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Article

Exploration of Intelligent Optimization Algorithm for Risk Management in Green Financial Market Driven by Science and Technology Innovation

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Abstract: Green finance driven by science and technology innovation, as an innovative financial model, is facing problems such as weak risk management prediction ability while developing rapidly worldwide. Green finance driven by science and technology innovation, as an innovative financial model, is rapidly developing globally while it faces challenges such as insufficient incentive and constraint mechanisms and weak risk management prediction ability. Based on this, this paper introduces the IPSO-BP model for green finance market risk prediction model. The model uses BP neural network to process green financial market data, and introduces the IPSO algorithm to optimize the parameters of the BP network, aiming to enhance the model's prediction ability of green financial market risk. The results of the study on the actual dataset found that the prediction accuracy of the IPSO-BP model on the green financial market reached a maximum of 95.38%, and the absolute error of most of the prediction results is less than 0.06. Relying on the risk prediction results of the green financial market obtained by the IPSO-BP model, it can assist investors in choosing a more reasonable investment strategy, and ensure the stable operation of the green financial market at the same time, and enhance the risk control ability of investors. , and enhance the risk control ability of investors.

Keywords: BP neural network; IPSO algorithm; green financial market; risk prediction

1. Introductory

Under the background of the wave of informationization sweeping the world, the empowerment of science and technology has become the root of the strength of a country or region, and finance is the "blood" of the modern economy, which is also the strongest fulcrum of scientific and technological innovation [1-2]. As an important part of the modern economic system, the stability and healthy development of the financial market is of great significance to the sustained economic growth and social stability [3]. In the past thirty years, by the profound influence of economic globalization and financial integration, the global financial market has developed rapidly, while the volatility of the global financial market has become more and more intense, and enterprises, financial institutions, and ordinary investors are facing unprecedented financial risks [4-5]. The occurrence of financial risks not only seriously affects the normal operation of enterprises, financial institutions and the survival of individuals, but also causes serious harm to the health and stability of the national and even global financial markets and economy [6]. At present, financial institutions still have certain deficiencies in risk management, insufficient attention to risk management, imperfect risk prevention system, as well as risk management personnel's business ability to be further improved, are important factors affecting the efficient development of risk management [7-8].

Intelligent optimization algorithms usually refer to iterative stochastic black-box algorithms inspired by evolutionary laws and swarming behaviors in nature and human societies that are designed for solving static or dynamic optimization models containing elements such as decision vectors, objective vectors, and constraints [9-10]. Compared to deterministic traditional optimization algorithms, they are free from the reliance on mathematical assumptions such as differentiability in optimization models, have greater flexibility and usability, and are better able to achieve the trade-off between accuracy and speed in the optimization search process [11-12]. Intelligent optimization algorithms play an increasingly important role in financial markets. From asset allocation to risk management, from option pricing to model calibration, many financial mathematical problems can be effectively solved by intelligent optimization methods [13]. And it has become an urgent need in the current financial field to strengthen the risk management in financial markets and enhance the risk resistance of financial institutions.

In recent years, the development of intelligent optimization algorithms provides new ideas to quantify the risk of financial systems. Yang and Lee (2012) [14] proposed a multi-region particle swarm optimization algorithm to estimate the parameters of the Levy model by increasing the diversity of particles and verified the effectiveness of this algorithm in risk management through the effect of option pricing. Sawik (2012) [15] described a three-objective optimization model for hybrid planning, which uses the expected worst return as a risk measure to optimize the portfolio return through a multi-objective portfolio model, through which the decision maker can effectively assess the return value and risk level of the portfolio. Pavao et al. (2017) [16] applied five financial risk indicators for risk management, and used an intelligent optimization algorithm to solve the two objective functions that Maximize the effect of financial risk avoidance, and successfully provide adapted investment solutions for different types of investors. Srinivasan and Kamalakannan (2018) [17] analyzed a large amount of financial data by using a multi-objective genetic optimization algorithm, and the memory component introduced in the algorithm for preserving the rules implements the financial data memory function, which provides a prediction of credit cards and credit applications with lower-risk and more scientific decision-making. Soui et al. (2019) [18] transformed credit risk assessment of financial institutions into a search-based optimization problem, and used multiple intelligent optimization algorithms to generate classification rules for credit score-first assessment, among which the search and multi-objective particle swarm optimization algorithms showed the best combined performance and improved the accuracy of credit risk assessment. Shen et al. (2020) [19] optimized the credit scoring model of financial institutions from the perspective of cost sensitivity, and the core intelligent optimization algorithm used was the multi-objective particle swarm algorithm, and the optimized model could effectively reduce the error rate and classification cost, and achieve accurate credit risk assessment. Leonel et al. (2021) [20] mined the financial information of the water conservancy generator market and proposed the stochastic optimization that incorporates the financial information model, which determines the weight values of random variables through the utility function of risk indicators, and the application practice shows that the optimization model reduces the risk level of the relevant industry and optimizes the financial risk control. Wang et al. (2022) [21], in order to minimize the default risk of credit portfolios, used a bivariate intensity model to represent the default correlation and default intensity of credit portfolios, and combined with the multi-objective genetic algorithm to optimize the credit portfolio, and the algorithm has great application prospects in credit risk management. Qu (2023) [22] constructed a financial credit risk assessment model based on an intelligent optimization algorithm to analyze the credit risk of financial data in order to reduce the default rate of financial institutions, and then to improve their ability to control and manage the risk in the financial market.

The article establishes an IPSO-BP model for green financial market risk prediction based on BP neural network and PSO algorithm optimized with various improvement strategies. The model uses BP neural network to capture the time-series characteristics of green financial market risk data, and optimizes the parameters of the BP model using the IPSO algorithm, which provides a new research perspective for accurately predicting green financial market risk.

2. Risk Management Modeling for Green Financial Markets

At present, coping with global climate change is a common challenge faced by all countries in the world, and it has become a global consensus to promote the low-carbon and green transformation of the economic and social development mode. Science and technology innovation is used as the basic driving force to promote the high-quality development of the green financial market. However, things always move forward on a winding road, and green finance is no exception. The impact of the external environment and the lack of internal incentives may cause the green financial market to generate greater risks, thus affecting the high-quality development of the global green economy. For this reason, there is an urgent need to establish a model for risk management in green finance markets, with the aim of accurately grasping the risks in green finance markets.

2.1. BP neural network model

2.1.1. Neural model structure

Neural networks can be categorized into supervised learning neural networks and unsupervised learning neural networks according to supervised or unsupervised learning. In this paper, BP neural network is chosen for the green financial market risk management prediction model, which belongs to the unsupervised learning neural network. BP neural network is a feed-forward neural network using the BP algorithm. The BP algorithm has no need for mathematical equations of input and output quantities and can learn the mapping relationship between them. Its usual learning method is the most rapid descent method, which consists of forward information propagation and error back propagation [23].

A typical BP neural network model usually consists of an input layer, a hidden layer, and an output layer. The number of nodes in the input and output layers is determined by the system constructed for the problem under study, and the number of nodes has to be determined by empirical methods combined with practical simulation experiments. The BP neural network works by inputting a set of vectors of only one size into the network, and the neurons are stimulated to pass the signals to the intermediate implicit layer, and then to the output layer, which carries out the output data. The system passes backwards and forwards through the error between the system's output data and the desired output data, constantly adjusting the weights and thresholds between the relationships of the layers in the process. This process is constantly cycling back and forth, the way the error between the output of the system and the ideal output value reaches the range specified by human, then stop the process of algorithm learning.

2.1.2. Model learning process

The BP neural network is trained by a supervised learning training approach for it as follows:

(1) The initial value of the weights $w_i(0)$ is usually randomly initialized to a small non-zero number to break the symmetry and contribute to the convergence of the network training.

(2) Calculate the actual output through the network given a reference input signal. Set the parameters of each layer of the network: $x_i(n)$ denotes the input layer node, c denotes the implicit layer node is, $y_l(n)$ denotes the output layer node is, $w_{ji}^{(1)}$ denotes the connection weights between the input layer and the implicit layer, and $w_{ij}^{(2)}$ is the connection weights between the implicit layer and the output layer, and the output of the implicit layer of the network when given the reference input signal $x_i(n)$ is:

$$o_j(n) = f\left(\sum_{i=0}^{n} w_{ji}^{(1)} x_i - \theta_j\right) = f\left(net_j\right) \tag{1}$$

The output of the output layer node is:

$$y_l(n) = f\left(\sum_{j=0}^{n} w_{lj}^{(2)} x_i - \theta_l\right) = f\left(net_l\right) \tag{2}$$

(3) Calculate the loss function. Assuming that the reference signal is tl at the output, let E_P be the loss function, so that:

$$E_P = \frac{1}{2}\sum_{l}\left(t_l - y_l\right)^2 \tag{3}$$

(4) When the loss function reaches the preset condition, the training is terminated; otherwise, the connection weights of each layer are updated sequentially from the output layer to the input layer in the direction of the error gradient, so as to continuously reduce the overall error of the network.

Firstly, the partial derivatives of the loss function E_P and the connection weights of each node in the output layer are calculated, i.e:

$$\frac{\partial E}{\partial w_{ij}^{(2)}}=\sum_{k=1}^{L}\frac{\partial E}{\partial y_k}*\frac{\partial y_k}{\partial w_{lj}^{(2)}}=\frac{\partial E}{\partial y_l}*\frac{\partial y_l}{\partial w_{lj}^{(2)}} \tag{4}$$

where:

$$\frac{\partial E}{\partial y_l}=\frac{1}{2}\sum_k\left[-2\left(t_k-y_k\right)\right]*\frac{\partial y_k}{\partial y_l}=-\left(t_l-y_l\right) \tag{5}$$

$$\frac{\partial y_l}{\partial w_b^{(2)}}=\frac{\partial y_l}{\partial net_l}*\frac{\partial net_l}{\partial w_b^{(2)}}=f'\left(net_l\right)*y_j \tag{6}$$

Then the simplified equation can be obtained as:

$$\frac{\partial E}{\partial w_{ij}^{(2)}}=-\left(t_l-y_l\right)*f'\left(net_l\right)*y_j \tag{7}$$

The partial derivatives of the error function E_P with respect to the connection rights of the nodes of the implicit layer are then computed as:

$$\frac{\partial E}{\partial w_{ji}^{(1)}}=\sum_i\sum_j\frac{\partial E}{\partial y_l}*\frac{\partial y_l}{\partial o_j}*\frac{\partial o_j}{\partial w_{ji}^{(1)}} \tag{8}$$

where:

$$\frac{\partial E}{\partial y_l}=\frac{1}{2}\sum_k\left[-2\left(t_k-y_k\right)\right]*\frac{\partial y_k}{\partial y_l}=-\left(t_l-y_l\right) \tag{9}$$

$$\frac{\partial y_l}{\partial o_j}=\frac{\partial y_l}{\partial net_l}*\frac{\partial net_l}{\partial o_j}=f'\left(net_l\right)*\partial w_{lj}^{(2)} \tag{10}$$

$$\frac{\partial o_j}{\partial w_{ji}^{(1)}}=\frac{\partial o_j}{\partial net_j}*\frac{\partial net_j}{\partial w_{ji}^{(1)}}=f'\left(net_j\right)*x_i \tag{11}$$

Then the simplified formula can be obtained as:

$$\frac{\partial E}{\partial w_{jl}^{(1)}}=-\sum_1\delta_1*w_{bj}^{(2)}*f'\left(net_j\right)*x_i=-\delta_j{}'*x_i \tag{12}$$

which, for the sake of simplification, makes:

$$\delta_1=\left(t_1-y_1\right)*f'\left(net_q\right)\cdot \tag{13}$$

$$\delta_j{}'=f'\left(net_j\right)*\sum_1\delta_1 w_{1j}^{(2)} \tag{14}$$

(5) Finally, the connection weights between the input layer, the implicit layer and the output layer are updated. According to the principle of gradient descent, the adjustment of connection weights is carried out according to the learning rate η. Finally, the connection weights of the nodes in the output layer will be updated as:

$$w_{lj}^{(2)}(k+1) = w_{lj}^{(2)}(k) + \Delta w_{lj}^{(2)} = w_{lj}^{(2)}(k) + \eta\delta_1 o_i \tag{15}$$

The implicit layer node connection weights are updated as:

$$w_{jl}^{(l)}(k+1) = w_{jl}^{(l)}(k) + \Delta w_{jl}^{(l)} = w_{ji}^{(2)}(k) + \eta'\delta_j' x_i \tag{16}$$

(6) Let $k = k+1$, and continue the computation from (2) until the loss function E_P is less than the set threshold, determine the training convergence and terminate the iteration.

2.2. Improvement of PSO optimization algorithm

2.2.1. Fundamentals of the PSO algorithm

Particle Swarm Optimization (PSO) algorithm is one of the many optimization algorithms currently available, which is designed to simulate bird feeding, mainly by defining a piece of food (i.e., the optimal solution of the optimization objective) in a given area, and letting the birds search for it, and report their positions through information exchange and so on [24]. Thus, it determines whether the optimal solution is found or not, and finally all birds arrive at the optimal solution, i.e., the optimization search is completed.

The theoretical explanation of PSO algorithm is mainly divided into the following steps:

(1) Initialize all particles, i.e., assign values to their speed and position, and set the historical optimal Best1 of an individual as the current position, and the optimal individual in the group as the current Best2.

(2) Calculate the fitness function value of each particle in each generation of evolution.

(3) If the current fitness function value is better than the historical optimum, update Best1.

(4) If the current fitness function value is better than the global historical optimum, update Best2.

(5) For each particle i, the velocity and position in the d-th dimension are updated according to the following equations, respectively, i.e:

$$V_i^d = wv_i^d + c_1 rand_1^d \left(Best1_i^d - x_i^d\right) + c_2 rand_2^d \left(Best2^d - x_i^d\right) \tag{17}$$

$$x_i^d = x_i^d + v_i^d \tag{18}$$

where V_i^d denotes the d-th dimensional velocity of the i-th particle, w denotes the inertia weight, c_1, c_2 denotes the acceleration coefficient, $rand_1^d$ and $rand_2^d$ denote the random number of $[0,1]$, and x_i^d denotes the d-th dimensional position of the i-th particle.

2.2.2. Improvement of the PSO algorithm

The optimization seeking performance of traditional PSO algorithms relies heavily on the setting of their inertia parameters, learning factors. The initial particles often ignore the differences between particles of different generations when the spatial position and velocity are updated during each iteration. To address this problem, the paper constrains the above parameters and adopts a linearly decreasing parameter setting method to improve the traditional PSO algorithm. Firstly, a larger inertia parameter and learning factor are set to start the algorithm iteration, then the parameters are adjusted in real time during each iteration, and finally a smaller inertia parameter and learning factor are used to end the iteration process. This method can effectively improve the global optimization ability of the initial particle swarm and prompt the particle swarm to jump out of the local optimal solution, and the specific update rules of the parameters are as follows:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} \cdot t \tag{19}$$

$$c_1 = c_2 = c_{\max} - \frac{c_{\max} - c_{\min}}{t_{\max}} \cdot t \tag{20}$$

where the values of $\omega_{\max}, \omega_{\min}$ are 0.8 and 0.6 and the values of $c_{\max}, c_{\min}$ are 1.5 and 1.2, respectively.

In addition, during the solution process of PSO algorithm, the history of search particles with the global optimum particles will be constantly updated and guide the rest of search particles to fly to the optimal position, so as to achieve the effect of convergence of the algorithm. However, the rapid aggregation of search particles will lead to the emergence of more proximity invalid solutions, and it is easy to make the algorithm fall into the local optimum. Therefore, the adaptive operator is introduced to set the particle optimization strategy, when the particles satisfy the position update condition of equation (22), the position transformation can be based on (23) for optimization. The specific strategy is as follows:

$$e = \begin{cases} L_{i,j} \times rand(-0.5, 0.5), L_{i,\text{gbest}} \geq e^{-k/k_{\max}} \\ L_{i,j} \times rand(-0.2, 0.2), L_{i,\text{gbest}} < e^{-k/k_{\max}} \end{cases} \tag{21}$$

$$\begin{cases} \dfrac{L_{i,j}}{L_{i,\text{gbest}}} < Q \\ Q = Q_0 \left(1 - \dfrac{k}{k_{\max}}\right) \end{cases} \tag{22}$$

$$x_i(k+1) = \frac{k}{k_{\max}} x_i(k) + e\left(1 - \frac{k}{k_{\max}}\right) x_i(k) \tag{23}$$

Where e is the adaptive operator, $rand(\cdot)$ is the random number function, $e^{-k/k_{\max}}$ is the adaptive threshold, $L_{i,j}$ is the Euclidean distance between particle i and the nearest particle j in the D-dimensional space constituted by the objective function, $L_{i,\text{gbest}}$ is the Euclidean distance between particle i and the optimal particle of the population, and Q is the optimality-seeking decision threshold.

Reverse learning is a method of finding the inverse solution of the current global optimal solution and selecting a more appropriate optimal solution through evaluation. The expression of introducing backward learning into the PSO algorithm is as follows:

$$G_{best,id}^{*k} = ub + r_3 \oplus \left(lb - G_{best,id}^{k}\right) \tag{24}$$

$$G_{new,id}^{k+1} = G_{best,id}^{*k} + b_1 \oplus \left(G_{best,id}^{k} - G_{best,id}^{*k}\right) \tag{25}$$

$$b_1 = (1 - k / \max gen)^k \tag{26}$$

where $G_{best,id}^{*k}$ is the inverse solution of the k-th generation optimal solution of the particle, ub and lb are the upper and lower bounds of the particle, respectively, and b_1 is the information exchange parameter.

Since the Cauchy stepwise density function is longer at both ends, it is easier to jump out of the local optimum. Therefore, in this paper, the Cauchy variation is chosen to improve the global convergence of the algorithm. The expression of the Cauchy variation is as follows:

$$G_{new,id}^{k+1} = G_{best,id}^{k} \times (1 + 0.3 * cauchy(0,1)) \tag{27}$$

$$cauchy(0,1) = \tan\left(r_4 - 0.5\right)\pi \tag{28}$$

In order to improve the algorithm's optimization seeking performance, the backward learning and the Cauchy variation are executed alternately with a certain probability P_s .

2.3. Risk management modeling

2.3.1. Data collection and processing

This paper selects the relevant data of Chinese A-share listed companies in Shanghai and Shenzhen from 2015 to 2023 as the research sample, and takes the introduction of the green financial reform and innovation pilot zone policy in 2017 as a quasi-natural experiment, and for the convenience of empirical research, the samples are treated as follows:

(1) Excluding the companies of ST, *ST, and PT in the sample, because the delisting risk of these companies is relatively high and the quality of their related financial information is poor.

(2) Excluding companies with too many missing values in the main data and linearly interpolating the few missing values of the main variables.

(3) Exclude companies listed after the policy year 2017, as these companies are not comparable before and after the policy.

(4) Extreme values and outliers are excluded and all continuous variables are shrink-tailed up and down by 1%.

The treatment finally yields 11,220 annual observations for 1024 listed companies, including 457 heavy polluters and a total of 567 green companies.

From the experimental data, 100 sets of data are selected for model training and 20 sets of data are used for model validation. Due to the large gap in data magnitude and value range, the data were normalized and disposed of in order to reduce their impact on data analysis, i.e:

$$X_n' = \frac{X_n - X_{\min}}{X_{\max} - X_{\min}} \tag{29}$$

Where X_n' is the output data after normalization process, $X_{\min}$ is the minimum value of data in the same variable and $X_{\max}$ is the maximum value of data in the same variable.

2.3.2. Modeling Process

BP neural network in the pattern recognition, classification, prediction and other aspects of the performance is more prominent, but its own existence of some defects and shortcomings, including the number of neurons and the learning rate need to be set by artificial experience, the stability of the model is poor. The training speed is slower, the convergence time is longer, and the phenomenon of local minima is prone to occur. To address such deficiencies, the BP neural network is improved using the Improved PSO algorithm (IPSO) to ensure that the prediction model has a good global search capability and convergence speed. The IPSO-BP neural network prediction model is shown in Fig. 1, with the dashed area as the part of the IPSO algorithm.

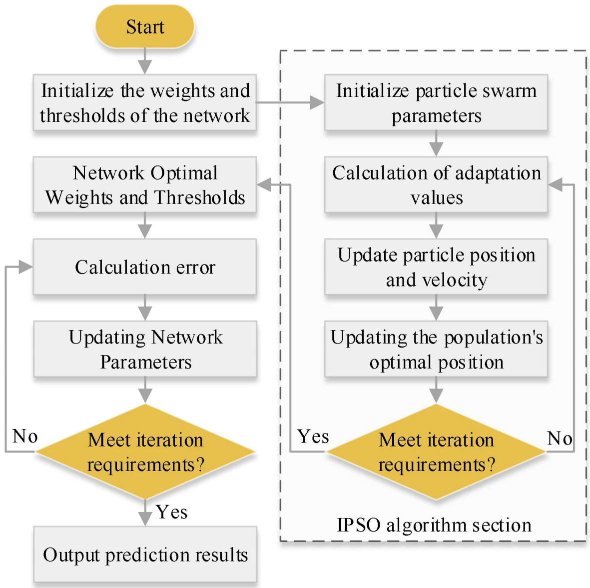


Figure 1. The IPSO-BP neural network prediction model

The steps of IPSO-BP neural network are as follows:

(1) Initialization operations are performed on the parameters such as weights and thresholds of the BP neural network.

(2) Initialize the parameters of the IPSO algorithm for initialization, including the velocity and position of the particles, inertia weights, and acceleration constants.

(3) Calculate the fitness of each particle in the population, and continuously update the position and velocity of the particle according to the fitness value, and obtain the optimal position of the population. The algorithm is terminated when the maximum iteration requirement is met, and the result is the optimal solution of the network weights and thresholds, which can be updated accordingly. Conversely, the optimization search continues until the requirements are met.

(4) Calculate the error between the output value of the prediction model and the actual value, and update the parameters of the network accordingly until the error meets the prediction requirements.

(5) Continuously iterate, and when the maximum number of iterations is reached, the model outputs the final prediction results.

3. Optimization Analysis of Risk Management in Green Financial Market

The industrial revolution, while promoting scientific and technological progress and raising productivity levels, also led to the growing contradiction between economic development and the ecological environment. Green finance is an important mechanism for environmental governance and a key hand in realizing the goal of carbon neutrality. How to effectively improve the risk management ability and forecasting ability of green finance market has become an important thesis to further promote the high-quality development of green finance.

3.1. Performance Analysis of IPSO Algorithm

3.1.1. Benchmark function testing

The purpose of introducing the IPSO algorithm in this paper is to better obtain the parameters of the BP neural network model, so that it can get more accurate results when performing risk management prediction in the green financial market. In order to test the performance of IPSO algorithm, three kinds of single-peak (FUN1~FUN3) and multi-peak (FUN4~FUN6) test functions are selected for validation in this paper to verify the convergence accuracy of the algorithm as well as the convergence speed through the test functions. Among them, the single-peak function has only one extreme point in the search range, which can effectively quantify the development ability of the algorithm. The multi-peak function contains multiple local extremes and is often used to test the global search capability of the algorithm.

When the benchmark test function is tested, its test dimension is set to 200, the population size is set to 100, and the maximum number of iterations is set to 1200. The test function selected in this paper covers the common types of test functions, which can well show the solution ability of the test each comparison algorithm. Table 1 shows the results of the individual algorithms solving the test functions. As can be seen from the table, compared with the other two algorithms, the optimal value obtained by the IPSO algorithm is closer to the actual solution of the test function, and the integrated mean and standard deviation are also better. This shows that the strategy designed in this paper to improve the PSO algorithm is feasible, which further improves the computational efficiency of the algorithm while ensuring that the algorithm has a stronger optimization capability.

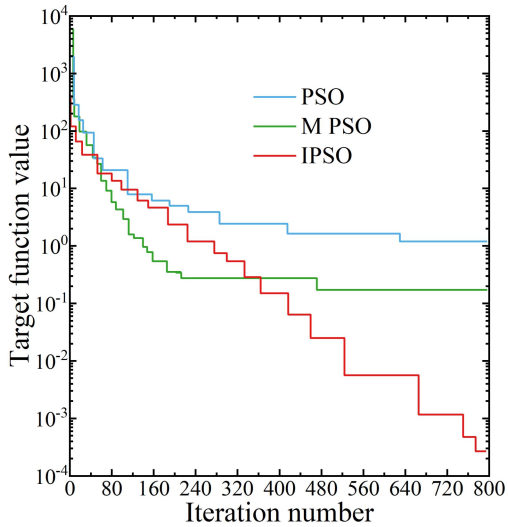
Table 1. Solve the test function results of each algorithm

Test function	Algorithm	Optimal value	Mean value	Standard deviation
	PSO	9.45E+02	1.45E+03	5.18E+02
FUN1	MPSO	4.93E+03	1.62E+05	6.27E+03
	IPSO	5.63E-24	1.66E-19	5.59E-20
	PSO	4.51E+00	2.53E+01	1.43E+01
FUN2	MPSO	1.35E+02	4.36E+02	2.15E+01
	IPSO	4.63E-03	6.26E-01	4.73E-01
	PSO	4.02E-05	8.13E-03	9.98E-02
FUN3	MPSO	5.52E-02	4.65E+01	2.76E+01
	IPSO	3.03E-13	3.56E-02	4.38E-03
	PSO	2.25E+00	4.93E+01	1.46E+00
FUN4	MPSO	3.23E+00	4.25E+01	5.38E-01
	IPSO	4.01E-16	5.81E-02	7.35E-01
	PSO	2.52E+03	5.63E+01	2.73E+01
FUN5	MPSO	5.61E+04	1.35E+04	3.31E+02
	IPSO	1.05E-05	6.45E-01	8.15E-01
	PSO	-7.83E-15	-7.79E-14	8.35E-15
FUN6	MPSO	5.93E-15	2.89E-08	4.95E-08
	IPSO	-8.02E-16	7.92E-14	6.98E-16

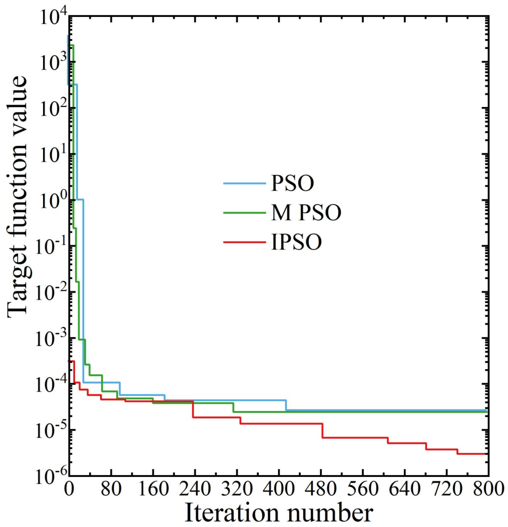
3.1.2. Convergence curve analysis

In order to analyze the gap between the algorithms and further illustrate the effectiveness of the IPSO algorithm, the convergence curves of the three algorithms for solving the test function at T=800 are obtained as shown in Fig. 2, taking the single-peak functions FUN1 and FUN2 as an example, and the multi-peak functions FUN5 and FUN6 as an example. From the convergence curves, the convergence effect of the three algorithms can be observed more intuitively and their ability to jump out of the local extremes can be analyzed.

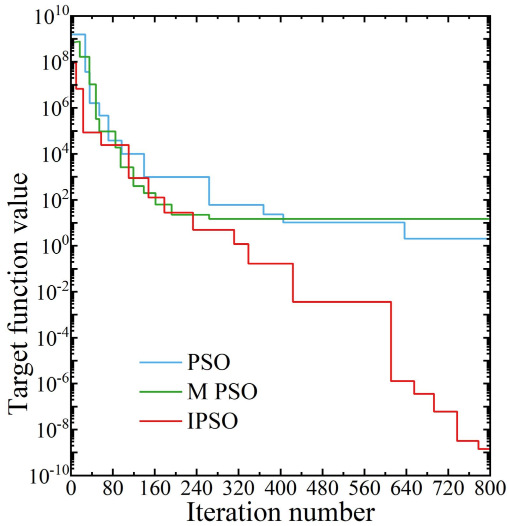
Combined with the quantitative evaluation results given in the previous section, it can be seen that for the single-peak functions FUN1 and FUN2, the IPSO algorithm decreases faster in the convergence curve in the pre-iteration period, which indicates that the introduction of adaptive particle optimization strategy, inverse learning and Cauchy's variant fusion strategy in this paper significantly improves the algorithm's ability to search for the global optimum, and combined with the linearly decreasing parameter setting method, it can avoid the algorithm from falling into the local optimum situation. Combined with the convergence curve comparison results, it can be seen that although the IPSO algorithm did not reach the optimal solution in 800 iterations, compared with other algorithms, the IPSO algorithm is optimal and has a smaller optimal value. In addition, in the convergence curves of the multi-peak functions FUN7 and FUN8, it is obvious that the convergence speed of the IPSO algorithm has a great advantage over the other algorithms. Therefore, the IPSO algorithm has strong optimization ability for both single-peak and multi-peak test functions, and has higher convergence accuracy and operation efficiency compared with other algorithms.



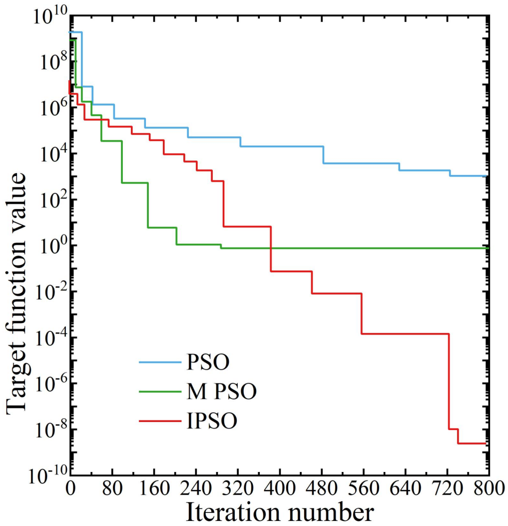
(a) FUN1



(b) FUN2



(c) FUN5



(d) FUN6

Figure 2. The convergence curve of the test function

3.2. Risk management optimization analysis

3.2.1. Model training results

Through the continuous learning and iteration of 1000 sets of data in the IPSO-BP neural network code program written in MATLAB, the process of changing the network fitness value is shown in Fig. 3. With the continuous iteration of the improved particle swarm algorithm, the fitness value decreases, i.e., the BP network error decreases, and finally tends to be stable, and the IPSO algorithm is in the convergence state after evolving to the 36th generation.

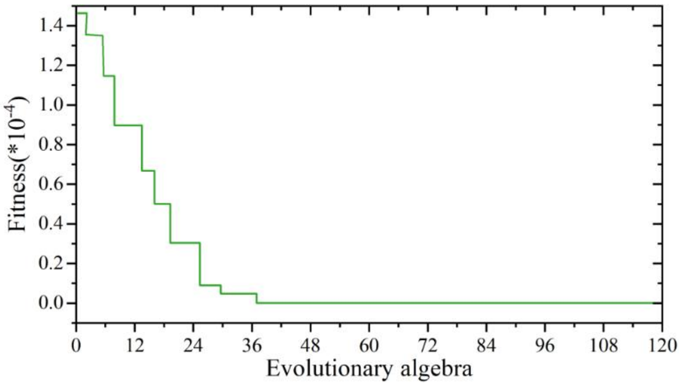


Figure 3. Fitness curve

The optimal initial weight threshold obtained from the IPSO iterations is assigned to the BP neural network for training, and some of the training results are shown in Table 2, where 1 sample corresponds to 2 output values, and the line number where the maximum output value is located indicates the final predicted classification. For example, for sample S6, its maximum output value is 0.9958, which means that the final predicted classification result [0,1] is consistent with the actual value. The predicted values of the output of the training samples listed in Table 2 correspond to the actual values of the output of the training samples, and the comparison shows that the predicted results are consistent with the actual results, and the neural network meets the training accuracy requirements.

Table 2. Partial training results of neural network

No.	Training results	No.	Training results
S1	[0.0061,0.9912]	S6	[0.0047,0.9958]
S2	[-0.0005,1.0028]	S7	[-0.0015,1.0027]
S3	[0.0042,0.9932]	S8	[0.0063,0.9989]
S4	[-0.0001,1.0015]	S9	[1.0001,-0.0018]
S5	[0.0028,0.9939]	S10	[-0.0023,0.9946]
……	……	……	……

The test set is used to verify the training of the neural network is good or bad, and the prediction error of the 600 sets of test samples is plotted as shown in Fig. 4, the prediction results are highly accurate, and the IPSO-BP neural network model is successfully trained. Combined with the prediction error, under the 600 test samples, only a dozen samples appeared with prediction error between [-0.8,0.8], which indicates that the IPSO-BP model is trained better, and the overall prediction is within the acceptable range. It can provide accurate prediction results for risk management and prediction of green financial market, and enhance the anti-risk ability of green financial market.

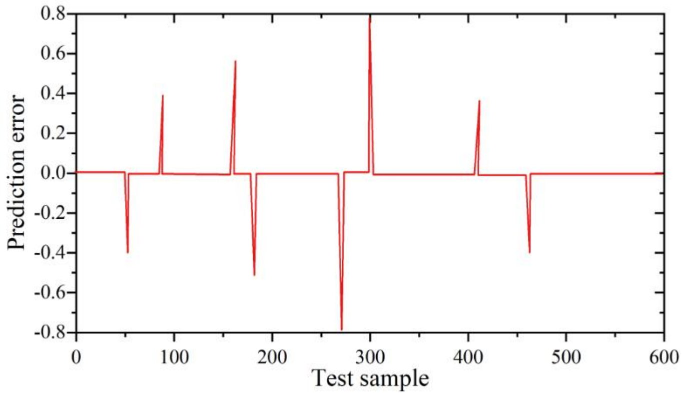


Figure 4. Test error of IPSO-BP neural network

3.2.2. Risk prediction performance

In order to further illustrate the predictive accuracy of the IPSO-BP model for risk management in the green financial market, this paper chooses accuracy, specificity under the subject's work characteristics (ROC) curve, sensitivity and area under the curve (AUC) values as model evaluation indexes. The traditional BP model is used as a comparison, and the experimental data are organized using Excel tables, the measurement data are all in line with normal distribution, and the comparison between groups is made using independent samples t-test. The count data were expressed as percentages and χ^2 -test was used, and the difference was considered statistically significant at P<0.05.

The STI-driven green financial market risk data were input into the test set and training set of traditional BP model and IPSO-BP model, respectively, and the results of green market financial risk prediction and identification were recorded as shown in Table 3.

The results show that the AUC value, accuracy, sensitivity and specificity of risk data recognition in the test set with IPSO-BP model are 0.856, 95.38%, 98.02% and 97.64%, respectively, and the AUC value, accuracy, sensitivity and specificity of risk data recognition in the training set are 0.883, 93.67%, 93.08% and 96.51%, respectively, which are higher than that of the traditional BP model, and the difference is statistically significant (P<0.05). It can be seen that relying on the IPSO-BP model established in this paper can realize the early prediction of green financial market risk, and the use of IPSO algorithm has a high value of application to the green financial market risk model, which can significantly improve the effect of risk identification in the green financial market, and accurately and timely detection and prediction of risk. This helps to better ensure the safe operation and development of green finance driven by scientific and technological innovation, and lays the foundation for further promoting the sustainable development of the economy.

Table 3. Risk prediction identification results

Model	**Training set**			
	AUC	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
BP	0.731	86.51	88.14	91.08
IPSO-BP	0.856	95.38	98.02	97.64
χ^2	6.792	7.543	5.593	3.127
P	0.001	0.002	0.000	0.005
Model	Test set			
	AUC	Accuracy (%)	Sensitivity (%)	Specificity (%)
BP	0.751	82.16	83.25	87.42
IPSO-BP	0.883	93.67	93.08	96.51
χ^2	3.792	4.035	4.927	4.903
P	0.000	0.001	0.003	0.000

3.2.3. Risk control effectiveness

The trained IPSO-BP neural network model is utilized to assess the risk of green financial market for 904 enterprises outside the training and test sets. In conducting the risk assessment, this paper divides the risk level into four levels in total, i.e., low, lower, medium and high risk. On this basis, the overall risk assessment results are obtained as shown in Table 4.

According to the assessment results, it can be concluded that among the 904 enterprises listed on the A-share market, there are a total of 687 enterprises at low risk and lower risk, with their overall risk scores of 8.71 and 6.42, respectively, with the higher scores indicating that their risk-resistant ability is stronger and their overall risk level is lower. There are a total of 163 listed companies at medium risk level and 54 listed companies at high risk level. Overall, there are a total of 217 medium-risk and high-risk listed companies in A-shares, accounting for 24% of the total number of A-share listed companies. For the enterprises in the green financial market, their risk factors lie more in the data such as asset-liability ratio and shareholders' equity ratio, and the risk assessment results can better reflect the risk level of the listed enterprises in the green financial market and provide data support for their optimized risk management mechanism, so as to better realize the risk control in the green financial market.

Table 4. Risk control effect

Risk level	Number	Score
Low risk	472	8.71
Relatively low risk	215	6.42
Medium risk	163	4.19
High risk	54	1.58

3.3. Green finance market optimization

3.3.1. Sound financial system

At present, with the rapid expansion of the scale of green financial business, some market players take advantage of the policy ambiguity to implement “greenwashing”, “greenwashing” and other irregularities, i.e., ordinary projects packaged as green projects to extract resources, seriously disrupting the market order. Therefore, it is necessary to speed up the process of green finance legislation, and clearly define the specific circumstances of “greenwashing” and “greenwashing” in the law. At the same time, we should formulate step-by-step penalties, impose fines of 5%~10% of the project financing amount for the first time, cancel the qualification of green finance business for repeated offenders, and establish a platform for sharing information on corporate violations, so as to subject them to social supervision and significantly increase the cost of violating the law. By improving the details of policies, enhancing the transparency and operability of policy implementation, forming a closed regulatory loop covering the whole process of green finance, and building a solid institutional defense for the sustainable development of the industry.

Innovate green financial products and services, vigorously develop carbon financial derivatives such as carbon futures, carbon options, carbon forwards, etc., to enrich market risk management tools and enhance the price discovery function of the carbon market. Promote green asset securitization products, and package and securitize the future earnings of green projects such as sewage treatment and photovoltaic power generation, so as to broaden the financing channels for green projects. Encourage insurance organizations to develop environmental liability insurance, green building quality assurance insurance and other innovative insurance types to improve the green risk protection system. At the same time, it will strengthen the synergistic development of regional green financial markets, break market segmentation, establish a nationally unified green project database and carbon asset registration and trusteeship system, and promote the efficient allocation of green resources across regions.

3.3.2. Optimizing the talent framework

Optimize the talent training system with the goal of green financial talent training. Firstly, the State should actively formulate guiding policies, formulate objectives, programs and plans for green financial talent training, and raise the importance of the entire financial industry to the concept of green development. Secondly, the level of professional cognition of financial practitioners in green credit, green bonds, green funds, green insurance and other aspects of production, cleanliness and environmental protection should be enhanced. Finally, all relevant organizations in the financial industry should proactively join forces, integrate advantageous resources, promote the cultivation of green financial talents, regularly carry out practical and theoretical training activities, enhance the service level of green financial service institutions, improve the efficiency of green financial institutions' services, and enhance the risk management and control capacity of the green financial system.

3.3.3. Building synergies

In order to effectively promote the synergistic development of fintech and green finance, fintech companies and green financial institutions should strengthen cooperation, build mutual trust and cooperation mechanisms, realize the complementarity and cooperation of their strengths through the establishment of joint research projects, the cooperative development of green investment tools, the sharing of technological resources, and the joint formulation of technological standards and industry norms, so as to promote the application of fintech in the field of green finance and innovation, and achieve effective integration of data sharing and risk management, and stronger anti-risk ability while ensuring the stable operation of the green financial market.

At the same time, financial institutions can also promote cross-field cultivation and professional skills training of green financial talents and fintech talents through diversified and interactive forms of education such as training courses and seminars in various forms and with rich contents. Provide all investors with detailed knowledge and key skills on green finance, and provide technical and talent support for synergistic development. To help practitioners gain a deeper understanding of the core concepts and essence of green financial products and help them make investment decisions that are more informed, rational and in line with the development trend of green finance.

4. Conclusion

In order to improve the risk management effect of green financial market driven by science and technology innovation and enhance the risk prediction effect of green financial market, this paper combines BP neural network and IPSO algorithm, and constructs IPSO-BP model to predict the risk of green financial market. In this paper, based on meeting the demand of green financial market risk management prediction, the research uses multiple strategies to optimize the PSO algorithm, which makes the model's prediction ability of green financial market risk further improved. And based on the risk prediction results, it can help investors choose investment strategies that are more in line with the market rules, thus realizing risk control.

In this paper, while the research results are achieved, there are also some research limitations. For example, the BP neural network in the training process there is an obvious lack of generalization ability, although the application of the IPSO algorithm enhances the generalization ability, which also has an impact on the operational efficiency of the model. In addition, only two states, whether the green financial market is risky or not, were considered in the data analysis, and more diverse states may exist for the rapidly changing financial market. In the future research, the optimizer selection of the BP neural network training method will be further explored, and further combined with the specific data of the green financial market, to explore the risky situation of the green financial market in different states, in order to provide support to ensure the stable operation of the green financial market.

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