus completing the search for the optimal solution.

PSO algorithm first generates a particle swarm, analyzes the particles in the particle swarm, and initializes each particle with the position and velocity of the particle as the characteristic parameter. In a D-dimensional search space, suppose there is such a particle population, the population

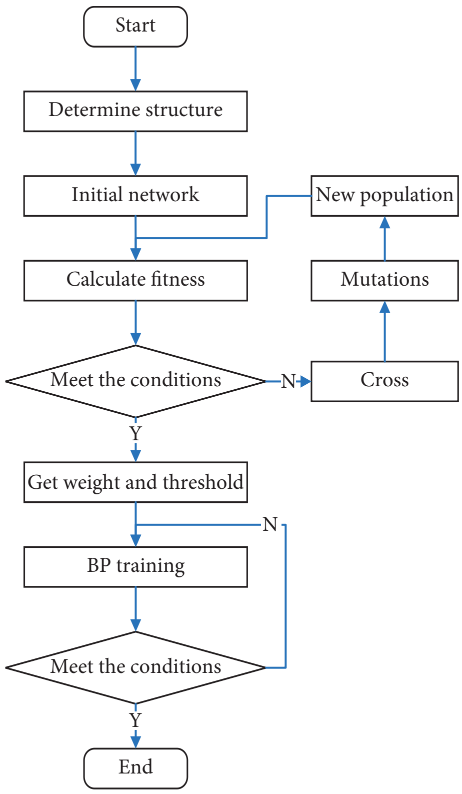

Figure 4: The workflow of GA-BP.

includes K particles, denoted as $y = [y_1, y_2, \ldots, y_K]$. Then, y_i represents the position of particle i, and v_i represents the flying speed of particle i. p_p is optimal position pbest when the position is updated last time, and p_g is optimal position gbest found by the entire particle swarm when position is updated last time. After pbest and gbest are searched, the speed and position of the particles are updated:

$$\begin{aligned} v_{id}(k+1) &= w v_{id}(k) + \alpha_1 \varepsilon_1 \left(p_{pd} - y_{id}(k)\right) \\ &\quad + \alpha_2 \varepsilon_2 \left(p_{gd} - y_{id}(k)\right), \\ y_{id}(k+1) &= y_{id}(k) + v_{id}(k+1), \end{aligned} \tag{1}$$

where w is inertia weight, k is the number of iterations, α_1 and α_2 are the learning factors, and ε_1 and ε_2 are constants.

The inertia weight in the PSO algorithm has a great impact on algorithm. In initial stage, due to the large number of samples, the inertia weight will increase the algorithm's global search and optimization ability. When it enters the middle and late stages, the range of the particle swarm is constantly shrinking. At this time, to speed up convergence speed, the inertia factor should be reduced, so the inertia factor should be adjusted as the algorithm progresses so that the algorithm can run better. Nowadays, the most used method is the linear decrement method, but this method also has many problems. For example, at the beginning, the algorithm quickly determines the range of the optimal solution. At this time, we hope to speed up the convergence rate, and we need to make the inertia weight factor smaller. However, since the linear weighting factor is linearly decreasing, this cannot achieve the purpose of fast optimization. In the middle and late stages, the inertia weight factor becomes smaller, which speeds up the convergence speed and also increases the risk of falling to a local minimum.

To solve this problem, this work uses an exponential function to modify the inertia weight so that the inertia weight decreases monotonically within a certain interval. In the early stage of the algorithm, the global optimization is based on the experience of each particle, and in the later stage of the algorithm, the information sharing between the particles is used to make the particles reach a new search space. On this basis, the compression factor λ is introduced. The compression factor can change the flight speed of the particles to the local or global optimal particles. This improves the convergence speed of the algorithm to a certain extent and at the same time makes the algorithm run more smoothly. The speed update formula is

$$\begin{aligned} v_{id}(k+1) &= \lambda v_{id}(k) + \lambda \alpha_1 \varepsilon_1 \left(p_{pd} - y_{id}(k)\right) \\ &\quad + \lambda \alpha_2 \varepsilon_2 \left(p_{gd} - y_{id}(k)\right), \\ \lambda &= \frac{2}{\left|2 - A - \sqrt{A(A-4)}\right|}, \\ A &= \alpha_1 + \alpha_2. \end{aligned} \tag{2}$$

In this paper, the exponential function and compression factor are combined to optimize the PSO algorithm. The algorithm not only has good convergence ability, but also avoids falling into the local optimum and effectively improves the lack of linear weights. The improved algorithm model is

$$\begin{aligned} v_{id}(k+1) &= \lambda w(k) v_{id}(k) + \lambda \alpha_1 \varepsilon_1 \left(p_{pd} - y_{id}(k)\right) \\ &\quad + \lambda \alpha_2 \varepsilon_2 \left(p_{gd} - y_{id}(k)\right), \\ w(k) &= \exp\left(\frac{-k}{M}\right), \end{aligned} \tag{3}$$

where M is the maximum training number.

The improved particle swarm algorithm improves the convergence ability of the basic particle swarm algorithm and the algorithm's global search and local optimization capabilities and has good operability. The main feature of the PSO algorithm is to perform calculations through the sharing of information resources among particle groups. It also has good performance in dealing with nonlinear problems. The advantage is that the algorithm is simple and easy to operate, and the algorithm needs to set fewer parameters. In the process of searching for the optimal solution, the iterative process can be controlled by the optimal individual in the group, and at the same time it has a certain memory performance. Although the genetic algorithm has a good global search ability, it needs to set many parameters and the operation is more complicated. This will reduce the convergence speed of the algorithm to a certain extent, and when the population changes, it has no memory function.

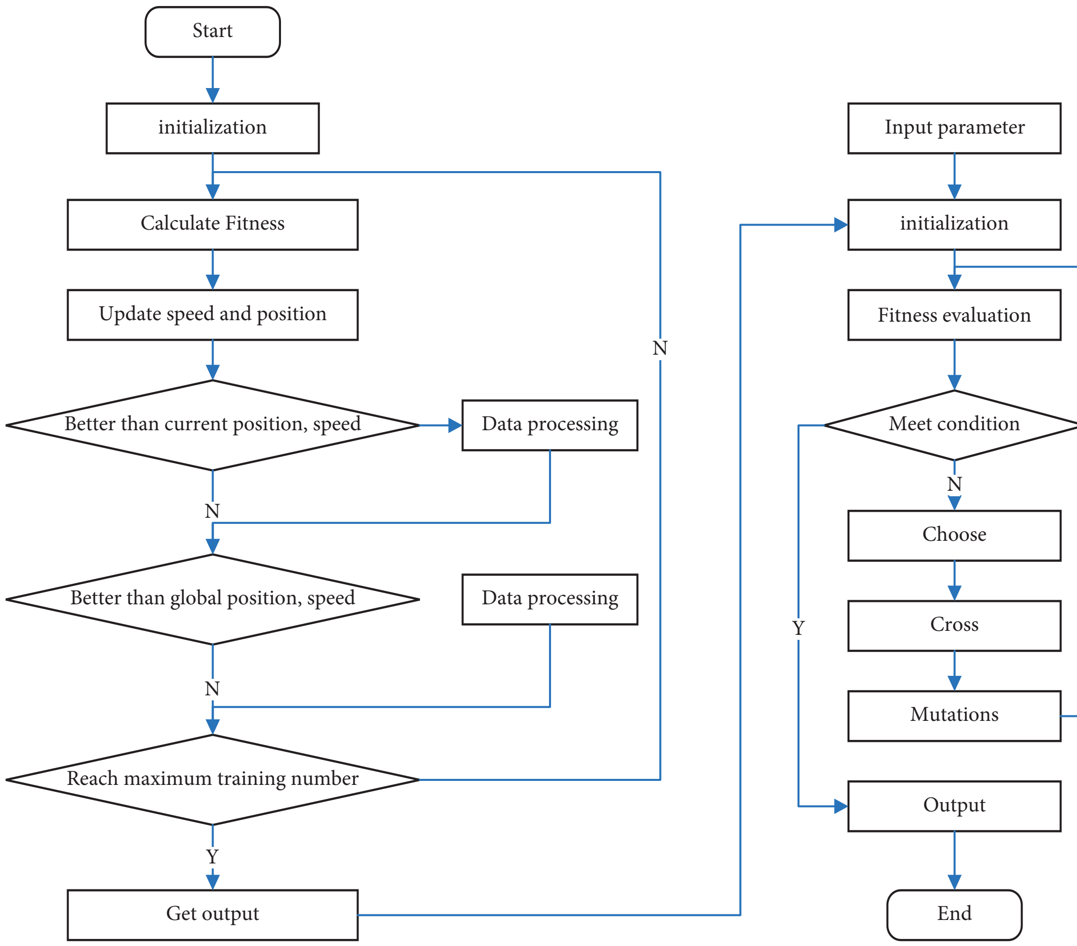

Figure 5: The workflow of IPSO-GA.

Therefore, it was decided to combine particle swarm algorithm with memory performance and genetic algorithm to obtain an improved hybrid algorithm. The flow of the IPSO-GA hybrid algorithm is shown in Figure 5. This paper also proposes a particle swarm algorithm with memory performance combined with genetic algorithm to optimize the BP neural network, establish an IPSO-GA-BP neural network model, and evaluate the cultural industry efficiency of cultural enterprises.

4. Experiment and Discussion

This section provides the results of the proposed improved model. These results will carry out experiments to verify the accuracy and efficiency of the proposed model. The CIE1 and CIE2 datasets are utilized for this research to show the applicability of the proposed research idea. The detail of the dataset is provided in the next section. The implementation is carried out using the Python programming language. The machine learning libraries are utilized to train the model.

4.1. Dataset. This work collects industrial efficiency data of cultural enterprises in two provinces and produces two datasets, namely, CIE1 and CIE2. CIE1 contains a total of 2874 pieces of data, of which 1653 pieces of data are training sets, and the remaining 1221 pieces of data are testing sets. CIE2 contains a total of 3619 pieces of data, of which 2285 pieces of data are training set, and the remaining 1334 pieces of data are testing set. The input features of each piece of data include 9 types of features, as shown in Table 1. The evaluation indicators are based on the confusion matrix. They include precision, recall, and F1-score.

Table 1: The input feature of the data.

Item	Feature
Number of employees	$X1$
Total corporate assets	$X2$
Enterprise investment in fixed assets	$X3$
Number of corporate cultural relics	$X4$
Corporate financial investment	$X5$
Paid-in capital of corporate culture industry	$X6$
Corporate culture market demand	$X7$
Value-added corporate culture industry	$X8$
Total income of corporate culture industry	$X9$

4.2. Evaluation on Network Training. The convergence of network training is the utmost significant indicator in NN. To evaluate whether the network converges, this work evaluates the loss and precision during network training. The results are illustrated in Figures 6 and 7.

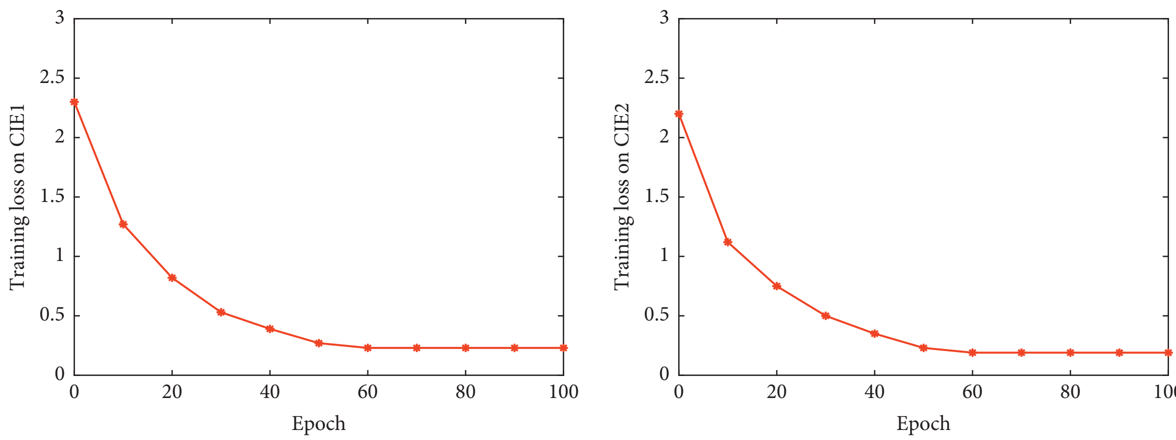

Figure 6: The training loss on CIE1 and CIE2.

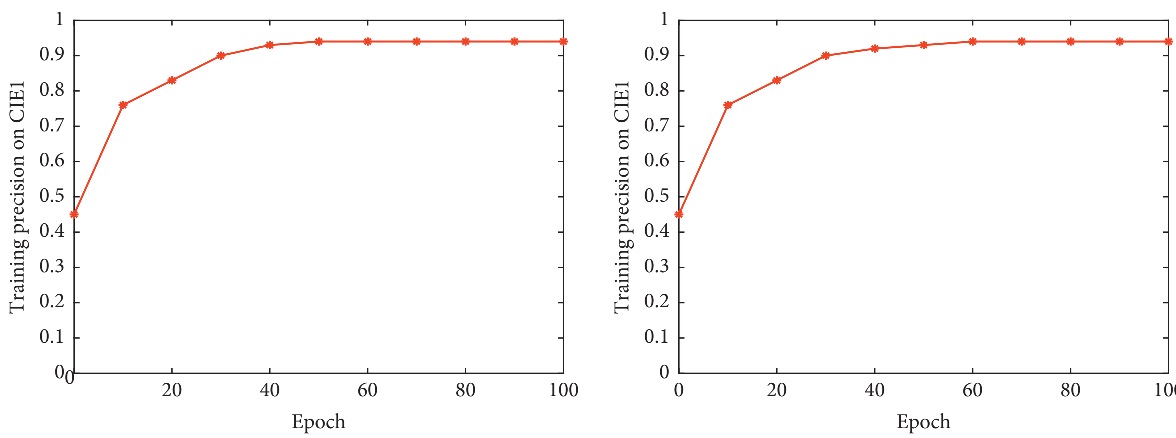

Figure 7: The training precision on CIE1 and CIE2.

Table 2: Comparison with other methods.

Method	CIE1			CIE2		
	Precision (P)	Recall (R)	$F1$-score	Precision (P)	Recall (R)	$F1$-score
Logistic	82.8	79.7	81.5	82.5	79.9	81.8
DT	85.4	81.5	83.4	85.8	82.9	83.5
AdaBoost	87.8	84.9	85.8	88.9	85.7	87.4
SVM	89.9	86.3	88.5	90.3	87.4	88.9
Ours	91.8	88.2	89.9	92.6	88.9	91.8

The loss of the designed network on the two datasets gradually decreases as the number of iterations increases, and the precision gradually increases. On the other hand, the loss no longer drops when there are 60 epochs, and the precision no lengthier rises. This shows that the network training at this time has reached a state of convergence, and it also shows our method can perform efficient fitting on the training set to achieve optimal performance.

4.3. Comparative Analysis. To prove the validity and correctness, the proposed work method is compared with existing models dealing. The techniques involved regression (logistic), (decision tree), SVM, and AdaBoost. The comparison is shown in Table 2.

From the statistical data in the table, the IPSO-GA-BP method designed in this paper can obtain the best performance and can perform the most efficient evaluation of the cultural industry efficiency of cultural enterprises. These data can prove the validity and reliability of our method. Figures 8–10 demonstrate the overall precision, recall, and F1-score.

4.4. Evaluation on Genetic Algorithm. The validation of the improved GA is also provided separately. The proposed research applies GA to BP network for improved results. The network performance is compared when the genetic algorithm is not used and used for optimization to validate the efficacy and reliability of proposed improved model. The result is illustrated in Figure 11.

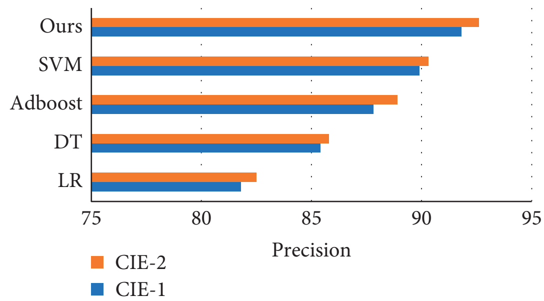

Figure 8: The precision on CIE1 and CIE2.

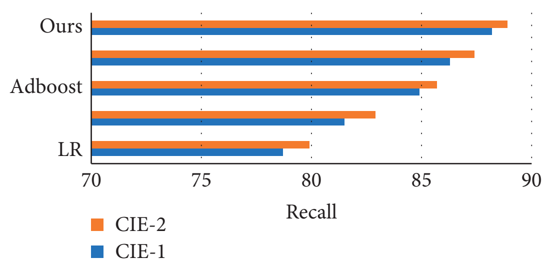

Figure 9: The recall on CIE1 and CIE2.

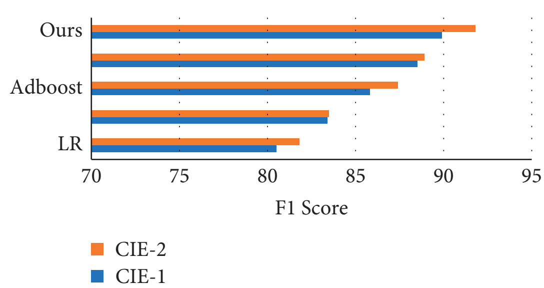

Figure 10: The F1-score on CIE1 and CIE2.

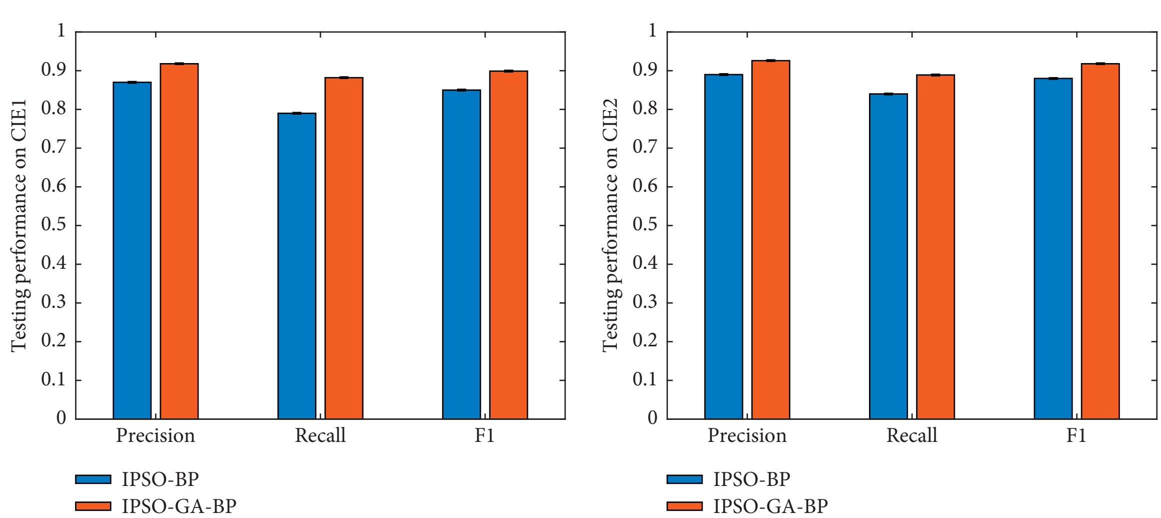

Figure 11: Evaluation of genetic algorithm.

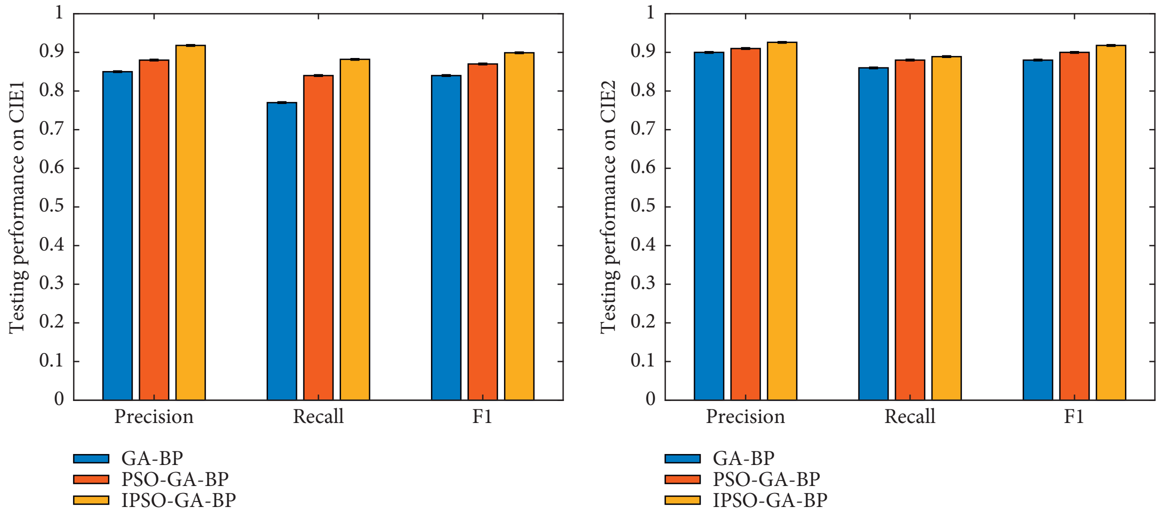

FIGURE 12: Evaluation of improved PSO.

TABLE 3: Evaluation on hidden layer.

Nodes	CIE1			CIE2		
	Precision	Recall	*F*1-score	Precision	Recall	*F*1-score
10	90.5	87.5	88.4	91.3	88.1	89.5
15	91.8	88.2	89.9	92.6	88.9	91.8
20	91.4	87.9	89.1	92.1	88.5	90.3
25	90.7	87.2	88.3	91.3	87.9	89.6
30	90.1	86.5	87.8	90.7	87.3	89.1

The performance of the network will decrease when the genetic algorithm is not used to optimize the BP network. On CIE1 dataset, the corresponding declines in the three performance indicators are 4.8%, 9.2%, and 4.9%. On CIE2 dataset, the corresponding declines in the three performance indicators are 3.6%, 4.9%, and 3.8%. This proves that the combination of genetic algorithm and BP network can effectively improve network performance and improve the accuracy of evaluation.

4.5. Evaluation on Improved PSO. The validation of the improved PSO is also provided separately. The proposed research applies improved PSO to BP network. This proposed improved PSO compares the network performance when PSO is not used. The network performance when PSO is not improved, with the network performance when PSO is improved for optimization. The result is illustrated in Figure 12.

Noticeably, the model performance is the lowest when PSO is not used to optimize the BP network. The PSO is used to improve the BP network, but this improvement is relatively limited. After improving the PSO, combine it with the GA to optimize the BP. These data verify the validity and reliability of the IPSO method designed in this paper.

4.6. Evaluation on Hidden Layer. The number of nodes in the hidden layer is variable in the BP network. It varies depending on the requirements in the BP network. To explore the influence of different hidden layer nodes on the network performance and mine the optimal hidden layer node parameters, this work conducts experiments on different hidden layer node numbers. The results are shown in Table 3.

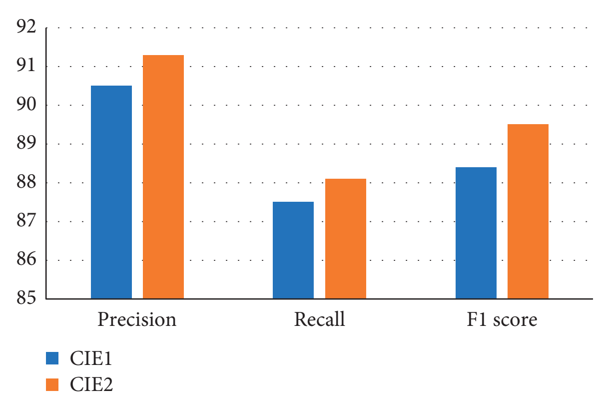

FIGURE 13: Precision, recall, and F1-score with 10 nodes.

It is not difficult to find that when the number of nodes in the hidden layer is 15, the performance of the network reaches the optimal state. And at the beginning, as the number of nodes increases, the performance of the model gradually rises. However, after a certain threshold is exceeded, as the number of nodes further increases, the performance of the network will gradually decrease instead. The precision, recall, and F1-score of the CIE-1 and CIE-2

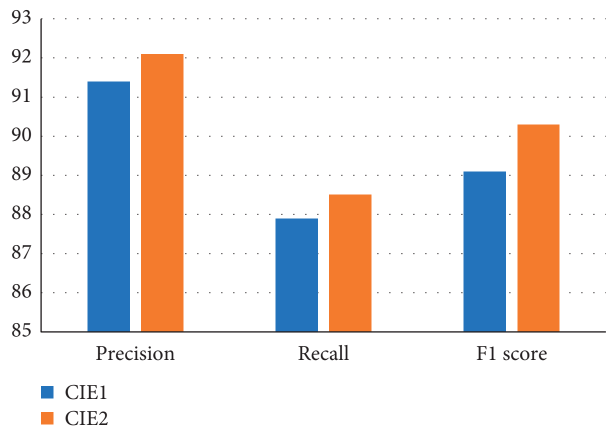

Figure 14: Precision, recall, and F1-score with 20 nodes.

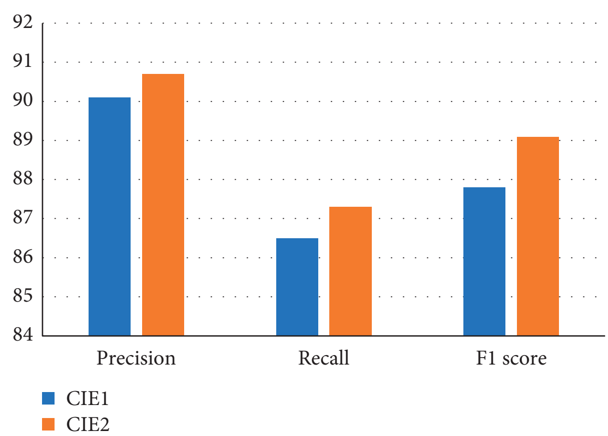

Figure 15: Precision, recall and F-1 with 30 nodes.

are also depicted in Figures 13–15 with respect to nodes 10, 20, and 30, respectively.

5. Conclusion

Vigorously developing the corporate cultural industry and attaching importance to improving the efficiency of the cultural enterprise industry is the development trend of the current era. The cultural enterprise industry has the characteristics of high value, green environmental protection, and low pollution. In this new era, the cultural industry, as an emerging industry, is actually a strategic emerging industry. The industry has gradually become a powerful booster for the country's sustained economic growth. However, there are few studies on the efficiency evaluation of cultural industries for cultural enterprises. The excellent performance of the neural network in evaluation makes it possible to evaluate the cultural industry efficiency of cultural enterprises. Considering that the BP neural network is easy to fall local smallness and often nonconvergence, this work proposes the use of the genetic algorithm to optimize the BP network. Although a genetic algorithm has a powerful global optimization, it needs to set many parameters and the operation is more complicated. This will reduce the convergence speed of the algorithm, and it does not have a memory function. Therefore, this work proposes a particle swarm algorithm with memory performance. PSO algorithm is mainly calculated through the sharing of information resources between particle groups. It also has good performance in dealing with nonlinear problems. In finding the optimal solution, the iterative process can be controlled by the optimal individual in the group. PSO is improved and combined with genetic algorithm to obtain an improved hybrid algorithm. Optimize the BP neural network, establish an IPSO-GA-BP network, and conduct a high-quality evaluation of the industrial efficiency of cultural enterprises.

Data Availability

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Xiaoyan Hao puts forward the conception and compilation of the paper, and all the work is completed by Xiaoyan Hao.

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