An Effective Financial Crisis Early Warning Model Based on an IFOA-BP Neural Network

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Abstract

Existing financial crisis models have weak effects and low accuracy in prediction. We propose a financial crisis early warning model based on the improved fruit fly optimization algorithm-back-propagation neural network (IFOA-BP). First, we select listed enterprises in the manufacturing industry as the research object and use quantum computing to select financial crisis indicators. In view of the shortcomings of the FOA, which has low convergence accuracy and easily falls into the local optimum, we propose the IFOA, which introduces orthogonal experimental arrays in the initialization of the population to improve the diversity of the solutions and optimizes the individual crossing to avoid the algorithm falling into the local optimum. Finally, the IFOA is used for the optimization of the BP neural network's weights and thresholds to improve the model prediction performance. In the simulation experiments, we verify the IFOA's performance with the benchmark function. In the simulation experiments, we verify that the IFOA has good performance, and the IFOA-BP model has a good advantage over the ACO-BP, PSO-BP, FOA-BP, WOA-BP, and CSO-BP models in terms of MSE, MAE, and MAPE indices.

Keywords: Financial crisis, Neural network, Early warning model

1 Introduction

Financial crisis forecasting has always been the center of attention of companies, and it is very important for the company, the industry and even the country's economic impact. When the company's financial prediction results are reliable, it can help the company's shareholders and managers to further invest in the development of the enterprise; in contrast, it is necessary for enterprise managers to take remedial measures to avoid further deterioration of the company's financial crisis and even adjust the investment strategy to reduce the expected investment-related losses. Therefore, it is very important to use tools to study the prediction of financial crises, and the BP neural network is widely used in the prediction of financial crises because it shows better prediction results [1]. Most financial crisis prediction methods are based on the PCA method to screen out the data reflecting the indicators of the financial crisis and combined with the BP neural network model to make predictions, which has achieved good results, but there is still the problem of accuracy to be improved. In this paper, we use the improved fruit fly optimization algorithm-back propagation neural network model, which uses the fruit fly optimization algorithm to optimize the weights and thresholds of the BP neural network to improve the model performance. The fruit fly optimization algorithm (FOA) [2] is a metaheuristic algorithm invented by Pan in 2012 to study fruit flies in nature. It is mainly used to simulate the foraging behavior of fruit flies to seek a new method of global optimization, which has the advantages of simple operation and ease of implementation and is widely used in the application problem optimization model.

The structure of this paper is described as follows: Section 2 describes the research related to the financial crisis early warning model, Section 3 describes the design of the financial early warning model, Section 4 describes the algorithms that need to be used in this model, Section 5 describes the IFOA-BP neural network model based on the IFOA-BP neural network model, Section 6 carries out the simulation experiments to verify the effect of the model, and Section 7 summarizes the whole paper.

2 Related Knowledge

How to find a better financial early warning model has always been the focus of scholars' research. The current research on financial early warning models is mainly divided into univariate analysis, multivariate analysis, multivariate logistic review analysis and neural network application analysis in four aspects.

(1) In univariate analysis, study [3], for the first time in econometrics, widely used univariate analysis and creatively introduced it into the field of financial crisis early warning. Using the data of 20 companies as a sample, research found that in the prebankruptcy period, the general net interest rate of shareholders' equity and shareholders' equity to debt ratio will be anomalous; study [4] combined the two major fields of statistics and financial early warning to establish a one-dimensional financial warning model based on a single financial ratio of the one-dimensional financial early warning model, resulting in a relatively complete single-variable analysis model, which plays a great role in the early stage of financial early warning for the subsequent emergence of a

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large number of prediction models to provide a reference.

(2) In multivariate analysis, the Z value model proposed by [5] created the application of the multivariate analysis model in the study of financial crisis early warning; study [6] proposed the ZETA model including seven financial ratios, and the practical effect showed that the prediction accuracy of this multivariate analysis had a better effect compared with univariate analysis;

(3) In multivariate logistic retrospective analysis, study [7] analyzed financial data through the established logistic model, and the experiments illustrated that the model can improve the prediction accuracy. Study [8] proposed a logistic financial crisis prediction model based on a mixture of logistic and SVM, and the practical effect illustrated that the prediction accuracy has been improved to a certain extent. Study [9] used LSSVM for enterprise financial crisis prediction, and compared with SVM, LSSVM has a better prediction effect. Study [10] analyzed the logistic regression and multivariate discriminant methods and illustrated their respective scope of application in a financial crisis from the perspective of the actual situation. Study [11-12] used the logistic regression model to effectively reduce the risk of the enterprise's finances.

(4) In the analysis of neural network application, study [13] found that the neural network model is more suitable for financial early warning; study [14] used a multivariate analysis model, multivariate logistic regression model, K-approximation method, neural network model, and many other models used in financial early warning, and all of them obtained better prediction results. Study [15] proposed a neural network for financial crisis prediction, and practice shows that neural networks do have a better prediction precision and accuracy; study [16] described the establishment of a neural network early warning model in different enterprises because the enterprise's financial management has played a very good effect; studies [17-20] were based on the BP neural network prediction of financial crises in different companies, and practice shows that this method can effectively predict financial crises but also avoid financial crises. The practice shows that it can effectively avoid the occurrence of financial crises. Study [21] used an LSTM neural network to analyze stock market funds for a short period of time, and the experiment showed that the neural network had a certain effect in stock market fund early warning. Study [22] put forward a financial early warning model of listed companies in the stock market based on the SOM-BP neural network, and the experiment showed that the early warning accuracy of the financial model has a significant improvement. Study [23] proposed a model based on deep learning and a back-propagation neural network. Through the data of Shanghai, China, from 2006 to 2020, the financial risk of Shanghai in 2021 was predicted, and practice has showthat the method has a certain effect. Study [24] designed an economic early warning system based on an improved genetic and BP hybrid algorithm and neural network, and the results show that the improved genetic and BP hybrid algorithm and neural network economic early warning system is effective and feasible. Meanwhile, studies [25-26] provided new research ideas in terms of financial early warning models.

The results of these studies show that there are an increasing number of methods to find the indicators reflecting a financial crisis, from univariate and multivariate methods to neural networks, which shows that the indicators reflecting a financial crisis have become increasingly abundant, ensuring the validity of the prediction results of a financial crisis. It is also found that from a large number of studies, neural networks and other information technology means methods are being gradually applied to the prediction of a financial crisis, which is receiving increasing attention.

3 Design of the Financial Early Warning Model

3.1 Research Sample

Each industry has its own characteristics, which are manifested in various aspects, such as production mode, sales channels, and business objects. Therefore, they are definitely different in the content of financial indicators reflecting financial crises. To make the model of our research valid, we chose the samples of ST companies in the manufacturing industry in the two largest stock markets of China, Shanghai and Shenzhen, as the objects to be analyzed. This is because (1) China's manufacturing companies listed on the data are easier to obtain through the appropriate channels, and the authenticity of these data and credibility are higher, helping to predict the accuracy of the model; (2) China's manufacturing companies listed on the number of large industrial chains involve many aspects of China, and the number of these samples is sufficient to ensure the reliability of the results of the study; and (3) the manufacturing industry is the symbol of China's economy, the study of the manufacturing industry is the symbol of China's economy, the study of the manufacturing industry is the symbol of China's economy, and the study of the manufacturing sector is definitely different from the content of the indicators. (3) The manufacturing industry is the symbol of China's economy, and the study of the manufacturing industry has a strong industry representation, while other industries have higher financial risk, so the study of its financial risk is representative.

3.2 Financial Indicators

To better reflect the indicators of enterprise financial crisis, we chose 46 indicators in 5 categories of solvency, growth, operating ability, profitability and cash flow as the range of indicators reflecting a financial crisis. The financial indicators are shown in Table 1. The financial crisis indicators selected in this paper will be obtained from these indicators.

Table 1. Financial indicators

Type	Indicator
Solvency	Long-term debt to working capital ratio
	Interest earned multiplier
	Gearing ratio
	Tangible net worth debt ratio
	Equity ratio
	Quick ratio
	Current ratio

Growth Capacity	Earnings per stock (net of) growth rate Growth rate of undistributed earnings per stock Net assets per stock (adjusted) growth rate Growth rate of net assets per stock Earnings per stock growth rate Growth rate of return on net assets Profit from main business growth rate Revenue from main business growth rate Total assets growth rate Growth rate of capital surplus per stock
Business Capability	Fixed assets turnover ratio Total assets turnover ratio Working capital/main business revenue Cost margin Accounts receivable turnover ratio Inventory turnover ratio
Profitability	Net income after nonrecurring gains and losses Growth rate of shareholders' equity Return on net Assets Net asset margin Gross sales margin Earnings per stock (net of) Capital surplus per stock Profit margin from main business Undistributed earnings per stock Net assets per stock (after adjustment) Net assets per stock Net sales margin Earnings per stock
Cash Flow	Cash flow per stock Cash return on assets Cash flow per stock growth rate Operating cash flow per stock Operating cash flow per stock growth rate Cash flow debt ratio Net operating cash margin Cash from sales ratio Total cash debt ratio

3.3 Early Warning Thresholds

In this paper, we set the threshold method for ST firms. Under the condition that the confidence probability *alpha* is 95%, the confidence coefficient *nor* min *v*(*alpha*) is 1.6449, the mean *mean* of the state is 0.043 8 and the standard deviation *std* is 0.1191 for the ST sample, then the upper and lower confidence limits for the occurrence of crisis in the ST sample companies are *mean* ± *nor* min *v*(*alpha*)×*std*, and the lower and upper confidence limits are calculated as -0.152 and 0.2397, respectively. When the predicted value of the listed financial status is less than -0.152, the listed company may have a serious financial crisis, and when the predicted value of the listed financial formula is greater than 0.2397, the listed company is in good financial condition. If the prediction result is in between, then it indicates a slight possibility of risk occurrence for the listed company.

4 Algorithm Introduction

4.1 FOA

The FOA mainly simulates the foraging behavior of Drosophila populations, and it usually uses the method of finding the optimal individual based on the group collaboration mechanism. The algorithm is roughly divided into four steps as follows.

Step 1: Initial value setting of the Drosophila algorithm. Set the population size of the entire Drosophila algorithm to *Popsize*, the maximum number of iterations of the algorithm to *Num*, the maximum flight range of the population to *Lr*, and the maximum flight range of each individual in the population to *Fr*. Additionally, the information of each individual Drosophila in the Drosophila population corresponds to two-dimensional coordinates, which are represented as follows:

$$\begin{cases} X\_axis = rand(Lr) \\ Y\_axis = rand(Lr) \end{cases}. \tag{1}$$

Step 2: Olfactory search process

Step 2.1 In the whole Drosophila population, each individual Drosophila flies forward by olfaction, and we set the flight direction and flight distance at the current Drosophila individual position so that the new position of individual *i* is:

$$\begin{cases} X_i = X\_axis + rand(Fr) \\ Y_i = T\_axis + rand(Fr) \end{cases}. \tag{2}$$

Step 2.2 The length of food distance from each individual Drosophila is different, which will lead to the olfactory search of individual Drosophila being different. In this algorithm, we calculate the distance of each individual Drosophila location from the center point and then set the concentration value of individual Drosophila as the inverse of the distance, which illustrates that the concentration value is inversely proportional to the distance length. The distance is shown in expression (3), and the concentration value is shown in expression (4)

$$Dist_i = \sqrt{X_i^2 + Y_i^2}. \tag{3}$$

$$S_i = 1/Dist_i. \tag{4}$$

Step 2.3: Calculate the flavor concentration $Smell_i$ for each individual Drosophila *i* in the current population by Equation (5),

$$Smell_i = fitness(S_i). \tag{5}$$

In Equation (5), $fitness(S_i)$ represents the concentration judgment function, which is the objective function of the optimization problem solved by the FOA.

Step 2.4: Select the best concentration value of Drosophila in the current population, record the concentration value and the corresponding location of the taste

$$[bestSmell, bestIndex] = \min(Smell). \tag{6}$$

Step 3: Visual search process

The Drosophila population flies to the corresponding position of the optimal concentration in step 2, i.e., expressed as follows.

$$SmellBest = bestSmell. \quad (7)$$

$$\begin{cases} X\_axis = X(bestIndex) \\ Y\_axis = Y(bestIndex) \end{cases}. \quad (8)$$

Step 4: Repeat Step 2 and Step 3 until the algorithm reaches the maximum number of iterations. The location of the best concentration obtained is the optimal solution of the FOA.

4.2 BP Neural Network

The BP neural network is a multilayer, complex neural network based on a backpropagation mechanism. As its initial parameters need to be set less, most of the parameters are corrected by its unique training mechanism, its output value is less different from the expected value, and the convergence accuracy is higher.

The number of each layer in the BP neural network is set to 1. The input vector of the input layer is $\lambda = (\lambda_1, \lambda_2, \lambda_3, ..., \lambda_n)^T$, n denotes the number of nodes in that layer, and T denotes the transpose operation on that matrix. The output vector of the implicit layer is $Y = (y_1, y_2, y_3, ..., y_{n1})^T$, where n_1 is the number of nodes in the layer, and the actual output vector of the output layer is $D = (d_1, d_2, d_3, ..., d_m)^T$, where m is the number of nodes in the layer; thus, the expected output vector of the BP neural network set in advance is $O = (o_1, o_2, o_3, ..., o_m)^T$. $w1_{ij}$ (i = 1, 2, ..., n, j = 1, 2, ..., $n1$) and $w2_{jj}$ (j = 1, 2, ..., $n1$, k = 1, 2, ..., m) denote the input layer weights and output layer weights of the implicit layer, respectively, and $B1_j$ (j = 1, 2, 3, ..., $n1$) and $B2_k$ (k = 1, 2, 3, ..., m) denote the implicit layer threshold and output layer threshold, respectively.

5 Financial Early Warning Model Based on the IFOA-BP Neural Network Model

5.1 Quantum Computing

To better reflect the selection of financial sample indicators in the financial prediction model by the FOA, we introduce the concept of quantum computing; i.e., the individual fruit flies constantly update the positions of the fruit fly quanta in the FOA through the quantum rotation angle and quantum rotation gate in the quantum computing theory while obtaining the positions of the fruit fly quanta through certain mapping criteria, i.e., the selection of financial indicators, under the rules of their own algorithms. In quantum computing, each Drosophila population contains N Drosophila quanta, and its quantum position is $\hat{x}_i = (x_{i1}, x_{i2}, ..., x_{iD})$, $i \in [1, N]$, $\hat{x}_{ij} \in [0,1]$, $j \in [1, D]$. The position $\hat{v}_i = (v_{i1}, v_{i2}, ..., v_{iD})$ for an individual Drosophila is obtained through the quantum position, whose position is the possible solution waiting to solve the problem, taking the values 0 and 1.

5.2 IFOA

Similar to most metaheuristic algorithms, the FOA also suffers from the problem of easily falling into a local optimum and low solution accuracy. To solve this problem, we optimize it separately from the following two aspects and propose an improved fruit fly optimization algorithm.

(1) Population initialization

To ensure that the effective solutions are evenly distributed in the solution space, this paper adopts the experimental method based on orthogonal arrays to initialize the FOA population so that the initial solutions can be evenly distributed among the feasible solutions and improve the speed of the algorithm in searching for the optimal solution.

Step 1: Divide the feasible domain $[l, u]$ of the FOA population problem into $[l_1, u_1]$, $[l_2, u_2]$, ..., $[l_S, u_S]$, which is divided into

$$\begin{cases} l_i = l + (i-1)\left(\dfrac{u(s)-l(s)}{S}\right) l_S \\ u_i = u - (S-i)\left(\dfrac{u(s)-l(s)}{S}\right) l_S \end{cases}, i = 1, 2, ..., S. \quad (9)$$

where $u(s) - l(s) = \max\limits_{1 \le i \le D} \{u_i - l_i\}$.

Step 2: After quantizing the subset $[l_i, u_i]$ Q_1 times, we obtain

$$a_{ij} = \begin{cases} l_i, & j = 1 \\ l_i + (j-1)\left(\dfrac{u_i - l_i}{Q_1 - 1}\right) & 2 \le j \le Q_1 - 1. \\ u_i & j = Q_1 \end{cases} \quad (10)$$

where Q_1 is an odd number. The orthogonal array $L_{M_1}(Q_1^N) = \left[a_{ij}\right]_{M_1 \times N}$ is constructed according to Equation (11)

$$\begin{cases} (a_{1,a_{11}}, a_{2,a_{12}}, ..., a_{N,a_{1N}}) \\ (a_{1,a_{21}}, a_{2,a_{22}}, ..., a_{N,a_{2N}}) \\ \cdots \\ (a_{1,a_{M_11}}, a_{2,a_{M_12}}, ..., a_{N,a_{M1N}}) \end{cases}. \quad (11)$$

Select M_1 individuals, where $L_{M_1}(Q_1^N)$ is constructed according to the following rules, when the smallest J_1 satisfies $(Q_1^{J_1} - 1)/(Q_1 - 1) \ge N$. When $(Q_1^{J_1} - 1)/(Q_1 - 1) = N$, then $N' = N$; otherwise, $N' = (Q_1^{J_1} - 1)/(Q_1 - 1)$, and construct the basic column of the array $j = \dfrac{Q_1^{k-1} - 1}{Q_1 - 1} + 1$, $a_{ij} = \left\lfloor \dfrac{i-1}{Q_1^{J_1 - k}} \right\rfloor \bmod Q_1$, i = 1, ..., M_1, k = 1, ..., J_1. Not listed as $j = \dfrac{Q_1^{k-1} - 1}{Q_1 - 1} + 1$,

$a_{j+(s-1)(Q_1-1)+t} = (a_s \times t + a_j) \bmod Q_1$, $s = 1, ..., j-1$, $t = 1, ..., Q_1$. This completes the construction of the array $L_{M_1}(Q_1^{N'})$. Delete the last column $N' - N$ of $L_{M_1}(Q_1^{N'})$ to obtain $L_{M_1}(Q_1^{N})$, where $M_1 = Q_1^{J_1}$.

Step 3: Among the M_1S individuals, the SN individuals with the highest fitness were selected as the initial population.

(2) Boundary processing

It is extremely possible that the individuals in the FOA may exceed the boundary of the feasible domain. When the k th dimension of an individual x_i exceeds the boundary, the Drosophila individual that exceeds the boundary is mapped to a new location according to Equation (12), which is defined as follows:

$$\hat{x}_{i,k} = \begin{cases} x_{o,k} + \dfrac{x_{i,k} - x_{o,k}}{\| x_i - x_o \|} * | x_{LB,k} - x_{o,k} | \ \ if\ x_{i,k} < x_{LB,k} \\ x_{o,k} + \dfrac{x_{i,k} - x_{o,k}}{\| x_i - x_o \|} * | x_{UB,k} - x_{o,k} | \ \ if\ x_{i,k} > x_{UB,k} \end{cases} . \quad (12)$$

In Eq. (12), $x_{UB,k}$, $x_{LB,k}$ are the upper and lower boundaries of the k th dimension in the solution space, and x_o denotes the origin of the solution space. The processing of this formula prevents individual individuals from being outside the boundary range and avoids the algorithm from falling into a local optimum.

5.3 IFOA-BP Neural Network Prediction Process

In this paper, we use a financial crisis model based on an IFOA-BP neural network for forecasting. First, we use the IFOA to screen the indicators of the sample between t-4 and t-1 years, and the output of the FOA is 1 if the indicators in this column are selected and 0 if the opposite is true. Second, the selected indicators are input to the BP artificial neural network for financial situation prediction, and finally, the prediction results are compared with the actual financial situation of the company according to the criteria of the warning threshold to verify the accuracy of the model. The specific process is as follows.

Step 1: Input the financial sample index data from year t-4 to t-1, set the initial values of the relevant parameters of the FOA and the maximum number of iterations, and set the maximum training number of learning accuracy and initial weights of the BP neural network.

Step 2: The position of the fruit fly quantum corresponds to the indicator of the financial warning.

Step 3: Initialize the Drosophila population using equations (9-11).

Step 4: In the process of visual search, if there is an out-of-bounds situation during the flight, the out-of-bounds treatment according to Eq. (12) is applied.

Step 5: Make a comprehensive judgment on the current number of iterations, determine whether it is the maximum number, and then output the whole Drosophila quantum position, which corresponds to the specific financial index. Then, go to step 6; otherwise, the number of iterations is accumulated plus 1, and go to step 3.

Step 6: Input the specific financial index data into the BP neural network.

Step 7: Calculate the input and output values of each layer of the BP neural network.

Step 8: Calculate the output layer error of the BP neural network.

Step 9: Determine whether the layer reaches the maximum number of iterations or whether the error is less than the expected value; if so, output the training results; otherwise, return to step 7 to continue.

The flowchart of the algorithm is shown in (Figure 1):

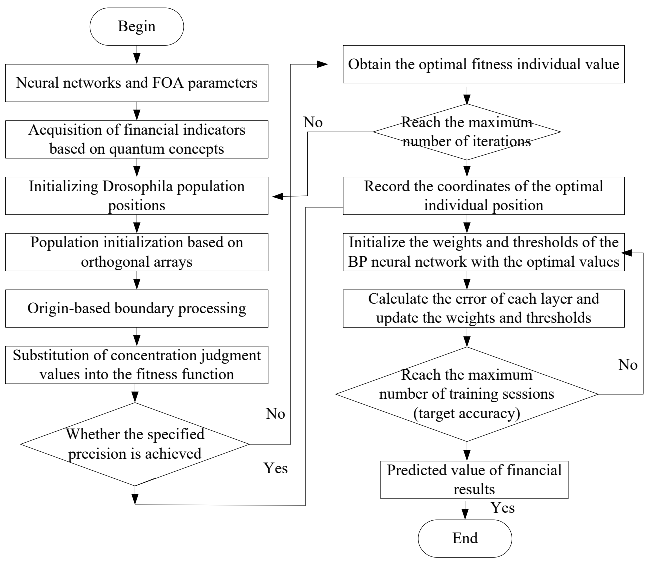


Figure 1. Flowchart of the algorithm

6 Simulation Experiments

To further illustrate the effect of a financial crisis model proposed in this paper, we conducted the following three experiments. Experiment 1 verified the performance of the algorithm in this paper through the benchmark function and illustrated that the improved Drosophila algorithm significantly improves the performance of the algorithm. Experiment 2 specifically verified the effect of the prediction model in this paper. Experiment 3 compared the effect of the prediction model in this paper with the prediction model of the comparison algorithm. Our computer hardware platform is a Core I7 processor, 16 G DDR4 memory, and 1 T hard disk capacity, and we choose MATLAB 2021a as the simulation software and Windows 10 as the operating system. The comparison algorithms are the ACO algorithm, PSO algorithm, and FOA. In terms of the sample data of financial data needed for the model, we selected the financial data of 48 manufacturing listed companies in the period of 2015-2019 as the research sample from the publicly available Wind database, the financial annual reports of listed companies in China's Shanghai and Shenzhen stock exchange software, and among these 48 companies, we selected 12 companies with a financial crisis situation and no financial crisis condition and classified the samples of these listed companies into two categories: One is the training sample and the other is the test sample. In the training sample, 24 companies without financial crisis and 8 companies with financial crisis are included. For the test sample, 12 companies without financial crisis and 4 companies with financial crisis are included.

6.1 Algorithm Performance

To verify the performance of the IFOA, we compare the IFOA with ACO, PSO, and the FOA under different dimensional conditions (2-dimensional, 5-dimensional, 10-dimensional and 30-dimensional) with six standard benchmark test functions (as shown in Table 2). The results are shown in Table 3 to Table 8, and the contents are maximum, minimum, mean and standard values. Setting the number of iterations as 1000 and the population size as 100, Figure 2 shows the results of the fitness values of the four algorithms.

Table 2. Benchmark function

No	Benchmark function
F1	$\sum_{i=1}^{n-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$
F2	$20\exp(-\frac{1}{5}\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2})-\exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i))$
F3	$\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10)$
F4	$\sum_{i=1}^{n}([x_i+0.5])^2$
F5	$\frac{1}{1000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$
F6	$\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$

Table 3. F1 test function comparison

Algorithm	Dim	Min-Value	Max-value	Mean	St-deviation
ACO	2	2.1516	99.9015	41.8923	45.35198
	5	5.9796	99.8704	78.0387	29.6412
	10	29.8743	100.6369	91.6036	14.5750
	30	88.0623	100.8343	97.5832	4.8063
PSO	2	3.333E-06	2.1167	2.0079	2.0178
	5	2.0515	6.4855	2.8557	2.8847
	10	6.1968	20.5127	13.6521	4.6671
	30	16.8414	40.9061	28.7126	6.9851
FOA	2	9.1732E-08	3.349E-02	3.893E-03	5.220E-03
	5	3.9221E-03	8.3461E-02	4.728E-02	2.487E-02
	10	2.823E-02	9.9751E-02	7.390E-02	3.171E-02
	30	7.550E-02	2.6971E+01	2.353E+01	3.146E-02
IFOA	2	8.408E-11	5.8827E-05	4.069E-06	9.231E-06
	5	3.442E-10	4.8148E-05	2.846E-05	7.841E-05
	10	4.383E-10	2.6005E-03	5.980E-05	3.352E-04
	30	3.187E-11	2.3632E-03	6.199E-05	3.174E-04

Table 4. F2 test function comparison

Algorithm	Dim	Min-Value	Max-value	Mean	St-deviation
ACO	2	2.1722	9.93187	4.81745	2.15231
	5	20.8453	104.76211	72.08212	76.17841
	10	61.8797	78.1529	70.1326	72.1662
	30	76.0331	98.1325	85.1292	78.5125
PSO	2	5.536E-07	8.7018	1.2493	3.1026
	5	2.6381	1732.3531	166.4846	362.1874
	10	217.6602	623.2061	419.2939	458.5928
	30	26.4012	74.2501	56.3618	63.3001
FOA	2	8.135E-10	3.314E+02	8.926E-03	3.812E-03
	5	9.137E-02	7.9193E+02	4.912E+02	3.349E+01
	10	6.374E+02	2.716E+03	3.338E+02	4.318E+02
	30	3.312E+03	9.916E+04	3.816E+03	3.713E+03
IFOA	2	2.6015	2.9892	2.6557	2.0939
	5	5.5985	5.9743	5.8919	2.1064
	10	10.4986	11.0698	10.8758	2.0954
	30	30.4938	30.8485	30.7043	2.0466

Table 5. F3 test function comparison

Algorithm	Dim	Min-Value	Max-value	Mean	St-deviation
ACO	2	2.0337	39.3893	29.4607	32.1455
	5	2.31684	5..9269	3.7123	3.7733
	10	3.7993	7.6917	5.4212	5.7512
	30	26.1264	29.8163	28.9819	24.1252
PSO	2	4.242E-10	2.0045	2.0003	2.0008
	5	2.0281	14.3334	12.2429	11.1208
	10	14.1754	61.9040	44.5521	36.6854
	30	64.98862	74.0984	70.1193	72.6255

FOA	2	6.704E-12	11.922E-04	8.431E-05	3.951E-04
	5	1.987E-04	4.929E-01	6.114E-02	6.6711E-02
	10	1.370E-02	3.588E+01	6.122E-02	3.791E-02
	30	2.314E+01	2.214E+02	5.299E+01	3.124E+01
IFOA	2	0	3.372E-03	2.578E-04	5.201E-04
	5	6.947E-12	5.362E-02	2.590E-03	7.378E-03
	10	7.447E-07	2.770E+01	2.180E-02	3.834E-02
	30	3.843E-06	5.927E+00	5.621E-01	9.8234E-01

Table 6. F4 test function comparison

Algorithm	Dim	Min-Value	Max-value	Mean	St-deviation
ACO	2	3.7772	56.2793	26.3270	14.1595
	5	34.0471	134.3065	82.6387	19.5753
	10	89.0779	240.8592	174.6402	36.0953
	30	485.4056	646.3190	545.7706	39.1596
PSO	2	8.322E-10	3.0012	2.1596	2.3501
	5	5.00500	24.8812	10.2732	6.6295
	10	15.8636	64.0298	36.9549	13.0675
	30	121.8476	265.78831	202.0472	129.5858
FOA	2	2.601E-11	2.992E+01	4.0641E-02	6.5251E-02
	5	2.061E-06	3.009E+01	6.128E+00	4.697E+00
	10	9.031E-01	6.856E+01	4.281E+01	3.020E+01
	30	3.572E-01	4.215E+02	3.238E+02	8.525E+01
IFOA	2	5.552E-15	10.092E-05	5.813E-06	3.362E-05
	5	4.567E-15	3.815E+00	5.827E-02	4.566E-01
	10	3.065E-13	9.285E-01	5.273E-02	3.438E-01
	30	10.343E-11	11.239E+00	5.920E-01	3.563E+00

Table 7. F5 test function comparison

Algorithm	Dim	Min-Value	Max-value	Mean	St-deviation
ACO	2	3.1717	22.7335	12.18269	5.75730
	5	3.8474	5.7149	4.0521	1.1378
	10	7.7276	47.9212	29.5456	33.0461
	30	3.642E+10	3.669E+21	4.921E+18	6.121E+16
PSO	2	6.611E-07	3.012E-05	3.001E-04	3.4712E-06
	5	3.0042	4.2703	3.2266	3.2595
	10	4.0877	11.4470	7.5504	4.8924
	30	18.01764	69.9716	35.4898	13.5643
FOA	2	4.921E-07	8.802E-03	6.905E-04	1.117E-05
	5	3.316E-05	3.792E-02	5.832E-03	5.821E-03
	10	4.252E-04	3.471E+01	5.436E-02	5.124E-02
	30	3.218E-02	10.858E+01	4.126E+01	4.089E+01
IFOA	2	6.253E-10	6.496E-04	7.868E-05	3.064E-04
	5	5.511E-10	0	3.776E-04	6.490E-04
	10	9.058E-09	6.866E-03	5.574E-04	11.304E-04
	30	3.433E-07	9.016E-02	5.241E-03	3.116E-02

Table 8. F6 test function comparison

Algorithm	Dim	Min-Value	Max-value	Mean	St-deviation
ACO	2	2.0256	72.4115	40.9162	60.2597
	5	3.0189	119.4365	98.1912	75.9339
	10	3.1763	33.6568	28.8746	30.6602
	30	3.1592	14.0158	11.4368	17.9571
PSO	2	7.079E-11	12.0016	13.935E-05	3.0296
	5	1.607E-11	3.0014	3.1153	3.0002
	10	4.9165E-09	3.0139	3.0005	3.0020
	30	1.924E-3	3.0396	3.0017	3.0059
FOA	2	9.881E-11	5.115E-04	5.171E-05	6.781E-05
	5	1.461E-05	6.365E-03	5.662E-04	8.331E-04
	10	7.719E-07	4.8993E-02	4.6612E-03	6.0481E-03
	30	6.727E-05	1.4893E-03	3.3016E-03	3.9832E-03
IFOA	2	0	1.5384E-04	5.7521E-05	3.3676E-04
	5	5.720E-10	3.5871E-02	3.3300E-03	4.9698E-03
	10	5.882E-08	9.2073E-02	6.9116E-03	3.3323E-02
	30	6.660E-07	1.0665E+01	3.0012E+01	3.9562E+01

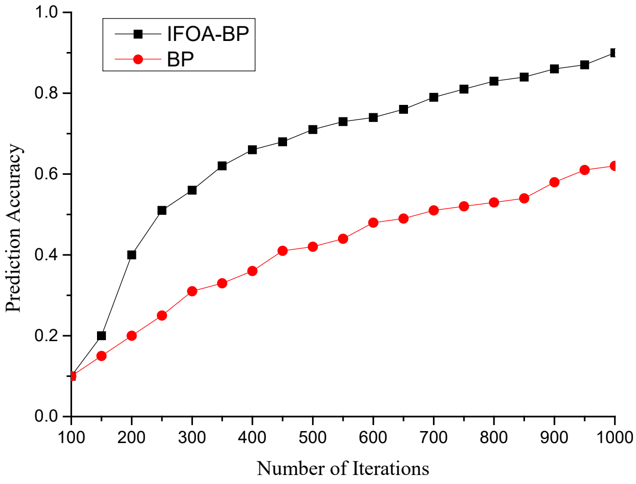


Figure 2. Comparison of predicted effects

Based on the data presented in Table 3 to Table 8, it is evident that the IFOA outperforms other algorithms in terms of minimum, maximum, mean, and standard value results for the six functions under investigation. The superiority of the IFOA is clearly demonstrated when compared to ACO and PSO, as indicated by the findings in these tables. Furthermore, the IFOA exhibits significant performance advantages over the FOA, specifically for functions F3, F5, and F6. Notably, when the dimension is 2 or 5, the IFOA achieves a minimum value of 0, while for dimensions 10 and 30, IFOA consistently delivers favorable outcomes across all six functions. This suggests that the overall performance of the IFOA has been greatly enhanced through strategies such as population initialization, call behavior optimization, and individual screening. The consistently superior results obtained by the IFOA in terms of various statistical measures, along with its notable advantages over competing algorithms, validate the effectiveness of the population initialization, call behavior optimization, and individual screening strategies employed in optimizing its overall performance.

6.2 Prediction Effect of the Model in this Paper

We conducted experiments using two neural network models: the IFOA-BP model and the BP model. A set of sample indicators was input into both models, and the results were compared, as depicted in Figure 1. The prediction accuracy analysis revealed a clear advantage of our proposed algorithm over the conventional BP neural network. The primary reason for this disparity lies in the BP neural network's inability to choose suitable indicators that adequately reflect the financial early warning model. When fed with a set of sample indicators, the BP neural network processes all the indicator data without discernment, leading to inefficiency and reduced accuracy. Consequently, the prediction results suffer. In contrast, our IFOA-BP model significantly enhances the prediction accuracy of the BP neural network by selectively screening the sample indicators. By leveraging the screening process, our approach eliminates irrelevant or noncontributing indicators, enabling the model to focus on the most informative inputs. This targeted approach leads to improved efficiency and accuracy, resulting in superior prediction performance compared to the traditional BP model.

6.3 Comparison with Other Prediction Models

To further illustrate the prediction effect of the algorithms in this paper, we add two current newer prediction algorithms, WOA-BP [27] and CSO-BP [28], on the basis of the existing ACO-BP, PSO-BP and FOA-BP neural networks for comparison.

(1) Comparison of the prediction classification effect

The results we predicted by the BP neural network are classified into three categories: using 0 to indicate that the mild risk is set to 0, using 1 to indicate that the heavy risk is set to 0, and using -1 to indicate that the risk does not exist. We input 20 groups of test samples into the model, and the results are shown in Figure 3 to Figure 8. In the ACO-BP shown in Figure 3, for samples 3, 5, 7, 12, 15, and 19, the difference between the predicted and true values is relatively large. In the PSO-BP neural network shown in Figure 4, the predicted values of samples 2, 4, 8, 12, 15, and 18 are more different from the real values. In the FOA-BP neural network in Figure 5, samples 2, 4, 6, 11, 15, and 18 have some gap with the true values. In the WOA-BP neural network in Figure 6, samples 4, 7, 12, and 15 have some gap with the true values. In the CSO-BP neural network in Figure 7, samples 2, 5, 9, and 13 have some gap with the true values. In the IFOA-BP neural network in Figure 8, only sample 6 has a gap with the real value, and the prediction of other samples are the same as the real value, which shows that the prediction value of the IFOA-BP neural network is closer to the real value and shows the effect that the algorithm of this paper has.

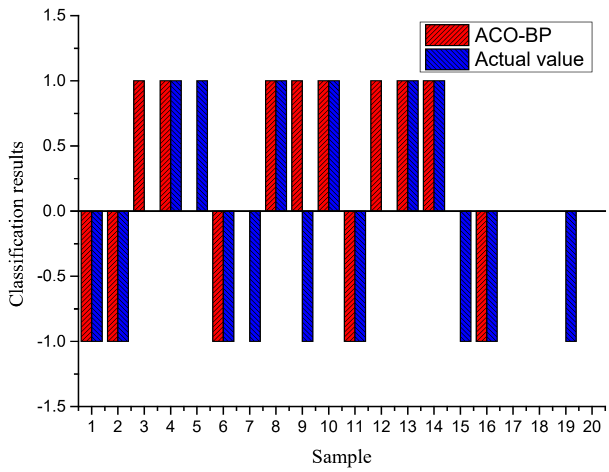


Figure 3. ACO-BP neural network classification results

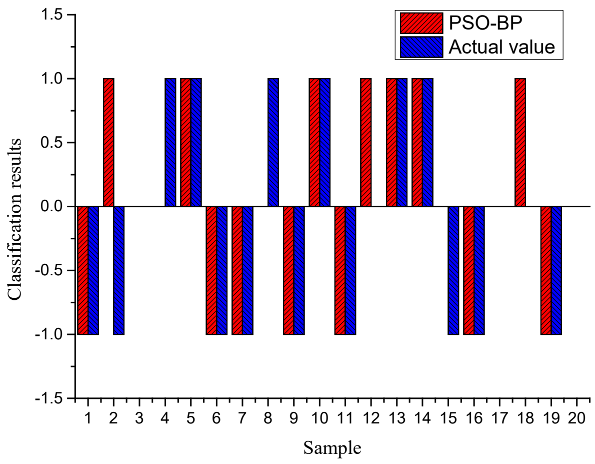


Figure 4. PSO-BP neural network classification results

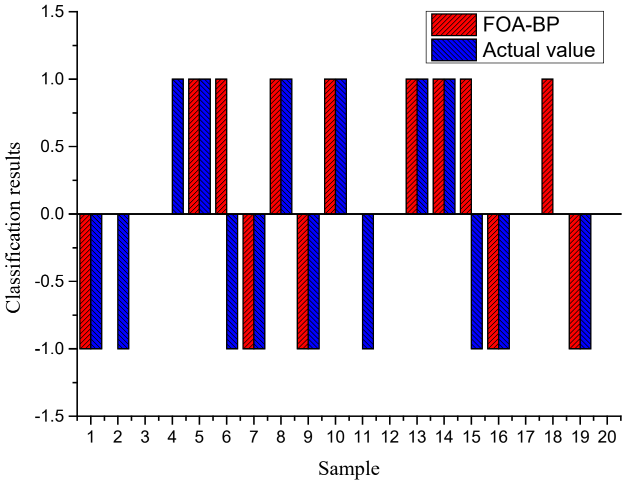


Figure 5. FOA-BP neural network classification results

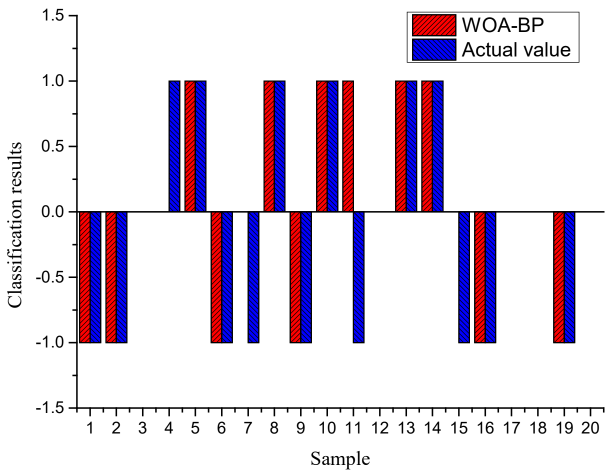


Figure 6. WOA-BP neural network classification results

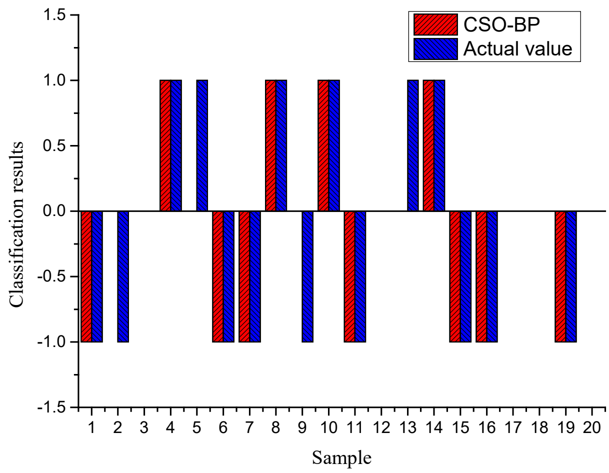


Figure 7. CSO-BP neural network classification results

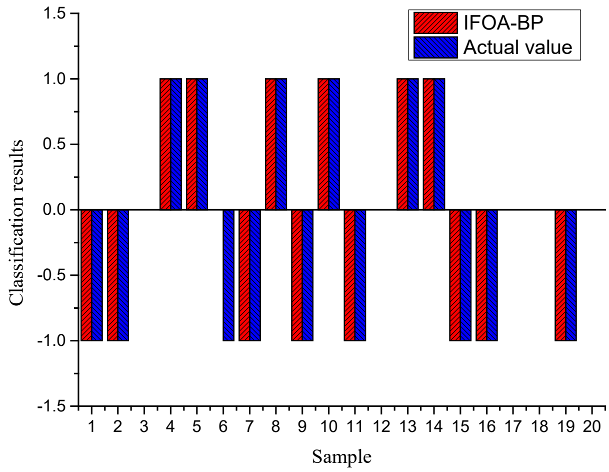


Figure 8. IFOA-BP neural network classification results

(2) Numerical analysis of prediction indicators

Studies [29-31] suggests that the prediction effect should use a standard model used to judge the idea. According to the prediction results of the BP neural network, we use MSE, MAE, and MAPE indicators as the prediction results of this paper's algorithm. The results are shown in Table 9.

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(y_k - y_k^*)^2. \quad \textbf{(13)}$$

$$MAE = \frac{\sum_{k=1}^{n}| y_k - y_k^* |}{n}. \quad \textbf{(14)}$$

$$MAPE = \frac{100\%}{n}\sum_{k=1}^{n}| \frac{y_k^* - y_k}{y_k} |. \quad \textbf{(15)}$$

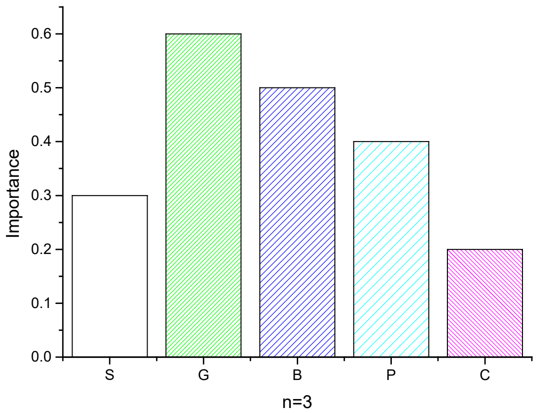
In the above three formulas, n denotes the number of predicted samples, y_k denotes the true value of the k th sample, and y_k^* denotes the predicted value of the k th sample.

Table 9. Comparison of the prediction performance of six algorithms

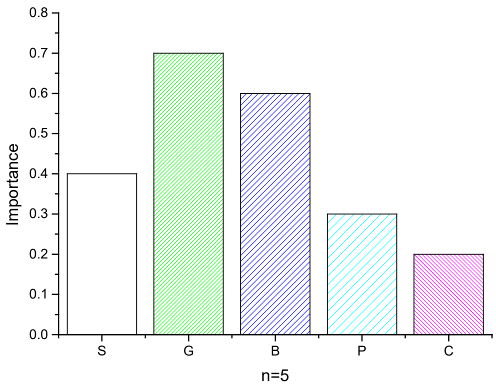
Predictive model	MSE	MAE	MAPE
ACO-BP	2.19732	1.73813	30.291%
PSO-BP	1.90325	1.59032	29.492%
FOA-BP	0.29312	0.49031	17.391%
WOA-BP	0.16932	0.36932	15.943%
CSO-BP	0.15931	0.34793	14.821%
IFOA-BP	0.13892	0.33201	13.291%

From the table, it is found that this paper's algorithm has obvious advantages in three metrics. In MSE metrics, this paper's algorithm reduces 2.0584, 1.76433, 0.1542, 0.0304, and 0.02039 compared to ACO-BP, PSO-BP, FOA-BP, WOA-BP, and CSO-BP, respectively. In MAE metrics, this paper's algorithm reduces 1.40612, 1.25831, 0.1583, and 0.03731 compared to ACO-BP, PSO-BP, FOA-BP, WOA-BP, and CSO-BP by 1.40612, 1.25831, 0.1583, 0.03731, and 0.01592, respectively. In the MAPE metrics, this paper's algorithm reduces ACO-BP, PSO-BP, FOA-BP, WOA-BP, and CSO-BP by 17%, 16.201%, 4.1%, 2.652% and 1.53%, respectively. The above results show that the algorithm of this paper can improve the prediction effect of the BP neural network after optimization in three aspects.

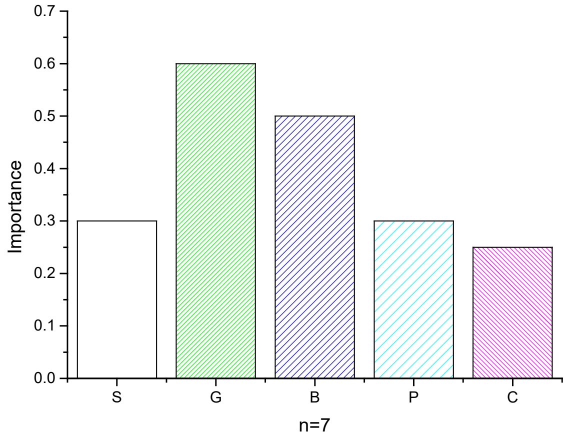
(3) Indicator importance analysis



(a) n=3



(b) n=5



(c) n=7

Figure 9. Results of the analysis of the importance of each indicator in the forecasting model

The traditional BP neural network prediction model only gives the predicted output value based on the black-box algorithm, while the BP-Garson combined model can analyze the contribution of each factor of the training model. In this study, we use the Garbon algorithm of the "Neural Net Tools" package in R language to write the analysis code and compare the importance of each parameter of the prediction model to visualize and analyze the results. To ensure the typicality of the training effect, we established a prediction model with different hidden layer neurons to analyze the importance of the model parameters. The importance of the model parameters is analyzed, as shown in Figure 9, where n represents the number of different hidden layer neurons, and the five main financial indicator factors solvency (S), growth capacity (G), business capability (B), profitability (P) and cash flow (C). The result of the importance ranking of the five performance parameters indicates that growth capacity and business capability are the primary factors and that solvency (S), profitability (P) and cash flow (C) are the secondary factors.

6 Conclusion

In this paper, we propose a prediction model based on the IFOA-BP neural network, which takes listed enterprises in the manufacturing industry as the research object, adopts the concept of quantum computing to screen financial indicators, generates IFOA through population initialization and boundary optimization measures, and optimizes the parameters of the BP neural network model using the IFOA. The simulation experiment verifies that the model has a good prediction effect. In the next step, we will carry out research on AI-LSTM technology, discuss in depth how to use this technology in the enterprise financial early warning model, and, at the same time, combine the meta-heuristic algorithm for model parameter optimization to further improve the model prediction ability.

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