Research on Financial Risk Crisis Prediction of Listed Companies Based on IWOA-BP Neural Network

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Abstract

To avoid the risk brought by the financial crisis, the Improved Whale Optimization Algorithm-Back Propagation neural network (IWOA-BP) financial crisis early warning model is proposed. This paper selects the data from financial statements of some of the listed Chinese manufacturing companies from 2015-2019 as the research sample. First, the financial data of enterprises are screened by principal component analysis, and the early warning model is constructed from the financial and nonfinancial factors of six indicators: solvency, operating capacity, profitability, development capacity, cash flow and risk level factors. Second, the Whale Optimization Algorithm is optimized by the chaos strategy, as well as by the dynamic weight and sine cosine algorithm. Finally, the improved Whale Algorithm is optimized for BP neural network parameters. In the simulation experiments, the performance of the improved whale optimization algorithm is substantially improved. In addition, in the empirical analysis, compared to the prediction model with other algorithms, the prediction model of this paper has better results in terms of prediction accuracy.

Keywords: Financial risk, Crisis prediction, Whale optimization algorithm, BP neural network

1 Introduction

Due to the influence of COVID-19, the current global economy is in a decline. However, information technology for assisting enterprises with financial crisis prediction can effectively help enterprises carry out reasonable cost control and avoid risky investments. The BP neural network has advantages, such as a simple structure and a few parameters. Additionally, it has been applied in the study of financial crisis prediction by scholars, and has achieved good results, but due to its own parameters, the lack of optimization has led to a decrease in prediction accuracy [1]. Many scholars have achieved good results using metaheuristic algorithms to optimize neural network parameters [2]. In this paper, based on the study of existing theoretical research on financial crises, the Whale Optimization Algorithm (WOA) proposed by Australian scholar, Mirjalili Seyedali [3], is applied to the financial crisis prediction model in combination with a BP neural network. The main contributions of this work are as follows: (1) Principal component analysis is used to assist the listed companies' financial indicators with selecting indicators suitable for reflecting the financial crisis. (2) The problem of a lack of optimization of BP neural network model parameters is addressed, and WOA is introduced to complete this work. (3) In addition, problems, such as the slow convergence of the algorithm and the low accuracy of the solution that exists in the whale optimization algorithm itself are addressed. Moreover, optimization strategies are proposed from the following three aspects: the first aspect is to use a new chaotic strategy to optimize the whale population to improve the solution diversity; the second aspect is to use a dynamic inertia weight factor to optimize the individuals of the local solution to avoid falling into the local optimum; the third aspect is to use a sine cosine algorithm to select the global individuals after each iteration, which ensures the quality of the solution for the next iteration.

The structure of this paper is organized as follows: Section 1 describes the research background. Section 2 describes the current state of the research on the financial crises, as well as finding the direction of this paper from these studies. Section 3 is based on the study of financial indicators using principal component analysis. Section 4 is based on the IWOA-BP neural network financial prediction model. Section 5 compares the prediction model of this paper with other models in simulation experiments, which is used to illustrate and compare the prediction model of this paper with other models in simulation experiments. Finally, in Section 6, we summarize the description process of this paper.

2 Related Knowledge

(1) The Variable Discriminatory Model

Literature source [4] proposed the first early warning model for financial crisis, described studies of 19 enterprises, and discussed finding that the return on net assets and equity ratio are important factors for determining the emergence of the financial crisis. Literature source [5] also describes finding that the cash flow debt ratio and the gearing ratio can effectively predict the financial crisis. Literature source [6] established a multivariate discriminant model for financial early warning prediction from the perspective of a multivariate discriminant. Literature source [7] proposed constructing a multivariate linear model for financial early warning. Literature source [8] proposed a Z-financial model for early warning, which was empirically shown to be able to predict the financial crisis 1-3 years in advance (literature [9]).

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(2) The Logistic Regression Models

Logistic regression models have better advantages over variable discriminant models [10]. Literature source [11] used a logistic model in financial data, and empirically illustrated that the model can improve the prediction accuracy. Literature source [12] proposed a corporate financial crisis prediction model based on a logistic and SVM, and empirically illustrated a substantial improvement in the prediction effect. Literature source [13] used an LSSVM for corporate financial crisis prediction, and empirically illustrated that the prediction effect on a considerable improvement compared with the SVM. Literature source [14] analyzed logistic regression and multivariate discriminant methods, while pointing out the scope of the application of the two methods in the financial crisis with the actual situation. Literature source [15] proposed that the logistic regression model can effectively reduce the financial sub-risk of enterprises. Literature source [16] used regression analysis in corporate finance to help enterprises effectively reduce the financial risk.

(3) The Neural Network Early Warning Model

With the development of cloud computing, big data and other technologies, the use of neural network models for early warning of a financial crisis has become the main direction of scholars' research. Literature source [17] first proposed neural networks for financial crisis prediction, and empirical evidence showed that compared with previous prediction techniques, they had better prediction accuracy and precision. Literature sources [18-20] described the establishment of early warning models based on neural networks in different enterprises. They had a good effect on the financial management of enterprises. Literature sources [21-23] proposed the prediction based on a BP neural network in the financial crisis of the company, and the practice all illustrated that the prediction effect was good and could effectively avoid the occurrence of a financial crisis. In terms of stock market funds, [24] used an LSTM neural network to analyze short-term stock market funds. [25] proposed a financial warning model based on an SOM-BP neural network for listed companies in the stock market, while [26-27] used a neural network based on a metaheuristic algorithm to analyze stock market data. These practices show that the neural network could provide better results. In finance, literature sources [28-30] proposed a neural network for risk prediction in financial loans. Literature source [31] proposed Evolino neural network-based financial market prediction. Literature source [32] proposed a financial time series prediction based on a stochastic data time effective RBF neural network. Literature source [33] proposed using a spiking neural network for financial time series forecasting. Literature source [34] used a combination of artificial neural networks and a random wandering model for financial time series forecasting. These practical results show that forecasting in finance has good results. In other aspects, literature source [35] proposed a crisis early warning model based on rough set and radial basis function neural network for financial aspects of human resources. Literature source [36] proposed the use of advanced artificial neural networks for quantitative modeling in economics. Literature sources [37-38] presented the latest research results of the current neural networks, although they have not been applied to the prediction of financial crises, which provide current financial crisis forecasting tools for a better reference.

3 The Study of the Financial Warning Indicators Based on Principal Component Analysis

3.1 Selection of Financial Early Warning Analysis Indicators

The selection of financial warning indicators is of great importance for identifying the financial sub-risk of an enterprise, which is an important criterion for reflecting the financial status of an enterprise. Combined with the characteristics of the existing financial warning models, this paper selects a total of 16 indicators from solvency, operating capacity, profitability, development capacity, cash flow and risk level for analysis. The system content is shown in Table 1.

Table 1. Selection of financial analysis indicators

Type	Variable	Indicator name
Solvency	X1	Current ratio
	X2	Quick ratio
	X3	Gearing ratio
Operating capacity	X5	Inventory turnover ratio
	X6	Current assets turnover ratio
	X7	Total assets turnover ratio
Cash flow	X8	Cash to total profit ratio
	X9	Net cash content of operating income
Profitability	X10	Return on assets
	X11	Return on net assets
	X12	Operating profit ratio
Development capacity	X13	Total assets growth rate
	X14	Net income growth rate
	X15	Operating profit growth rate
Risk level	X16	Financial leverage

3.2 Principal Component Analysis

The principal component analysis method mainly transforms multiple linear variables into indicators with weak correlation through the method of dimensionality reduction, and can avoid the influence of the correlation on indicators. Thus, we believe that this approach is beneficial to the acquisition of the financial crisis indicators. In this paper, 13 financial indicators of 36 manufacturing listed companies in 6 major categories from 2015-2019 are selected for positive transformation and standardization, and the correlation between the existence of these variables is tested by Kaiser–Meyer–Olkin (KMO) and Bartlett's sphericity. The results are shown in Table 2, with a KMO value of 0.621. This exceeds the KMO value of 0.621, which is more than the 0.5 specified by the indicator value.

Thus, the analysis concludes that this paper can use the principal component analysis method, as shown in Table 3.

Table 2. Results of the KMO test and Bartlett's test

Kaiser–Meyer–Olkin metric	0.621
Bartlett's sphericity test value	894.893
Df	107
Sig	0.000

The common factors extracted by principal component analysis must be developed through repeated experiments to ensure that the cumulative contribution rate is greater than 80%. In this paper, six common factors are extracted by the maximum variance rotation method, and their contribution rate reaches 85.23%, indicating that the six common factors are selected to represent the basic information of the 16 financial indicators used to analyze the original indicator variables, as shown in Table 3.

Table 3. 16 financial indicators
(a) Initial eigenvalues

Ingredients	Initial eigenvalue		
	Total	Variance %	Accumulation %
1	3.817	29.609	29.162
2	1.904	13.908	40.991
3	1.512	9.921	54.171
4	1.307	9.171	67.152
5	1.211	9.009	74.531
6	1.131	9.321	81.971
7	0.992	7.409	85.761
8	0.909	6.893	89.932
9	0.902	4.893	91.892
10	0.817	4.208	91.899
11	0.701	3.609	92.162
12	0.689	2.912	93.732
13	0.282	1.897	94.612
14	0.199	0.983	96.831
15	0.138	0.693	98.332
16	0.038	0.051	100.000

(b) Initial eigenvalues

Ingredients	Extraction of squares and loading		
	Total	Variance %	Accumulation %
1	3.912	29.619	28.257
2	1.914	13.902	42.151
3	1.312	10.921	56.121
4	1.317	9.314	67.352
5	1.272	9.009	73.821
6	1.323	9.214	83.271
7	0.893	7.431	87.161
8			
9			
10			
11			
12			
13			
14			
15			
16			

(c) Initial eigenvalues

Ingredients	Rotate square and load		
	Total	Variance %	Accumulation %
1	3.142	27.124	27.189
2	3.162	14.028	41.235
3	2.617	10.807	57.182
4	1.451	9.347	65.194
5	1.342	9.191	66.734
6	1.136	8.152	74.282
7	1.173	7.192	83.381
8			
9			
10			
11			
12			
13			
14			
15			
16			

The influencing factors are determined by Table 3, and to maximize the total variance loadings of each factor, the rotated variance is used to elaborate the meaning of each factor by eliminating the small factor method and showing only the factors with rotated factor loadings greater than 0.6. If the absolute value of the rotated factor loadings is larger, it is more likely to indicate that the factors are representative of the original situation. Therefore, six representative variables and their corresponding factors can be obtained: the X2, X4, X6, X16, X12, and X13 variables. The six variables selected through Table 4 can reflect the financial crisis of the company.

Table 4. Rotation factor loading values

No	1	2	3	4	5	6
X2	0.961					
X1	0.782					
X3	0.914					
X4		0.712				
X7		0.932				
X8		0.879				
X6			0.812			
X5			0.739			
X10			0.613			
X16				0.533		
X15				0.341		
X12					0.933	
X11					0.869	
X13						0.218
X9						NULL

4 The IWOA-BP Neural Network-based Financial Forecasting Model

4.1 BP Neural Network

The backpropagation neural network is one of the most widely used neural network models and mainly uses backpropagation for multilayer feedback training network models. It can achieve the mapping capability from input to output, and it is widely used for pattern recognition, data prediction and fault identification. However, the BP neural network has certain limitations, specifically, the BP neural network lacks simple and effective parameters, resulting in the lack of stability of the BP algorithm. In addition, BP neural networks have local minimization and slow convergence, and the global optimum must be found by resetting the initial parameter values, which increases the algorithm running time.

4.2 The Whale Optimization Algorithm

In nature, whales are animals that obtain food through group behavior. The whale optimization algorithm is a bionic intelligent optimization algorithm that imitates the predation of whales in nature. The predation process of whales is mainly divided into three stages: surrounding and predation, bubble attack and hunting for prey.

(1) Surrounding and Predation

The way whales obtain food in the sea is by group encirclement. Therefore, at the beginning of the algorithm, due to a lack of prior knowledge, humpback whales first need to determine the approximate location of their prey, and then the humpback whale calls other whales to the location of the food to obtain the food. In WOA, because there is no determination of where the food is, it can only be assumed that the current humpback whale's position is the food position (the optimal individual position). Therefore, other whale individuals in the group move toward the current optimal individual position and surround the food. Formula (1) is used to update the position as follows:

$$X(t+1) = X_p(t) - A \times |C \times X_p(t) - X(t)| \tag{1}$$

In the formula, $X(t+1)$ represents the position after the t+1-th iteration, $X_p(t)$ represents the optimal solution within the current range of the t -th time, and $A \times |C \times X_p(t) - X(t)|$ represents the distance between the current optimal solution and the individual whale. The two very important vectors, A and C, are expressed as shown in (2) and (3), respectively. $rand_1$ and $rand_2$ denote the random numbers between (0,1), respectively, and serve to control the size of the two vectors, while a is the convergence factor, which ensures that the two vectors, A and C, have a certain convergence. This enables the algorithm to avoid coming to a stop, and setting the value of the decreasing trend in [2,0] as follows:

$$A = 2a \times rand_1 - a \tag{2}$$

$$C = 2 \times rand_2 \tag{3}$$

$$a = 2 - 2t/t_{\max} \tag{4}$$

In the formula, t_{max} is the maximum number of iterations.

(2) The Spiral Bubble Attack

After the whale obtains the position of the food, it does not directly take the food; it uses the unique air bubbles on its head to attack the food, knock the food out, and then obtain the food. The WOA simulates the whale through contraction, envelopment, and spiral renewal behavior. To prey on the behavior of spitting out bubbles, the goal of the WOA algorithm is to obtain the local optimal solution.

1) The Shrink Enveloping Mechanism

In Formula (1), the individual whale approaches the optimal solution position. In the formula, the factor $|A| < 1$ plays a more critical role. According to the formula, it was found that when $|A| < 1$, the individual whale is approaching the whale in the current optimal position, and $|A|$. The size of the array determines the size of the whale's walking pace.

2) The Spiral Update Position

Before obtaining food, the whale needs to calculate the distance between the individual whale and the food. The whale does not blindly call other whales to approach the food immediately; it needs to estimate its own position and the position between the food where it is located. The whale does not directly rush to the food; it takes a spiral approach to search and locate the prey. In the algorithm, the spiral update is expressed in Equation (5) as follows:

$$X(t+1) = D' \times e^{lb} \times \cos(2\pi l) + X_p(t) \tag{5}$$

In the formula, $D' = |X_p(t) - X(t)|$ is used to represent the distance between the i -th whale and its prey, the parameter b is mainly used for the shape constant when the whale is walking in a spiral, and l represents a random number between -1 and 1. The cosine function can be used to express the state when the position is updated, and the probability p represents the choice of the balance enveloping mechanism and the spiral position. According to the algorithm requirements, the set value is 0.5.

(3) Random Search for Prey

Individual whales can randomly swim in all directions to find food. Of course, this behavior is a random process. The essence of searching is also to determine a new location based on the location of other whales, which is expressed as follows:

$$X(t+1) = X_{rand}(t) - A|C \times X_{rand}(t) - X(t)| \tag{6}$$

In the formula, $X_{rand}(t)$ is the position of the individual whale randomly selected in the current population.

4.3 The Improved Whale Optimization Algorithm-IWOA

The optimization of BP neural networks using metaheuristic algorithms can improve the accuracy of neural networks. Therefore, we choose the excellent algorithm performance of whale optimization for BP neural network parameter optimization because the algorithm itself has the disadvantages of easily falling into a local optimum and having a slow convergence speed. We propose an improved whale optimization algorithm (IWOA) from the following three aspects for improvement. Strategy 1: We use the chaos algorithm to initialize the population to avoid the "premature" algorithm and maintain the population diversity. Strategy 2: We use the construction of the dynamic weight factor to improve the individual spiral update position in the bubble attack to avoid the algorithm becoming a local optimum. Strategy 3: After each individual iteration of the whale algorithm, to eliminate the poor quality individuals, we use the positive cosine algorithm for individual updates to produce a good quality global solution.

(1) Population Initialization

In the metaheuristic algorithm, none of the individuals are initialized with the population, which is caused by the simplicity of the algorithm. This tends to lead to the existence of slow convergence and a great impact on the convergence accuracy of the algorithm at a later stage, while the WOA uses a random method to initialize the position of each individual, which does not guarantee the population diversity. According to this property, we combine the characteristics of randomness, ergodicity and regularity in chaotic mapping and introduce it into the algorithm of this paper. The steps are as follows:
Step 1: We set the size of the entire whale population as N, the spatial dimension as D, and the maximum number of chaotic iteration steps as K.
Step 2: We generate new individuals according to the chaotic mapping of Equations (7) and (8) as follows:

$$x_{k,j} = x_{k-1,j} + 10 \times rand(0,1)) \bmod 10 \quad \textbf{(7)}$$

$$x_{i,j} = x_{\min,j} + x_{k,j} \times (x_{\max,j} - x_{\min,j}) \quad \textbf{(8)}$$

In Equations (7-8), $x_{k-1,j}$ and $x_{k,j}$ denote the individuals in the $k-1$ th and K th iterations in the j th dimension, where the latter are the individuals after the chaotic mapping of the former. $x_{max,j}$ and $x_{min,j}$ denote the maximum and minimum values in the j -dimensional space, respectively. $x_{i,j}$ denotes the new individual in the j th dimension.
(2) The Dynamic Inertia Weighting Factor

Inertia weights are a way to avoid falling into local optimum in metaheuristic algorithms, but the traditional linear inertia weights cannot help humpback whales jump out of local optimum in a spiral update due to the linear change. Thus, dynamic inertia weight factors are used to solve this problem. In this paper, we set ω to represent the dynamic weight factor, and as the value of ω gradually increases, the algorithm slowly appears to be the global optimum, and avoids falling into the local optimum too quickly. Therefore, it can effectively improve the performance of the algorithm as follows:

$$\omega = e^{\frac{t}{t_{\max}}} \times \left(\frac{1}{f_{obj}^{\max}(x_i^t) - f_{obj}^{\min}(x_i^t)}\right) \quad \textbf{(9)}$$

Then, the spiral update formula for individual whales in the WOA is updated to obtain the equation as follows:

$$\overrightarrow{X}(t+1) = \omega \times \overrightarrow{D'} \times e^{lb} \times \cos(2\pi l) + \overrightarrow{X*}(t) \quad \textbf{(10)}$$

(3) Individual Screening Based On the Sine and Cosine Algorithm

The Sine and Cosine Algorithm (SCA) is a new type of population intelligence optimization algorithm [39], which has a unique superiority. The periodicity and fluctuation of the sine and cosine functions make the sine algorithm have the characteristics of "global search" and "local exploitation" within a limited range. "This allows the algorithm to search in a wide range during iteration to ensure the comprehensiveness of the iterative update results and to get rid of the problem of easily falling into the local optimum in the local range or after the iterative update of the population intelligence algorithm. The expression is shown in (11) as follows:

$$x_i^{t+1} = \begin{cases} x_i^t + r_1 \sin(r_2) \times | r_3 x_j^t - x_k^t |, r_4 < 0.5 \\ x_i^t + r_1 \cos(r_2) \times | r_3 x_j^t - x_k^t |, r_4 \geq 0.5 \end{cases} (k, j \neq i) \quad \textbf{(11)}$$

where x_i^{t+1} denotes the position of individual i after the $t+1$ th iteration when the individuals in the current population are iterated after choosing the update method. x_i^t and x_k^t denote the specific positions of any two individuals in the population at the tth iteration, respectively, while the selection of these two positions is random and different from the position of the individual. r_1, r_2, r_3 and r_4 are four control parameters where r_1 controls the search direction and $p \times (1 - \frac{t}{t_{max}})$ k (t_{max} is the maximum number of iterations, t is the number of iterations, and p is a constant value), r_2 is the control search distance, and $r_2 \sim U[0,2\pi]$, r_3 control the two randomly selected population individuals and $r_3 \in (0, +\infty)$, r_4 control the update switch of this sine cosine and $r_4 \sim U[0,1]$.

The embedding of the sine cosine optimization strategy can, on the one hand, fill the defect of dependency in the WOA position update formula, whether it is the sine mechanism or the cosine mechanism. Individual whales can communicate with the food source in terms of position and promote the optimal information to be transmitted in the population, and each whale individual can better use the position difference information between itself and the food source to motivate other individual whales to move toward the optimal solution. On the other hand, it enables individual whales to further conduct global search and local exploitation in different ranges of the same search space. The sine mechanism enables the global search to find the optimal solution to reduce the blind spot of the cosine mechanism, and the cosine mechanism enables the local exploitation to fill the shortcoming of full convergence speed of the sine global search to improve the exploration ability and accelerate the convergence of the algorithm. The mutual use of sine and cosine can better balance the exploration and development ability of the algorithm, as well as jointly promote the optimization of the algorithm's performance.

4.4 Prediction Steps

Step 1: The data of six principal component indicators are obtained by principal component analysis for normalization to ensure that they are used as nodes in the input layer of the BP neural network. Each node corresponds to a principal component indicator, and the neurons in the output layer are set to one, i.e., the output results are yes and no, with yes indicating that the company has a greater financial risk and a higher probability of financial crisis, and vice versa, indicating a lower probability of financial crisis.

Step 2: We set the dimension in which the whales are located in the whale optimization algorithm, the size of the whole whale population size, the setting of the initial values of the relevant parameters of the algorithm, and the maximum number of iterations of the algorithm operation. We set the relevant parameters of the BP neural network, such as the input neurons and the number of output neurons. The initial weights and thresholds of the BP neural network need to be formed into a set of parameter sets, and the set of parameters corresponds to the whale individuals one-by-one. The best set of parameters, i.e., the best BP neural network parameters, can be obtained by obtaining the optimal whale individuals

Step 3: This step is for the optimization of the whale algorithm according to three improved strategies.

Step 4: In the fitness function of the whale algorithm individuals, the error function in the BP neural network model is used as the individual fitness function of the whale. Thus, the mean square error function of Equation (12) is used. During the iteration process, the individual fitness value of the whale is compared with the current individual optimal fitness value, and if the former fitness value is better than the latter, the latter is directly replaced; otherwise, it remains unchanged.

Step 5: When the algorithm reaches the maximum number of iterations, the algorithm ends, and thus, the optimal individual humpback whale corresponds to the optimal initial weight and the threshold value.

Step 6: The financial data is input into the optimized BP neural network model for prediction, and the financial risk warning data is obtained as follows:

$$fitness = E = \frac{1}{N}\sum_{i=1}^{N}(y_{reat} - y_i)^2 \tag{12}$$

where N denotes the overall number of training samples, y_{reat} is the expected output from the ith sample, and y_i is the actual predicted output from the ith sample.

5. Simulation Experiments

5.1 Algorithm Performance Comparison

To better verify the performance improvement effect of the IWOA, the ant colony algorithm (ACO), the particle swarm algorithm (PSO), and the WOA are selected for comparison with the algorithm in this paper. The comparison parameters are shown in Table 5. The population size is set to 100, and the number of iterations is set to 100. The parameters required by various algorithms are shown in Table 6.

In this paper, four representative classical test functions (Table 6) are selected to evaluate the performance of the algorithm in this paper. The reason for choosing these classical test functions is that they can measure whether the algorithm of this paper can converge or achieve the accuracy of the algorithm in high and low dimensions. Such a comparison can theoretically illustrate the performance advantage between this algorithm and the comparison algorithm. The choice of test metrics is a matter of whether the algorithm results have core illustrative power; we have chosen minimum, maximum, mean, and standard deviation as the metrics. These metrics have always been important indicators for algorithm performance measurement. Among these four metrics, the first two metrics mainly measure the quality effect of the solution, the third metric is used to measure the accuracy of the solution as needed, and the fourth metric compares the effect of the solution with different numbers of iterations in different dimensions.

The test results of the benchmark functions of the four algorithms in different dimensions are shown in Table 7 to Table 10. According to these tables, it was found that, especially when the dimension is 2, the minimum values of this paper’s algorithm are all 0. This shows that the IWOA has good solution quality in the four benchmark functions, while in other dimensions, the IWOA has almost the smallest values in the four indicators, which shows that the algorithm of this paper is superior to the WOA. The improved algorithm has good performance in both the quality and the accuracy of the solution.

Table 5. Algorithm description

Parameter name	Description
ACO	The value of pheromone is set to 0.01, the volatility coefficient is set to 0.01, and the path selection probability is set to 0.5
PSO	The inertia weight is set at 0.1, and the learning factor is 0.5.
WOA	a is [2,0] linearly decreasing
IWOA	a is [2,0] linearly decreasing, β value is 1.5, *rand* value is 1

Table 6. Test function

No	Function	Test function
F1	Sphere	$f(x)=\sum_{i=1}^{n}x_i^2$
F2	Schwefel2.22	$f(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$
F3	Schwefel1.2	$f(x)=\sum_{i=1}^{n}(\sum_{j=1}^{i}x_j)$
F4	Schewfel2.21	$f(x)=\max(abs(x_i))$

Table 7. Comparison results of the F1 test functions in 4 dimensions

Algorithm	Dimension	Minimum Value	Maximum value	Mean	Standard deviation
ACO	2	0.0203476	16456.500	1989.67792	4983.5158
	5	0.3707979	30581.9835	4471.44257	8648.6628
	10	562.4510	57141.6827	16120.5908	17758.7147
	30	26114.2603	132024.456	69169.7457	35162.8114
PSO	2	6.3461e-10	0.0021637	0.000139559	0.0003861
	5	0.005738	4.98512	1.01386505	1.3156749
	10	2.29394	481.84602	145.480588	105.66809
	30	1442.3533	6300.0227	3537.511730	1210.68219
WOA	2	1.441E-14	2.814E-05	1.254E-06	4.485E-06
	5	2.059E-07	5.326E-02	5.942E-03	1.082E-02
	10	1.168E-04	1.098E+00	9.542E-02	1.679E-01
	30	2.649E-03	1.041E+01	1.702E+00	2.222E+00
IWOA	2	0	1.1738E-67	2.4116E-69	1.6594E-68
	5	3.8768E-55	8.1156E-41	1.8560E-42	1.1518E-41
	10	2.0110E-49	6.0219E-35	1.3795E-36	8.5234E-36
	30	5.6653E-43	1.7244E-31	4.8737E-33	2.5423E-32

Table 8. Comparison results of the F2 test functions in 4 dimensions

Algorithm	Dimension	Minimum Value	Maximum value	Mean	Standard deviation
ACO	2	0.171701	90.7335	9.18269	24.75729
	5	0.847493	16850.7147	798.050	2890.376
	10	4.727616	333392446.90	10854563	49590932.044
	30	44551072.64	1.66977e+20	3.41849e+18	2.36061e+19
PSO	2	4.61154e-06	0.00995994	0.00100221	0.00200884
	5	0.004236052	1.2703288	0.2266671	0.2595154
	10	1.0877692	8.44706953	4.5504297	1.89244510
	30	15.01764810	66.971699	32.4898099	10.564354
WOA	2	1.921E-07	5.808E-03	3.905E-04	9.117E-04
	5	1.316E-04	1.798E-01	3.832E-02	3.802E-02
	10	2.252E-03	1.471E+00	3.436E-01	3.124E-01
	30	1.218E-01	8.858E+00	2.126E+00	2.089E+00
IWOA	2	0	5.383E-42	3.172E-43	1.052E-42
	5	1.277E-32	6.883E-26	2.344E-27	1.025E-26
	10	8.473E-30	1.525E-22	5.799E-24	2.216E-23
	30	3.240E-28	2.511E-21	2.215E-22	5.730E-22

Table 9. Comparison results of the F3 test functions in 4 dimensions

Algorithm	Dimension	Minimum Value	Maximum value	Mean	Standard deviation
ACO	2	0.025686	270.41155	38.91627	88.25971
	5	0.018994	1017.43652	96.19119	273.9338
	10	0.176349	3131.65679	280.8745	828.66022
	30	0.159286	13060.0157	758.43687	2825.95712
PSO	2	4.0795811e-11	0.0016373	9.93502e-05	0.00028406
	5	9.6079588e-11	0.00144573	0.0001186	0.00025395
	10	1.91657e-09	0.01397033	0.0005589	0.00206236
	30	8.92441e-11	0.039662004	0.0017298	0.0059671
WOA	2	6.880E-11	2.115E-04	2.178E-05	3.788E-05
	5	8.461E-07	3.365E-03	2.661E-04	5.333E-04
	10	4.719E-07	1.899E-02	1.661E-03	3.048E-03
	30	3.727E-05	9.489E-02	1.306E-02	1.983E-02
IWOA	2	0	3.7874E-10	3.6633E-11	7.0173E-11
	5	1.2057E-12	5.9425E-09	5.9048E-10	1.1155E-09
	10	1.1827E-11	1.6488E-08	2.5080E-09	4.0931E-09
	30	4.5880E-11	2.8673E-07	2.3932E-08	5.0602E-08

Table 10. Comparison results of the F4 test functions in 4 dimensions

Algorithm	Dimension	Minimum Value	Maximum value	Mean	Standard deviation
ACO	2	0.15161	98.9014	40.89212	44.35097
	5	3.97965	98.8703	77.03869	28.64099
	10	28.8742	99.63691	90.60360	12.575049
	30	87.06238	99.83433	96.58320	2.8063077
PSO	2	2.3331863e-05	0.1167497	0.0079861	0.01785393
	5	0.0515829	4.4855845	0.8557691	0.88475519
	10	4.1968123	19.512747	10.652086	3.66702843
	30	15.841233	39.906120	26.712640	4.98594719
WOA	2	9.173E-07	2.349E-01	1.893E-02	4.220E-02
	5	2.922E-02	7.346E-01	2.728E-01	1.487E-01
	10	1.823E-01	9.975E-01	6.390E-01	2.171E-01
	30	6.550E-01	1.697E+00	1.333E+00	2.146E-01
IWOA	2	0	3.5239E-15	1.4043E-16	5.8358E-16
	5	2.1804E-13	3.0607E-02	1.2986E-03	4.9925E-03
	10	7.3759E-06	4.8473E-01	7.7337E-02	1.0178E-01
	30	3.8849E-02	6.1964E-01	4.3101E-01	1.5206E-01

5.2 Sample Selection

To further verify the accuracy of the prediction model proposed in this paper, we select the WIND database, the stock exchanges of Shanghai, China, and Shenzhen, China, and the financial annual reports of listed companies for the past four years. We also select the financial data of 36 listed companies in China involving manufacturing industries between 2015 and 2019 as the research samples, including 12 manufacturing crisis companies and 24 nonmanufacturing crisis companies. The 24 and the sample of 36 listed manufacturing companies is divided into training and testing samples. The proportions of the involved subsamples are appropriately allocated considering the ratios of financial data of manufacturing and nonmanufacturing companies. The training sample consists of 16 nonmanufacturing crisis companies and 8 manufacturing crisis companies paired with them, while the test sample consists of 8 manufacturing noncrisis companies and 4 manufacturing crisis companies paired with them.

5.3 IWOA-BP Neural Network-Based Financial Data Forecasting

After the samples are prepared, we use a hardware platform with a Core i5 CPU, 1T hard disk capacity, 8GDDR3 memory, Win10 operating system as the software environment, and MATLAB 2012a as the simulation software. We first use principal component analysis to select 6 of the 13 indicators that satisfy the conditions. Second, the data corresponding to these 6 indicators are used as the model input of the BP neural network, and the 6 indicators correspond to the neurons of the 6 input layers in the neural network. Meanwhile, the number of output neurons is set to 1, while the number of neurons in the hidden layer is 10, the number of model training is 200, the learning efficiency is 0.1, and the error accuracy is 0.1. Finally, the parameters of the improved whale optimization algorithm are set. The maximum number of motion iterations of the algorithm is set, and the range of parameter a is [0,2] for decreasing. In the training process, a total of 200 sets of data are prepared, and 50 sets are used for comparison of predictions, while 150 sets are used for training.

(1) Comparison of the predictability of the models in this paper

To illustrate the prediction effectiveness of the model in this paper, several metaheuristic algorithms are chosen as comparison algorithms to highlight the prediction effectiveness of the algorithms in this paper. We choose a BP neural network, a genetic algorithm (GA)-based BP neural network and a WOA-based BP neural network. The results of the implementation comparison are shown in 1-4. The prediction results of the four different algorithms in the BP neural network are shown in Table 11.

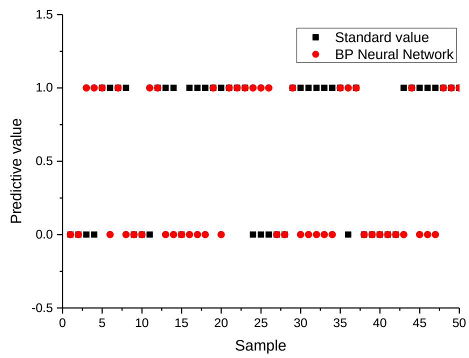

Figure 1. BP model prediction results compared with the standard results

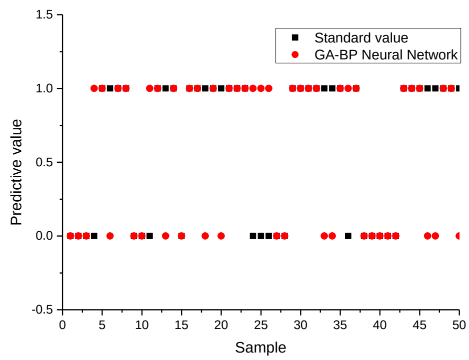

Figure 2. GA-BP model prediction results compared with the standard results

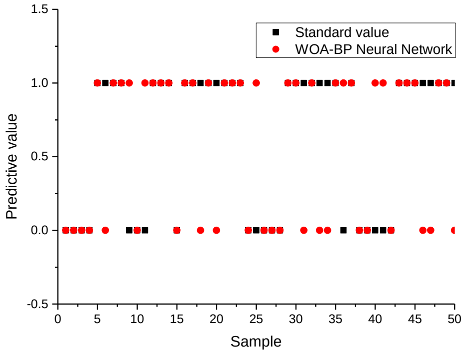

Figure 3. WOA-BP model prediction results compared with the standard results

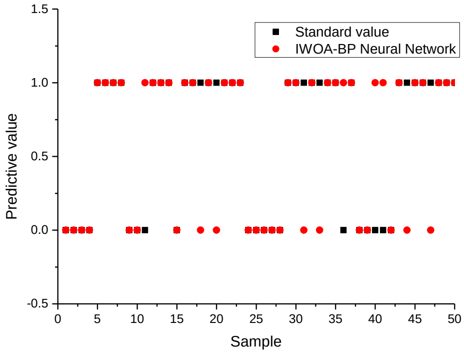

Figure 4. IWOA-BP model prediction results compared with the standard results

Table 11. Comparison results of the four models

	Number of test samples	Number of Misclassifications	Accuracy
BP prediction model	50	18	64%
GA-BP prediction model	50	13	74%
WOA-BP prediction model	50	9	82%
IWOA-BP prediction model	50	5	90%

Figure 1 to Figure 4 show the prediction results of four different BP neural networks. From the figures, it was found that the IWOA-BP neural network proposed in this paper has a good advantage in the prediction results. Next, we analyze them separately. In Figure 1, we do not use any metaheuristic algorithm, and the BP neural network falls into local minima, which leads to a decrease in prediction accuracy; thus, the prediction results are relatively different from the standard ones. In Figure 2, we optimize the BP neural network with GA, and the prediction accuracy in 50 sets of sample data is considerably improved, which is close to approximately 75%. This shows that the effect of the GA optimization of the BP neural network parameters is notable; in Figure 3, we use the WOA optimization of the BP neural network, and since the performance of the WOA is stronger than that of GA, the prediction effect is greater, overlapping most of the data in 50 sets of comparison data; in Figure 4, we use the IWOA algorithm with a stronger performance, and the prediction effect is also very obvious. The prediction effects of the four BP neural networks are shown in Table 7. The BP neural network model of the IWOA in this paper achieves a 90% recognition rate for the test samples, which is a substantial improvement compared with 64% of the prediction result of the traditional BP model, 74% of the prediction effect of the GA-BP model, and 82% of the prediction effect of the WOA-BP model in terms of correct recognition rate. It shows the effect of the optimization of the algorithm in three aspects in this paper, and the improvement of the performance of the algorithm leads to the improvement of the prediction accuracy of the neural network.

(2) Comparison with the other prediction models

To further verify the effect that the model has, this paper is tested with IGA-BP in reference [21], as well as with the MOS-BP algorithm in reference [25] for 10 samples with normal financial status and 10 samples with financial risk. Figure 5 represents the comparison of the test results of the IGA-BP, the MOS-BP and the model in this paper. The x-axis in the figure indicates the number of samples, and the y-axis indicates the probability value of the samples. The actual financial status of the first 10 samples in the test is normal, and the financial status of the last 10 samples is risky, making the value 1 as the prediction determination point of financial risk during the test. From the figure, it was found that the prediction results of the three algorithms are different, and the average sample results of this paper's algorithm are trendier and flat compared with the other two algorithms. From the whole sample, the probability of the IWOA samples is mostly greater than 0.5. Especially after the sample value of 12, the effect is more obvious, indicating that our optimization strategy in the IWOA is correct. It also shows that the IWOA is obvious in the prediction effect. From the results of these 20 samples tested, the probability value of sample 2 is 0.7, and the test result is a financial risk, which is not consistent with the actual value. The probability values of samples 11, 14, and 18 are all below 0.5, and the test result is financially normal, which is also not consistent with the actual value. Therefore, the financial warning of this paper's model is highly adaptable.

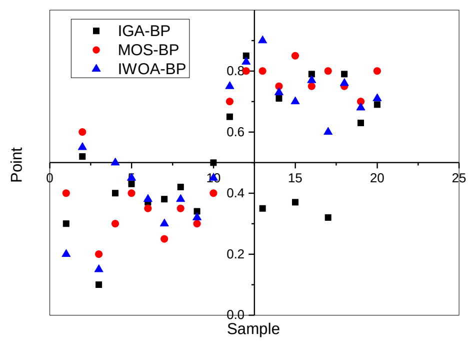

Figure 5. The comparison between the model in this paper and the model in the literature

6. Conclusion

Aiming at the possible financial sub-risk of listed companies, this paper proposes a strategy for financial forecasting using the IWOA-BP neural networks. First, the financial data samples of China's manufacturing industry are analyzed using principal component analysis, and six principal component key indicators are obtained that can meet the characteristics of manufacturing companies. The data of the past T-5 to T-1 years using the IWOA-BP have simulated prediction, and the financial risk early warning model of manufacturing companies is effective through empirical analysis because the time period chosen in this paper is mainly 2 years apart. Therefore, at the same time, the manufacturing industry is an important part of the country, and thus, the government policy has a certain variability, which has a certain impact on the accuracy of the prediction results of the model.

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