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Retraction

Retracted: Evaluation for Development Effect of Enterprise Innovation with Neural Network from Low-Carbon Economy

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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] S. Bai and S. Zhang, "Evaluation for Development Effect of Enterprise Innovation with Neural Network from Low-Carbon Economy," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1483665, 9 pages, 2022.

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Research Article

Evaluation for Development Effect of Enterprise Innovation with Neural Network from Low-Carbon Economy

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China has resolved to pay more and more attention to the sustainability of ecological construction and social development. The country has proposed a low-carbon economy policy; development and management of enterprises are also actively responding to the call for a low-carbon economy. Through a series of innovations and changes, it intends to realize its own low-carbon production and business development, thereby promoting transformation and optimization of industrial institutions. Innovation is a significant driving force of national economic development. In order to build China into an innovative country, there is a need of national innovation strategy and innovation system. The state vigorously promotes the implementation of innovation-driven development strategies. Enterprises are not only an important carrier for the state to implement mass entrepreneurship and innovation but also a powerful driving force for development of economy. There is a dire need and importance to identify techniques to evaluate impact of corporate innovation on development effects with low-carbon economy. Considering this aforementioned problem, random initialization parameters in back propagation network are used. This evaluation process can easily lead to the functioning of the model falling in the local optimum. The work designs an impact evaluation model (IGWO-BP) with improved gray wolf algorithm (IGWO) in order to optimize BP network. To improve optimization ability for GWO, the study uses the chaotic map to initialize the population. The nonlinear convergence factor strategy as well as dynamic weight strategy is used to promote GWO, so as to optimize initial weight as well as threshold point for the BP network. The IGWO-BP is applied to perform evaluation of the impact in case of enterprise innovation relevant to development effects with low-carbon economy.

1. Introduction

People must confront and seek chances for low-carbon growth in the face of the financial crisis as well as the climate and environmental crises. It will have a significant impact on all sectors of the economy, as well as society and business as a whole. Calling it a technical or industrial revolution is not overstating the case. As the low-carbon era dawns, corporate standards, such as value standards and evaluation systems, will undergo significant transformations. We urgently require the strong support of corporate strategy planning in the growing industrial revolution chances under the low-carbon economic growth model and therefore promote the economic development model from high-carbon economies to low-carbon economies. To achieve sustainable development and combine ecological and economic benefits, the low-carbon economy development model relies on energy conservation and consumption reduction. This concept can effectively regulate the behavior of various industries and enterprises. At present, with the rapid economic development, many enterprises will destroy the natural environment and increase the emission of pollutants as the price in order to obtain more benefits. In the long run, this approach will have all the harm and no benefit and will have a serious impact on the rational distribution of social resources. The application of concept for low-carbon economy as well as sustainable development can solve this problem, and severe penalties can be imposed on violations from the perspective of policy and law. With the implementation of the low-carbon economic model, enterprises are required to make continuous innovations in management models to better meet development needs of times [1–5].

At this stage, enterprises have become the backbone to support the sustained and stable growth of the national economy. While undertaking its due social responsibilities, one of the most important tasks of an enterprise is to obtain as much economic benefits as possible to maintain its own survival and development and give back to the society. Innovation plays an important role in this process. It introduces advanced equipment as well as technology to remove costs; it improves utilization rate and reduces investment. By continuously improving its own innovation and development capabilities, enterprises maintain their vitality and continue to grow. The innovation ability of an enterprise almost determines the development and even the survival of an enterprise [6–10].

The innovation model of the enterprise is also changing, from the closed innovation created by itself to the semiopen innovation of industry-university-research cooperation and then to the open innovation mode through the integration of internal and external resources of enterprise as well as collaboration. Enterprises are not only an important carrier for the country to implement mass entrepreneurship and innovation but also a powerful driving force for national economy and main body of market economy. Maintaining social harmony and stability, handling the problem of the unemployed people, fostering the continued and steady expansion of the national economy, and advancing science and technology are just some of the ways in which businesses play a vital role in our society today. It is critical to support and promote the long-term growth of businesses. Make full use of enterprise's accumulated data for many years to analyze, build its innovation and development capability index evaluation system, and the conclusion drawn through the evaluation model is bound to be more accurate and effective. According to the evaluation results, different development strategies are made for different enterprises, which is not only conducive to the growth of enterprises but also helps enterprises to improve their innovation and development capabilities. And it also has a very positive effect on economic development, effectively improving the level of innovation-driven upgrading and transformation of enterprises [11–15].

Climate change is one of the most threatening issues being apparent across the globe. The consequences of climate change are disastrous and are experienced in the form of storms, draughts, flooding, and similar calamities. These incidents have increased alarmingly in terms of its frequency and severity. But at the same time, the global energy transition is also evolving wherein a transition is being observed from the use of fossil fuels to low-carbon energy systems. AI and machine learning techniques especially neural networks have huge potential to stop the rise of global temperature by making enhanced predictions on the use of such enabling technologies. The use of neural networks has been predominant in transportation, civil architecture, government policies, and all sectors of human society. In case of electrical systems, neural networks are used to predict wind speeds, solar irradiance, and electrical demand. Smart meters use the technology to reduce optimized energy consumption. In case of autonomous vehicles, neural network is used to predict battery life and decide on the most appropriate time to recharge. The building in smart cities differs in terms of its design and construction. Neural networks help to come up with optimal decarbonisation strategies using smart controllers and also improve the electricity and temperature demands of specific buildings based on user needs. Neural networks also contribute in exploration of various climate policies and identify the best one for the decision-makers.

Various studies have been conducted using neural network implementations relevant to low-carbon economy. As an example, the study in [16] used statistical analysis techniques to understand the effects of various factors pertinent to carbon production in China. Also, a low-carbon economic neural network model was constructed in association with swarm optimization algorithm to study various aspects of carbon emissions. The study in [17] developed an index system for low-carbon-based sustainable development in urban environment using TOPSIS technique in association with neural network. The influencing factors were analyzed, and it was found that difference in low-carbon sustainable development has increased.

This work relies on the neural network, improves the BP network, and designs an evaluation model for evaluating the impact of enterprise innovation on the development effect from the perspective of low-carbon economy.

The present study uses an improved gray wolf optimization (IGWO) algorithm-based back propagation network to analyze the development effect of enterprise innovation from low-carbon economy. The traditional BP networks have been extremely successful in yielding accurate prediction results, and BP has been one of the most predominant approaches in artificial neural networks. But there exist issues in the way the BP algorithm finds solutions. The major drawback lies in being stuck in local minima rather than global one. The use of metaheuristic algorithm helps to resolve these issues. The unique contributions of the paper are as follows:

(i) Performing of a detailed study of various works done relevant to pollution reduction, low carbon emission, and related aspects

(ii) Determination of the most significant BP model parameters relevant to the area of study

(iii) Use of IGWO-BP algorithm to build an optimal model

(iv) Comparison of the model with traditional approaches based on precision and recall metrics

The rest of the paper is organized as follows. Section 2 reviews some of the recent studies related to pollution, emission, and related areas. Section 3 discusses the methodology in details followed by the experimental results in Section 4. Section 5 presents a consolidated conclusion of the paper.

2. Related Work

Practice has shown that economic growth and pollution reduction can be achieved at the same time, according to Reference [18]. There is a pressing need for new approaches to sustainable development in low-carbon industries, economies, and cities. Ultimately, climate change is not just an environmental issue, but increasingly an economic and financial issue, as well as a political one. Literature [19] pointed out that different countries have different studies and plans, and the target of 20% emission reduction by 2020 must be achieved. This requires more practical use of bioenergy and renewable energy. Literature [20] emphasizes that, to develop a low-carbon economy, first, government must be able to monitor the emission reduction. Government should release the signal of emission reduction targets in a timely manner, and the third is to deploy the international exchange of low-carbon technologies. Reference [21] pointed out that in order to reduce fossil fuel gas emissions, it is necessary to allow renewable energy to meet global energy demand and improve energy efficiency. Renewable energy technologies should be rapidly commercialized to play a greater role in reducing carbon dioxide emissions. Reference [22] considers it from the perspective of the consumption tendency of environmental services. Reference [23] showed an inverted U-shaped relationship between the total discharge of some environmental pollutants and the related long-term relationship of the factors involved. Environmental degradation, on the other hand, began to slow down or even disappear as people began to pay more attention to the preservation of the environment. From 1960 to 1999, literature [24] found that CO_2 emissions were linked to economic growth in an N shape rather than an inverted U shape. In the early stages of industrialization, according to literature [25], per capita CO_2 emissions will rise as the economy grows and per capita income rises. Per capita CO_2 emissions will become saturated at various levels after this point. Reference [26] conducted a long-term investigation of carbon dioxide, sulfur dioxide, and volatile organic compounds and verified the environmental Kuznets curve distribution.

Literature [18] found through data analysis and empirical research on OECD countries that R&D activities promote the growth of total factor productivity through independent innovation and technology transfer. Reference [19] focuses on investment and analyzes the promoting effect of R&D investment on total factor productivity. Reference [21] analyzes the differences in industrial green TFP due to the innovation impact of different behaviors caused by environmental regulation, and the main factor driving green productivity is invention patent innovation. Reference [27] uses innovation as an intermediary variable to study the long-term equilibrium relationship between urbanization and total factor productivity. Literature [28] found that the independent innovation generated by digestion and absorption has an obvious boosting effect on the development of productivity. Reference [29] designed an environmental innovation capability system evaluated by 22 indicators, using the set pair analysis method to conclude that the regional environmental innovation capability has a strong positive correlation with economic development. Reference [30] analyzed the connection and coupling coordination between regional innovation and economic development and found that the interaction between regional innovation and economic development has a high degree of coupling. Literature [31] believes that the optimization and upgrading of factor structure, industrial structure, and total social demand structure are the intermediary mechanism for independent innovation to promote the transformation of economic development mode. Literature [32] found that high-quality development is innovation-driven development by comparing the history of developed countries. To promote high-quality development, we must accelerate the transition from factor-driven development to innovation-driven development. Literature [33] believes that the improvement of the business environment can increase the enthusiasm of enterprises to invest in R&D. In a better business environment, the government will provide various favorable policies for enterprises, so as to reduce the constraints faced by enterprises in R&D investment and improve operability of enterprises in R&D investment. Reduce risk of conducting R&D activities. Reference [34, 35] carried out an econometric model analysis with financial data of listed companies. It is found that by promoting the market-oriented reform of the banking industry and regional financial development, the ability of enterprises to obtain credit has been improved, which has effectively promoted the investment of listed companies in innovation.

The study in [36] presented a multiobjective optimization algorithm which was adopted from the metaheuristic gray wolf optimization technique. The technique helped to generate Pareto-optimal solutions for reduction in carbon emission levels from hazardous pollutants.

The study in [37–39] proposed a fractional nonlinear gray Bernoulli model for predicting fuel combustions relevant to carbon emissions. The accuracy of the model is further enhanced using gray wolf optimizer which helps in searching the optimal emerging coefficients of the proposed model.

3. Method

The model involved in this chapter is an evaluation model for development effect with IGWO to optimize BP network. First, relevant strategies used to improve GWO are introduced. Next, build the IGWO-BP evaluation model. Finally, the performance of the IGWO-BP model is compared and analyzed by relevant experiments.

3.1. BP Network. BP network building, model training, and model prediction make up the method flow for nonlinear function fitting based on BP networks. There are multiple layers of feedforward neurons in the neural network. Because the error propagates backward, it is the primary advantage. The input information is processed layer by layer by the hidden layer nodes in the forward transmission of the signal until the neuron state of the output layer only impacts the state of the subsequent layer of neurons in the output layer. Transfer to the back propagation path if the predicted output is not achieved during the transfer process. Adjust network weights and thresholds based on prediction error. Consequently, the BP prediction model's output value is becoming increasingly near to the expected value. The topology of a typical BP network is illustrated in Figure 1.

It is the activation function's primary function to alter the linear relationship between earlier data. The multilayer network can be directly transformed into a one-layer neural network by matrix transformation if the network is all linear transformation. There are many advantages to having an activation function in a multilayer neural network. For one thing, it makes it easier to cope with complex and nonlinear input. The activation function also plays a vital role in normalizing complex data with a wide range. Usually, the input data is mapped to a fixed range and then passed down to prevent the risk of overflow caused by too large data range. Sigmoid has two main defects. One is that Sigmoid is easily oversaturated and loses gradients, resulting in the inability of training to achieve an ideal fit. It is challenging to match researchers' expectations for prediction accuracy and stability when the Sigmoid output mean is anything other than 0. When applied in practice, Tanh is more effective than Sigmoid since it is a deformation of the function, and its mean value is 0. Recently, the activation function ReLU has been widely used. The output is zero if the input signal is less than zero. As long as the input signal is larger than zero, the output will be equal to the input signal. As a result of ReLU's non-oversaturation and partial linearity, the stochastic gradient descent method developed by this method quickly converges. ReLU needs a threshold to output a specific activation and does not require particularly complex exponential operations, which reduces the difficulty of research. However, in the process of training, ReLU neurons are fragile and easy to lose their effect. If choosing ReLU as the activation function, you should start with a smaller learning rate when training the model.

Following are the steps in the BP network's training process. As a first step, the network is set up, with the number of nodes in each layer based on the system's input and output sequence. Then, the weight and threshold of the network's connections are set up, as well as the learning rate and neuron excitation function. Once these factors are taken into account, a hidden layer output is generated. The calculation method is

$$H_i = f\left(\sum w_{ij} x_i + a_i\right). \quad (1)$$

According to the output of hidden layer, connection weights and thresholds are calculated by the network to predict the output:

$$O_k = f\left(\sum w_{jk} H_j + b_k\right). \quad (2)$$

Calculate network error:

$$e_k = Y_k - O_k. \quad (3)$$

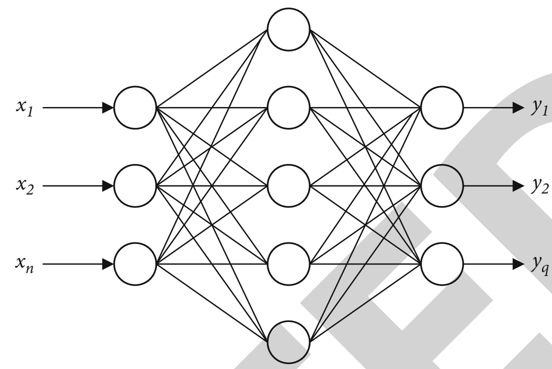

Figure 1: The BP network.

Based on the network error, update the weights and thresholds. Finally, it is judged whether the iteration of the step algorithm is over; if not, return to repeat the operation.

BP neural network has great advantages in dealing with nonlinear mapping ability, self-learning ability, and prediction ability, but it also has some associated shortcomings. To enlist a few of the same: (1) the BP network has local minimization problem. In the conventional BP network, it is easy to fall into local extreme values, resulting in network training failure. (2) The BP network's convergence rate is slow. As the gradient descent approach is used in BP network optimization, the optimization function is quite complex and susceptible to zigzags, which lowers network convergence efficiency. (3) The network structure selection criteria of BP network are not uniform. There is no unified and effective criterion for the structure selection of BP neural network. For the same case, designing different network structures usually produces different prediction effects. (4) There is contradiction between BP network training ability and prediction problem. In general, the higher the training ability, the higher the prediction accuracy, but when a limit value is reached, the improvement of the training ability cannot improve the prediction accuracy, and even the prediction ability will decrease.

3.2. Gray Wolf Optimization Algorithm. GWO is one of the swarm intelligence optimization algorithms, and the swarm intelligence optimization algorithm is derived from nature. Each individual in the swarm intelligence optimization algorithm has the same status; that is, their theoretical action mode is the same, and the influence is the same under the same conditions. Thanks to group cooperation, swarm intelligence algorithms have obvious advantages over individual algorithms and other algorithms, which are mainly reflected in four aspects. (1) The behavior of each individual has local characteristics, and it does not have the ability to solve non-globally. It can only explore its own vicinity, and the individual function is easy to realize. (2) When the algorithm is running, the failure of a local individual will not lead to the collapse of the entire system, and the overall function of the system can still be completed, with good robustness. (3) The individuals in the swarm intelligence algorithm are managed in a distributed manner and have good self-organization ability, and messages will be exchanged between individuals during group behavior. (4) Due to the independence of individuals, the increase or decrease of an individual will not have a serious impact on nearby individuals, and the adjustment of the number of individuals will not consume too much resources, which is conducive to changing the scale of the system. Benefiting from the above characteristics, the swarm intelligence algorithm can deal with most problems that can be solved in a distributed mode and achieve good results without systematically understanding the problem to be optimized.

The wolf group in the gray wolf algorithm has a strict hierarchical system. The gray wolf group is divided into four levels: α, β, δ, and ω according to the level. α wolf at the top of the pyramid is called the head wolf, leading the group of gray wolves. β wolf is a subordinate gray wolf who helps α wolf make decisions. δ wolf is called an ordinary wolf, following the instructions of α and β; it can also command other low-level wolves ω.

When hunting, α, β, and δ wolves lead the wolves, and their roles decrease in turn. ω wolves assist them in hunting, and the gray wolf algorithm simulates this relationship. For the optimization problem, if the size of the gray wolf population is N, the search space is d-dimensional, and x_i represents the position of a gray wolf individual in the search space. Calculate the solution value of the individual gray wolves in the group, and the wolf with the best solution value is regarded as the α wolf, followed by the β wolf, and then the δ wolf, and the remaining wolves are treated as the ω wolf.

After the rank is determined, the group of gray wolves begins to move, encircling the prey. The action of wolves to surround is

$$\begin{aligned} D &= \left| C X_p(t) - X(t) \right|, \\ X(t+1) &= X_p(t) - AD. \end{aligned} \tag{4}$$

According to the guidance of the alpha wolf, the gray wolf group moves towards the position of the prey and gradually completes the encirclement of the target. However, when solving the problem in practice, the position of the global optimal solution in the solution space is unknown and cannot be directly applied to the solution process, but the model can still be used to simulate the hunting of wolves. As can be seen from the previous description, the reason why α, β, and δ can become the leader wolves is that their position correspondence solution is better, which is equivalent to having better prey position information. Based on this premise, the three optimal solutions of α, β, and δ in the contemporary gray wolf group are preserved, and the remaining gray wolf individuals update their positions according to their information.

After the wolves have approached their prey, they make a final attack on the prey. The convergence factor becomes smaller as the iteration progresses, and the value range of the coefficient vector is also narrowed. When it is less than 1, the wolves tend to search locally and enter the state of attacking prey. The simulation of this process makes the gray wolf algorithm have excellent local search ability. According to the position and stage of α, β, and δ, the gray wolf group scattered to search for prey in a large range or called their companions to gather near the prey to attack. When the coefficient vector is greater than 1, the gray wolf tends to search for prey in a scattered manner, and the gray wolf algorithm has good global search ability.

The gray wolf optimization technique is much easier to implement due to its simple structure and less storage requirements. The convergence rate is much faster in comparison to the other approaches because there is continuous reduction in the search space. Also, the decision variables included in the approach are relatively lesser which makes computation faster avoiding local optima when being applied to composite functions.

3.3. BP Network with Improved GWO. In GWO algorithm, randomization of initial population individuals can easily lead to randomness of initial population; algorithm is easy to fall local optimum in later stage of iteration. The chaotic map can generate a relatively uniform initial population, so this chapter uses the two-dimensional chaotic map to initialize gray wolf population; its mathematical expression is

$$\begin{aligned} x_{n+1} &= a y_n^2 + b x_n + c, \\ y_{n+1} &= x_n. \end{aligned} \tag{5}$$

When $|A| > 1$, the group should conduct a large number of global searches; when $|A| < 1$, the group narrows search range to capture the prey. In the standard GWO algorithm, as the number of iterations increases, the convergence factor decreases from two to zero. Therefore, in order to balance local and global search, this chapter improves the linear convergence factor and proposes a nonlinear convergence factor strategy:

$$a = 2 - 2\left(2^{t/t_{\max}} - 1\right). \tag{6}$$

The original convergence factor drops linearly during the iterative phase, and the algorithm always maintains its global and local search capabilities during the optimization process. Nonlinearly decreasing convergence factor a and a decay rate that is relatively modest at the beginning of the iteration are favourable to a large-scale search for gray wolf populations. Increased convergence factor an attenuation and a narrower search range for gray wolf populations are used to improve algorithmic performance in later stages of the iteration. That is why we have made it easier for the gray wolf algorithm to better balance its local and global searching abilities.

In GWO algorithm, since α wolf is not always global optimal solution, in continuous iterative process, the ω wolf keeps approaching the three wolves. This makes it easier to get stuck in a local optimum during the solution process. Based on this, this chapter proposes a proportional weighting strategy based on position vectors. The proportion of the head wolf is continuously adjusted by the proportional weight, which improves the convergence speed and avoids falling local optimum. The weight ratio formula proposed in this paper is mathematically described as follows:

$$\sigma_1 = \left| X_\alpha - \frac{(X_\alpha + X_\beta + X_\delta)}{3} \right|,$$
$$\sigma_2 = \left| X_\beta - \frac{(X_\alpha + X_\beta + X_\delta)}{3} \right|,$$
$$\sigma_3 = \left| X_\delta - \frac{(X_\alpha + X_\beta + X_\delta)}{3} \right|, \quad (7)$$
$$W_1 = \frac{\sigma_1}{\sigma_1 + \sigma_2 + \sigma_3},$$
$$W_2 = \frac{\sigma_2}{\sigma_1 + \sigma_2 + \sigma_3},$$
$$W_3 = \frac{\sigma_3}{\sigma_1 + \sigma_2 + \sigma_3}.$$

In the optimization process of the standard GWO algorithm, using the same weight coefficient to update the position of the gray wolf can easily lead to the algorithm falling into a local optimum. The proportional weight of the proposed position vector is used to calculate the weight which changes continuously in each iteration of the algorithm. The gray wolf algorithm at the leadership level can thus dynamically guide the wolf group to move forward and avoid the algorithm from falling into a local optimum.

The IGWO-BP model uses the error sum function as the fitness function, and the error sum is calculated from the actual output and the predicted output, which is more convenient to calculate. Using the error sum function as the fitness function to optimize the BP network can obtain a better network model and reduce the amount of calculation, thereby improving the performance of the IGWO-BP model.

The central idea of using the IGWO algorithm to optimize the BP network is to find a set of gray wolf positions with the smallest error and function. At the end of training, this position is used as the optimal initial weight and threshold of the BP network to build a model, and the framework of the evaluation model based on IGWO-BP is shown in Figure 2.

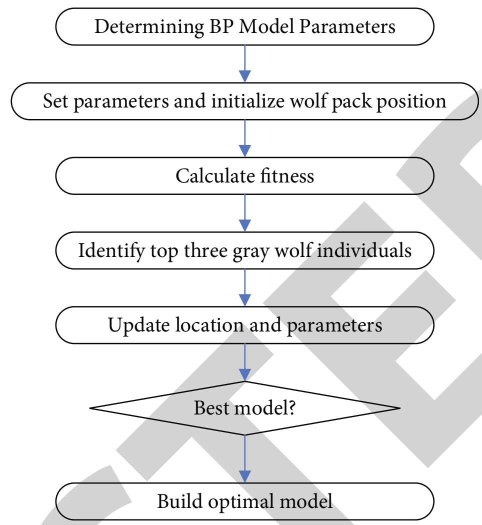

Figure 2: The pipeline of IGWO-BP.

4. Experiment and Discussion

4.1. Dataset. This work collects data related to enterprise innovation and development from the perspective of a low-carbon economy to complete the production of the dataset. The dataset contains a total of 17,394 samples, of which 12,983 samples form the training set and the remaining 4,411 samples form the test set. The input features of each sample are related innovation indicators. The specific information is shown in Table 1. The labels are the corresponding development status, which are divided into five different levels. This work adopts precision and recall as the evaluation metrics of the network.

Table 1: The detailed data information.

Index	Information
x_1	Technology research and development innovation
x_2	Product definition innovation
x_3	Product design innovation
x_4	Manufacturing innovation
x_5	Product marketing innovation
x_6	Sales execution innovation
x_7	Resource investment in innovation
x_8	Incentive mechanism innovation
x_9	Functional value innovation

4.2. Method Comparison. To verify the effectiveness of the method in this paper, comparison with other methods is indispensable. The comparison methods used in this work include decision tree, RBF, and SVM. The experimental results are shown in Table 2.

The IGWO-BP method proposed in this work can achieve the highest performance: 95.2% precision and 92.3% recall. Compared with the best performing methods in the table, 3.1% precision improvement and 2.0% recall improvement can also be obtained. This proves the effectiveness and feasibility of the method.

4.3. Evaluation on Chaos Map. The IGWO-BP algorithm uses the chaos map (CM) method to initialize the population. In order to verify the effectiveness of this strategy, a comparative experiment is carried out in this work. The experiment compares the network performance without CM and when CM is used, and the experimental results are illustrated in Figure 3.

Table 2: Result of method comparison.

Method	Precision	Recall
Decision tree	86.5	83.6
RBF	89.5	86.2
SVM	92.1	90.3
IGWO-BP	95.2	92.3

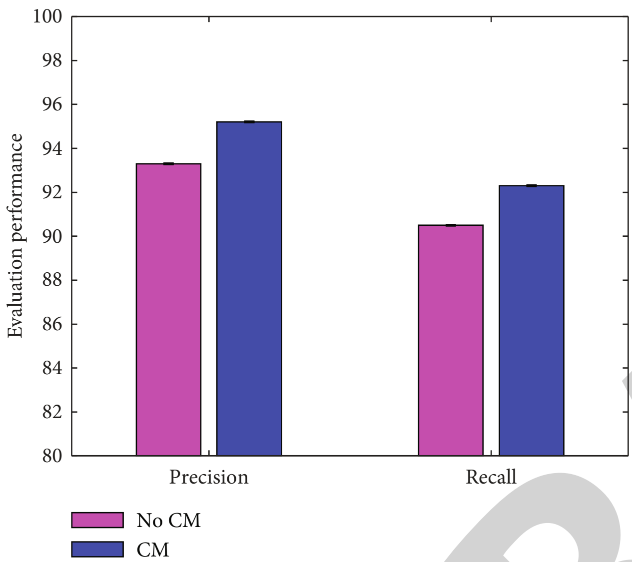

Figure 3: Evaluation on chaos map.

Compared with not using the CM strategy, after using this strategy, 1.9% precision improvement and 1.8% recall improvement can be obtained, respectively. This proves the effectiveness of the improved strategy.

4.4. Evaluation on Nonlinear Convergence Factor. The IGWO-BP algorithm uses the nonlinear convergence factor (NCF) method to enhance the search ability of the population. In order to verify the effectiveness of this strategy, a comparative experiment is carried out in this work. This experiment compares the network performance without and with NCF, respectively, and the experimental results are illustrated in Figure 4.

Compared with not using the NCF strategy, after using this strategy, 1.4% precision improvement and 1.3% recall improvement can be obtained, respectively. This proves the effectiveness of the improved strategy.

4.5. Evaluation on Dynamic Mutation. The IGWO-BP algorithm adopts the dynamic mutation strategy (DM) to improve the wild wolf algorithm. In order to verify the effectiveness of this strategy, a comparative experiment is carried out in this work. This experiment compares the network performance without DM and when DM is used, and the experimental results are illustrated in Figure 5.

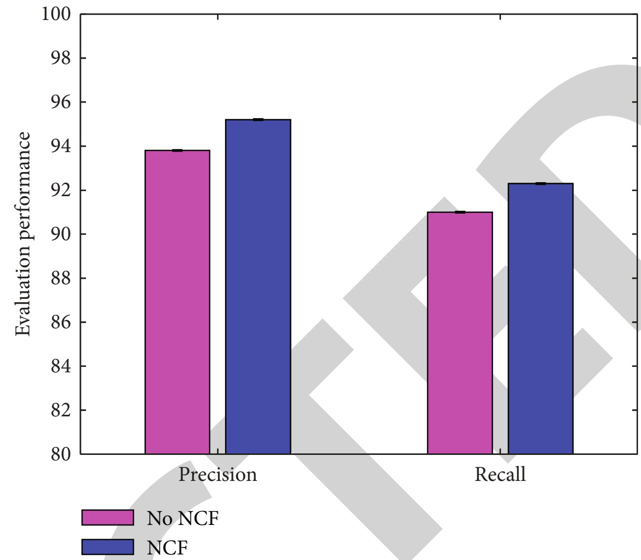

Figure 4: Evaluation on nonlinear convergence factor.

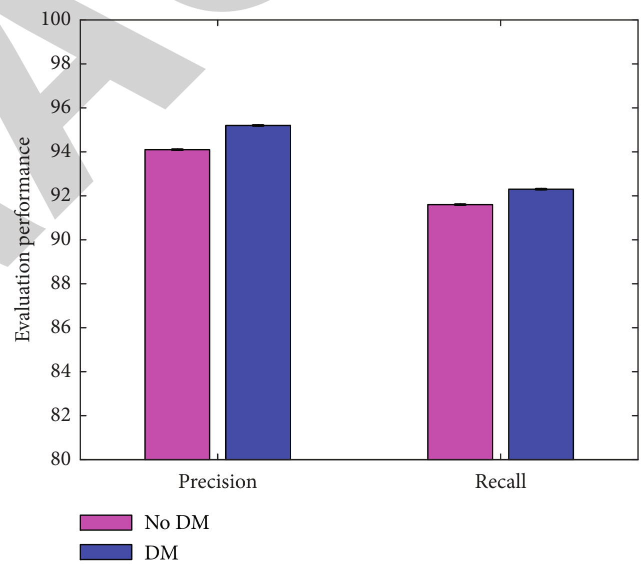

Figure 5: Evaluation on dynamic mutation.

Compared with not using the DM strategy, after using this strategy, 1.1% precision improvement and 0.7% recall improvement can be obtained, respectively. This proves the effectiveness of the improved strategy.

4.6. Evaluation on IGWO. The IGWO-BP algorithm adopts the IGWO to optimize BP network. To verify the effectiveness of these strategies, this work conducts comparative experiments. This experiment compares the performance of traditional BP network and IGWO-BP network, respectively, and the experimental results are illustrated in Figure 6.

Compared with not using the IGWO strategy, after using this strategy, 3.2% precision improvement and 2.1% recall

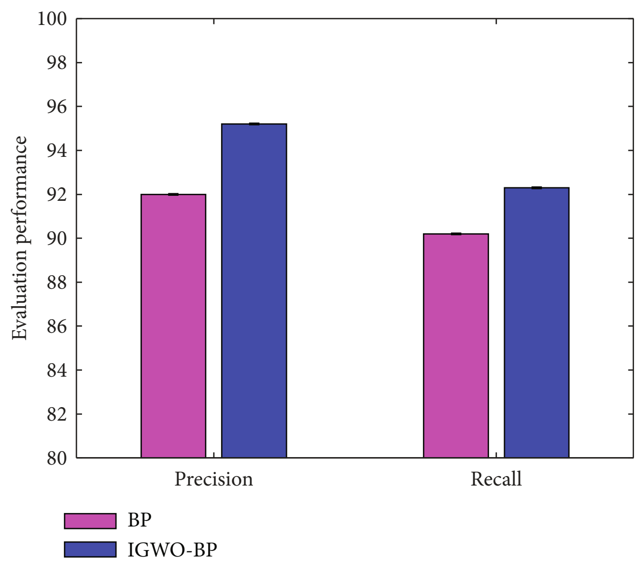

Figure 6: Evaluation on IGWO.

improvement can be obtained, respectively. This proves the effectiveness of the improved strategy.

5. Conclusion

China's economy has entered a new normal, and all walks of life have ushered in new development opportunities. The rapid development for enterprises has an important impact on development for national economy. Under low-carbon economic model, companies must make innovations and breakthroughs in their original development models if they want to gain more market share. Improving the independent innovation capability of enterprises is the key for China to realize the transformation from factor-driven to innovation-driven, to get rid of the low-end lock-in of the global value chain, and to become a powerful country. Actively promote corporate innovation and incorporate low-carbon concepts into corporate processes. It is helpful to promote the innovation of the enterprise's economic development model and the transformation and upgrading of the internal structure, so as to maximize the comprehensive benefit of the enterprise. Therefore, how to evaluate the impact of corporate innovation on development effects from the perspective of low-carbon economy has become an important topic. Relying on BP network, this work is committed to building an efficient effect evaluation network. To solve shortcomings of traditional BP network that initial value is relatively random, easy to fall local optimum, and training time is too long, this paper proposes an impact evaluation model with IGWO to optimize BP network (IGWO-BP). First, the improved gray wolf algorithm uses chaotic mapping to initialize the population, nonlinear convergence factor, and dynamic weight strategy to optimize BP network. Comprehensive and systematic experiments verify the validity and correctness of this work.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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