Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 5135260, 11 pages
https://doi.org/10.1155/2022/5135260

Research Article

Early Warning of Financial and Business Management Based on Three Improved BP-NN Algorithms

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Received 18 June 2022; Revised 3 August 2022; Accepted 18 August 2022; Published 1 September 2022

Academic Editor: Kapil Sharma

To address the issue of early warning in financial management and economics, this article presents a study based on our improved BP-NN algorithms. This approach improves the benefits of early warning systems in financial and business management based on BP neural network algorithm technology and improves BP neural network algorithms. Based on the analysis and calculation of the results, the inconsistency of the financial model industry estimates is 66.3% and 72.7% for CT and non-CT companies. The actual discrimination rate of the hedge fund model is 81.3% and 83.9% for ST and ST companies, respectively. Compared with the net structure of the financial index, the general guidance model improved the ability of ST companies and non-ST companies to withstand risks by 14.27% and 8.76%, respectively. It can be concluded that the integration of nonfinancial indicators into the estimation model can improve the accuracy of the estimation of the model. Experiments have shown that research based on our improved BP-NN algorithms can not only eliminate BP network inadequacies but also improve the accuracy of early warning in financial markets.

1. Introduction

In today's world, as the business environment continues to improve, businesses will face many challenges in entering a competitive market, and financial issues have always been an important aspect of business confusion. The sector is facing more risks and challenges in its development. How to prevent a financial crisis is an important concern for businesses. At this stage, a study of the financial crisis warning system has been conducted, and its application suggests that the financial crisis warning system began with financial market research. At the same time, more business management procedures need to be integrated, financial crisis early warning and management procedures need to be tightened, and strong support for forecasting models and forecasting technology is needed. Early successful and cost-effective financial reporting can help businesses better manage their finances.

The emergence of BP neural network has strong operability, and the prediction accuracy of crisis is relatively high. It is based on this feature that has attracted much attention. On this basis, it began to study from different fields, such as the combination of hierarchical genetic algorithm and BP neural network, the combination of grey theory and neural network, and the construction of financial early warning based on neighborhood rough set and neural network. These studies have played a certain role in preventing the outbreak of enterprise financial crisis to a certain extent, but from the reality, the standard BP-NNs still have some disadvantages, such as local optimization and relatively slow network training speed, which requires us to further improve the BP-NN algorithm [1]. Based on this, combined with the needs of enterprise financial and economic management early warning and crisis early warning management, this paper proposes a network

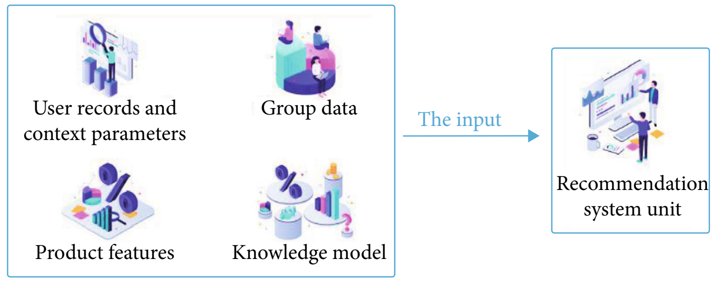

Figure 1: BP-NN improved algorithm.

algorithm based on HSDM-BP to further improve the BP neural network algorithm, as shown in Figure 1.

2. Literature Review

Exploring and constructing the system and method of predicting the operating risk of listed companies is the focus of the current theoretical and practical circles. In the current economic downturn situation, there is no significant upward inflection point, the increasing competition among companies and the rising business risks, establishing and improving the crisis prediction system of listed companies, and revealing the company's business problems in advance have become an issue of extraordinary concern to the company. The research on crisis prediction mainly includes the construction of prediction modeling and the setting of prediction indicators.

Schweiger et al. put forward many financial prediction models, such as univariate prediction model, multivariate linear discriminant model, principal component analysis, factor analysis, logistic regression model, combination of factor analysis and logistic regression, cluster analysis, decision tree, probit regression model, and y-score model [2]. Abreu et al. found that the previous prediction methods do have certain prediction functions, but there are some defects. For example, the financial information used in univariate prediction is one-sided, and the financial indicators themselves have limitations in evaluating the real income of the company [3]. Dai and Liu found that the multivariate linear discriminant model has strict requirements for the data used for prediction, but it lacks wide application and universality [4]. Zhang et al. proposed improved prediction models based on data mining technology, such as BP neural network, intelligent neural network, recursive partitioning algorithm (RPA), and artificial neural network system model (ANN) [5]. Han and Huang found that although the model adopts the latest research results of system science and informatics and has a certain scientificity, it is difficult to operate and does not have universality [6].

The research on financial crisis early warning continues to deepen with the improvement and perfection of the capital market. Some scholars used the univariate analysis method in econometrics to analyze and judge 19 companies as samples. The results show that among all the judgment indicators, the net interest rate of shareholders' equity and the ratio of shareholders' equity to liabilities have the best prediction effect, and these indicators have obvious signs in the three years before bankruptcy. Based on the principle of statistics, a unitary financial crisis early warning model based on single financial ratio is established. He selected samples according to the size of assets and the matching principle, selected 30 variable indicators from all report items, and tested the prediction of the selected samples within 5 years before bankruptcy. The study found that the misjudgment rate in the year before the dilemma was only 13%. The research results play a connecting role in the field of financial crisis early warning and lay a solid foundation for the next multivariable prediction model [7]. In addition to the above studies, many experts and scholars have developed mixed research models. Select listed companies that have been successful in the commodity exchange industry for the last 20 years, study data extraction techniques, and provide a variety of applications (analytical discrimination, logistic regression analysis, neural network, and timber decision making). Develop a hybrid approach. Empirical experiments show that the hybridization process has more accurate predictions than one method, which opens up new possibilities for early financial warning. Some scholars are constantly improving the neural network algorithm. On the one hand, cluster analysis is used to reclassify the degree of enterprise distress, which is more in line with the development trend of enterprise management. On the other hand, the rough set theory is used to screen the variable indexes, which increases the fitting degree of the network model to a certain extent. It can be seen that the model formed by the organic combination of the three is obviously better than the prediction ability of traditional ANN. In the study, factor analysis was used to eliminate the collinearity between indicators. The results show that the model has good predictability. Among all indicators, the influencing factor coefficient of profitability is the largest.

3. Related Algorithm Theory

3.1. Theoretical Basis of Harmony Search Algorithm. HS algorithm is similar to simulated annealing algorithm, which imitates physical annealing mechanism; particle swarm optimization algorithm imitates bird predation; genetic algorithm imitates biological evolution, etc. However, compared with other metaheuristic algorithms, the principle is simpler and easier to understand, less mathematical expressions and parameters are applied, and it is easier to be applied to various

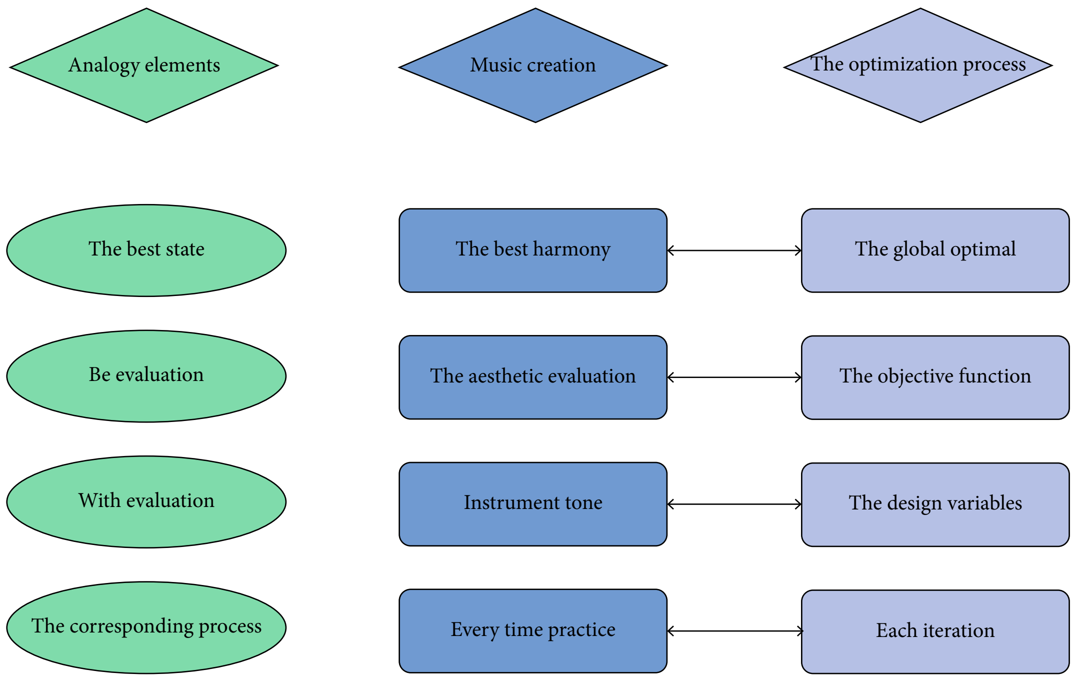

Figure 2: Comparison of music creation and optimization process.

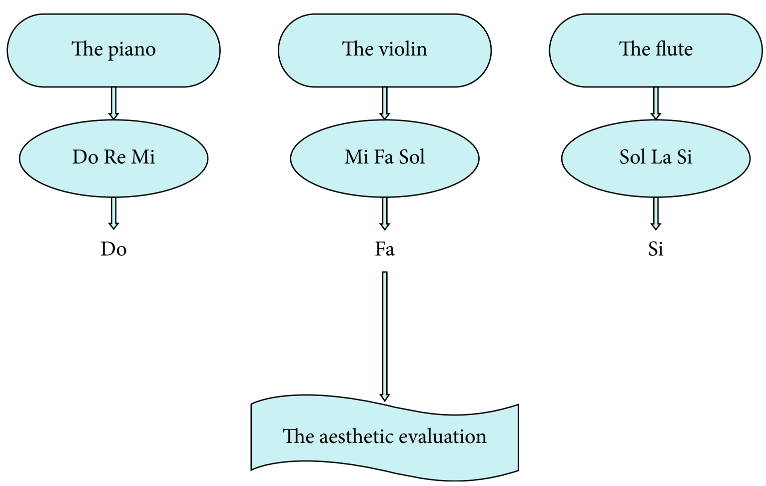

Figure 3: Schematic diagram of music creation.

engineering optimization problems. It is a prominent advantage of harmony search algorithm [9], as shown in Figure 2.

Harmony memory (HM) is a unique set of solution vectors in harmony search algorithm. Firstly, initialization operation is required, and then, new harmony is randomly generated. Compared with the original worst harmony in harmony memory, by worst case scenario, the best update is changed by HM and done in a cycle until the last event is encountered, as shown in Figure 3.

In the actual optimization problem, each musical instrument (piano, violin, and flute) in Figure 3 corresponds to a decision variable $\{x1, x2, x3\}$. At this time, the corresponding value of $\{\text{Do, Re, Mi, Fa, Sol, La, Si}\}$ is $\{100, 200, 300, 400, 500, 600, 700\}$. For the new harmony $\{\text{Do, Fa, Si}\}$, the corresponding new solution is $\{100{,}400{,}700\}$. If the target value obtained from the new drug f (100,400,700) is greater than that of the worst drug, the old drug is replaced by the new drug and repeated until the best solution [10].

Before the implementation of the algorithm, clarify the problem, determine the objective function $f(x)$ and constraints, and set parameters, harmony memory size HMS, decision variable size D, variable value range (xL, xU), iteration number Ni, harmony memory retention probability HMCR, tone adjustment probability par, tone bandwidth BW, etc. [11]. Determine the number of solutions HMS in HM, and each solution vector is composed of D solution

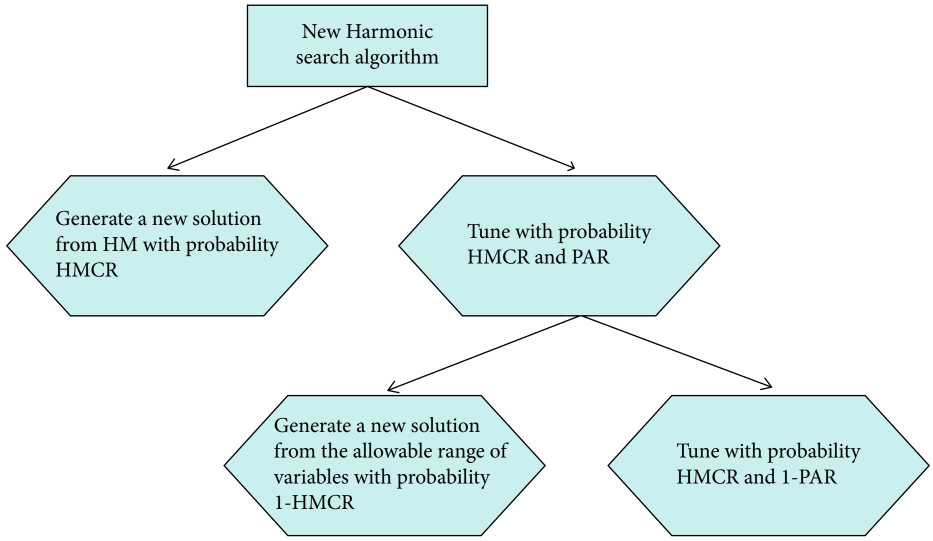

Figure 4: Probability tree of HS new solution generation.

components. A solution vector $xi(j) = \{xi(1), xi(2), \cdots, xi(D)\}$ is randomly generated in the way shown in formula (1), and the harmony memory is created, as shown in

$$x_i(j) = x^L + \left(x^U - x^L\right),\quad i = 1, 2, \cdots, \text{HMS},\quad j = 1, 2, \cdots, D. \tag{1}$$

The probability tree of the new solution of harmony search algorithm is shown in Figure 4.

Compare new drugs with the worst drugs of memory loss. If the new solution is worse than the worst solution, replace the worst solution; otherwise, do not operate, as shown in

$$\text{if}(f(X_{\text{new}})) < f(X_{\text{worst}})X_{\text{worst}} = X_{\text{new}}. \tag{2}$$

If the algorithm reaches the maximum number of iterations Ni or meets the convergence conditions, stop the operation; otherwise, return to step (3) to continue. For function optimization problems, standard differential evolution algorithm is a special genetic algorithms based on real numbers as well optimization-preserving greedy strategy. Considering the two operations of mutation and crossover, differential evolution algorithms can describe different kinds in the general way of DE/a/b/c [12], where c generally takes bin or exp, representing binomial crossover and exponential crossover, respectively. DE/rand/1/bin is the most commonly used version of all differential evolution algorithms.

3.2. Selection of Early Warning Indicators

3.2.1. Selection of Early Warning Indicators. Reasonable selection of early warning indicators is the premise and basis of establishing financial crisis early warning model. It is related to the early warning effect of the final model and whether the research conclusion is correct [13]. Although there is no unified opinion and standard on the selection of financial crisis early warning indicators in the academic circles, this paper will select according to the following principles to make the prediction effect reach the best state.

3.2.2. Specific Selection and System Construction of Early Warning Indicators. Based on the above options and research scientists, a financial crisis prevention system was created based on the specifics of high-tech companies and the choice of financial measures based on the specifics of problem solving, operational efficiency, and effectiveness (as shown in Table 1).

3.2.3. Optimization of Early Warning Indicators. In this paper, Spss17.0 software is used for principal component analysis of early warning indicators in T-1 and T-2 years. The correlation test between index variables by KMO sample measurement method and Bartlett sphere test method is provided in SPSS statistical software [14]. Only when there is correlation between variables, it is suitable for principal component analysis. This paper applies KMO test to detect the correlation of 28 financial crisis early warning indicators. The criterion of KMO test results is as follows: the test value is between 0 and 1. The closer it is to 1, the stronger the correlation between variables is, and vice versa, the more suitable for the analysis of the main components. The relative affinity of the allergen for the identification of the essential properties can be seen from the following table. A sample KMO test of 0.812 indicates a correlation of differences, and a SIG value of $0.007 < 0.05$ indicates a correlation of 28 differences. The options cannot be optimized by the analysis of the main components [15]. The results of the KMO test can be seen in the Table 2.

Then, we extract the principal components of the variables and extract the common factors according to the

Table 1: Financial early warning index system.

Serial number	Indicator name	Formula calculation
1	Current ratio	$\frac{\text{Ending current assets}}{\text{ending current liabilities}}$
2	Fast young ratio	$\frac{\text{Current assets} - \text{inventory}}{\text{current liabilities at the end of the period}}$
3	Cash ratio	$\frac{\text{Monetary capital} + \text{trading financial assets}}{\text{current liabilities}}$
4	Asset liability ratio	$\frac{\text{Total liabilities at the end of the period}}{\text{total assets at the end of the period}}$
5	Interest cover	Total profit + financial expenses
6	Inventory turnover	$\frac{\text{Cost of goods sold}}{\text{average inventory balance}}$
7	Total asset turnover	$\frac{\text{Sales revenue}}{\text{average total assets}}$
8	Turnover rate of accounts receivable	$\frac{\text{Net sales revenue}}{\text{average balance of accounts receivable}}$
9	Turnover rate of fixed assets	$\frac{\text{Net sales revenue}}{\text{average total fixed assets}}$
10	Turnover rate of current assets	$\frac{\text{Net sales income}}{\text{average total current assets}}$
11	Return on net assets	$\frac{\text{Net profit}}{\text{owner's equity}}$
12	Return on total assets	$\frac{\text{Total profit}}{\text{average total assets}}$
13	Operating net interest rate	$\frac{\text{Gross operating profit}}{\text{residential business income}}$
14	Cost interest rate	$\frac{\text{Total profit}}{\text{cost of residential business} + \text{period expenses}}$

Table 2: KMO and Bartlett's inspection.

KMO measurement of sampling adequacy		0.812
Bartlett's sphericity test	Approximate chi-square	2745.246
	df	349
	Sig.	0.007

criteria self-esteem more than 1 and their contribution more. All the differences described are shown in Table 3.

As can be seen from the above table, there are eight eigenvalues greater than 1 in the correlation coefficient matrix, which are 8.235, 3.126, 3.077, 2.690, 1.568, 1.266, 1.563, and 1.159, respectively, and the cumulative contribution rate of these eight factors is as high as 85.042%, which can reflect most of the financial characteristics of high-tech enterprises [16]. The eight main factors can also be seen intuitively through the gravel diagram, as shown in Figure 5.

In addition, based on the result of the unification of events (Table 4), the association of eight elements of difference is shown. This indicates that most of the key points of the early warning indicator are higher than 0.8, which shows that the key points of the early warning indicator are well explained by eight points [17].

In order to facilitate factor interpretation, based on 8 main factors, the factor load is converted by the maximum variance method in the orthogonal rotation method, so as to obtain the rotated factor load.

4. Financial Early Warning System Based on HSDM-BP

4.1. Error Back Propagation Neural Network

4.1.1. Artificial Neuron Model. For easy building of a neural network device, artificial neuron not only simulates the structure and function of biological neurons but also abstracts the information processing process of biological neurons. The main functions of artificial neurons include weighting function, summation function, and transfer characteristics [18].

Let the input vector of neuron J be as equation (3), $xi\,(i = 1, 2, \cdots, n)$ represents the input of the i-th neuron, and

Table 3: Total variance explained (%).

Ingredients	Initial eigenvalue			Extract sum of squares load			Rotation sum of squares loading		
	Total	Variance	Total	Variance	Total	Variance	Total	Variance	Total
1	8.235	29.322	29.322	8.235	8.235	29.322	7.356	25.604	25.443
2	3.126	13.177	42.338	3.126	3.126	42.338	3.422	13.499	38.781
3	3.077	11.026	53.203	3.077	3.077	53.203	3.369	12.261	50.881
4	2.690	9.733	62.775	2.690	2.690	62.775	2.120	8.608	59.328
5	1.568	7.285	69.899	1.568	1.568	69.899	1.965	7.318	66.485
6	1.266	6.521	76.259	1.266	1.266	76.259	1.458	7.275	73.600
7	1.563	4.992	81.09	1.563	1.563	81.09	1.897	7.174	81.09
8	1.159	4.113	85.042	1.159	1.159	85.042	1.381	4.430	85.042

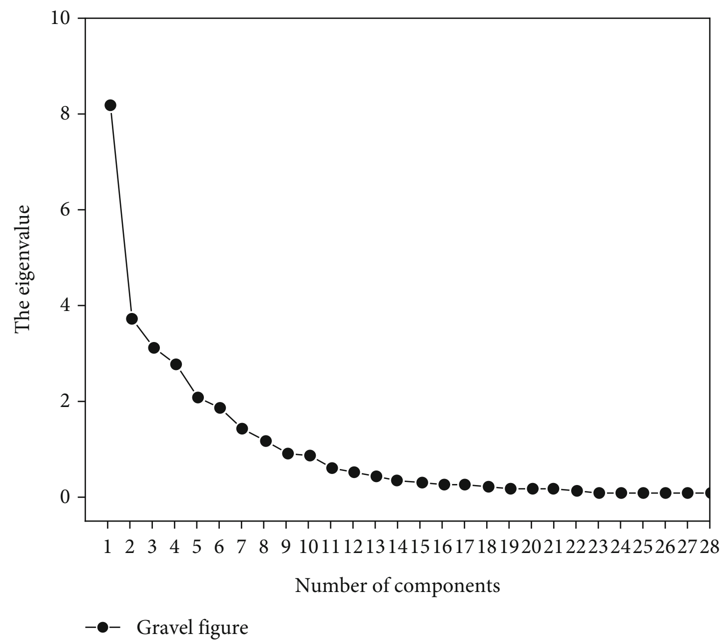

Figure 5: Gravel diagram.

Table 4: Common factor variance.

	Initial	Extract		Initial	Extract
Current ratio	1.000	0.967	Earnings per share	1.000	0.758
Quick ratio	1.000	0.971	Growth rate of operating revenue	1.000	0.948
Cash ratio	1.000	0.952	Net profit growth rate	1.000	0.850
Asset liability ratio	1.000	0.778	Growth rate of net assets	1.000	0.655
Interest cover	1.000	0.956	Growth rate of total assets	1.000	0.891
Inventory turnover	1.000	0.609	Net profit cash Net content	1.000	0.658
Total asset turnover	1.000	0.916	Business income Cash ratio	1.000	0.810

N is the number of input neurons.

$$X_j = (x_1, x_2, \cdots, x_n)^T. \quad (3)$$

Weighting vector of the input neuron node connected to the neuron node j is shown in equation (4), and $wij(i = 1, 2, \cdots, n)$ represents the weighting value from the input node i to the node j.

The weighting vector of the input neuron node connected to the neuron node j, as shown in equation (4), represents the weighting value from the input node i to the node j.

$$X_j = \left(w_{1j}, w_{2j}, \cdots, w_{nj}\right)^T. \tag{4}$$

The threshold value of neuron j is θj, and its input weighted sum is shown in formula (5). $x0 = 1$ fixed offset input node is used to represent the threshold node, and the connection strength between neuron j and neuron j is

$$w_{0j} = \theta_j. \tag{5}$$

Thus, equation (6) can be obtained:

$$s_j = \sum_{i=1}^{n} x_i w_{ij} - \theta_j. \tag{6}$$

The output of neuron j is shown in equation (7). Function $f(\cdot)$ reflects the nonlinear relationship between neuron input and output, which is called transfer function. The final output value yj can be obtained only after artificial neuron input excitation sj is processed by transfer function.

$$y_j = f\left(s_j\right). \tag{7}$$

4.1.2. Neural Network Learning Methods. If any neural network needs to realize some function, it must be trained first; that is, the network connection weight must be adjusted [19]. No matter what kind of learning algorithm is used, the network learning results before adjustment need to be evaluated according to the evaluation criteria. According to different evaluation criteria, it can be divided into guided or unsupervised learning. Guided learning needs to provide a certain evaluation standard to the network output. The network will judge the direction and size of the error according to the comparison results between the actual output and the expected output, so as to determine the adjustment method of network connection weight and reduce the error between the actual output and the expected output. Unsupervised learning does not need to provide network evaluation criteria. The learning system can independently adjust the connection weight according to its own unique network structure and learning rules.

4.2. Error Back Propagation Neural Network. Usually, the multilayer perceptron model of BP learning algorithm is called error back propagation neural network. The hidden layer neurons of BP neural network can have learning ability, which is closely related to its use of nonlinear continuous transformation function, with a typical three-layer structure [20].

N processing units in L1 layer are fully connected with P processing units in L2 layer. $W = \{wij \mid i = 1, 2, .., n, j = 1, 2, .., p\}$ represents the unit connection weight, $X = (x1, ..xi, .., xn)T$ is the unit input column vector, and $\theta j (j = 1, 2 \cdots, p)$ represents the unit threshold; then, the input weighted sum of each processing unit in L2 layer is shown in

$$s_j = \sum_{i=1}^{n} x_i w_{ij} - \theta_j. \tag{8}$$

This section introduces the artificial neuron model, learning rules, and error back propagation neural network process algorithm and points out the limitations of BP neural network. Aiming at the harmony search algorithm, this paper expounds the inspiration source and development status of harmony search algorithm [21]. At the same time, the mutation mechanism of differential evolution algorithm is introduced, and the important parameters and algorithm steps involved in the two algorithms are described in detail.

5. Construction of HSDM-BP Financial Early Warning Model

5.1. HSDM Algorithm Optimization BP Neural Network. In order to reflect the advantages of HSDM algorithm, the similar improved algorithms of two existing algorithms are selected for comparison [22]. The proposed differential harmony search algorithm DHS (differential harmony search) also uses differential evolution algorithm to improve the harmony algorithm, but DHS algorithm does not consider the original O3 operation but uses a pair of differential mutations to act on the decision variables generated by O1 operation and O2 selection operation. The scaling factor is sampled in a distribution between 0 and 1. In fact, it is not reasonable to use differential mutation to generate decision variables in O2 random selection operation. The effective icons provided by this method are only applicable to HM subregion. However, the decision variables generated by O2 operation often exceed this range. The adaptive harmony search algorithm SAHS (self-adaptive harmony search) proposed in literature modifies the original O3 operation through spacing adjustment to adjust the harmony distribution within HM, but the median range of memory cannot accurately express the global attributes; especially when changing in turn, it cannot provide a considerable mutation direction [23]. The global complexity of HS, DHS, SAHS, and HSDM algorithms is tested in 10 to 30 dimensions through five common test functions, as shown in the following formula:

$$f_1(x) = \sum_{i=1}^{n-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right], \tag{9}$$

$$f_2(x) = \sum_{i=1}^{n}\left[x_i^2 - 10\cos\left(2\pi x_i\right) + 10\right], \tag{10}$$

$$f_3(x) = \frac{1}{400}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1, \tag{11}$$

$$f_4(x) = -20 \exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(-\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right) + 20 + e, \tag{12}$$

$$f_5(x) = \sum_{i=1}^{n}\left(x \sin\sqrt{|x_i|}\right). \tag{13}$$

In the test, different algorithms are applied to each test problem for 25 times, and each independent operation is guaranteed to be given the same random initial value. At the same time, two termination criteria of the maximum order of magnitude and the minimum error function value EFV (error function value) of the test function are set. The optimization performance of the algorithm is evaluated by the best EFV and calculation success rate. The test function under 10 d and 30 d evaluates the empirical accumulation function distribution of the success times of each algorithm calculation function under the accuracy of 10-8. It can be seen that after 5000 (10 d) to 19000 (30 d) iterations, HSDM is always better than the other three algorithms.

5.2. HSDM Algorithm Optimization BP Neural Network. Gradient descent is similar to a person standing on a hillside, always looking for the section with the largest gradient and moving down the mountain, as shown in Figure 6. When someone falls along the maximum slope at point *A*, he will reach the local minimum point *B*. At this time, he cannot see a lower place than himself. If he is at point *C* and moves down along the maximum slope, he will reach the global minimum point *D*.

To sum up, the convergence of BP neural network depends on the initial position of the learning mode. Appropriately changing the initial connection weight can effectively avoid the local minimum in the convergence process. Compared with the original random initialization method, this paper adopts the method of optimizing the connection weight and threshold. Formulas (14)– (17) are the error formula:

$$E^k = \frac{1}{2}\sum_{t=1}^{q}\left(\delta_t^k\right)^2, \tag{14}$$

$$E^k = \frac{1}{2}\sum_{t=1}^{q}\left(y_t^k - c_t^k\right)^2, \tag{15}$$

$$E^k = \frac{1}{2}\sum_{t=1}^{q}\left[y_t^k - f\left(\sum_{j=1}^{p} v_{jt} b_t^k - \lambda_t\right)\right]^2, \tag{16}$$

$$E^k = \frac{1}{2}\sum_{t=1}^{q}\left[y_t^k - f\left(\sum_{j=1}^{p} v_{jt}\left(\sum_{i=1}^{n} w_{ij} x_i^k - \theta_j\right) - \lambda_t\right)\right]^2. \tag{17}$$

Each harmony vector in the harmony memory (HM) is regarded as a complete set of connection weights and thresholds of BP neural network [24]. Among them, SSE represents the sum of squares of errors between the expected target output and the actual output value. If the sum of squares of errors is smaller, it indicates that the individual is better. On the contrary, if the SSE value is larger, it indicates that the individual is worse.

In Table 5, the connection weight from the entry of j of the primitive layer is represented by the node of the i layer W_{xiyj}, and the beginning of the j node of the hidden layer is denoted by θyj. The weight of the connection from node j of the latent process to the output phase P node is expressed as W_{yjzp}, and the initialization of the output layer P node is denoted by θzp. At the same time, they jointly form a harmony vector. In addition, since the network weight values are often in the same range, the value range $[xL(d), xU(d)]$ should be determined for the decision variables according to the premise.

5.3. Empirical Analysis of Improved BP Neural Network

5.3.1. Prediction Index Screening. In order to reduce the computational complexity in the empirical analysis and ensure the significance of the model, 37 prediction indexes such as profit, debt repayment, operation, development, EVA, ownership structure, and management structure of the sample companies in T-3 years were screened [25]. Sample screening procedure: firstly, calculate Kolmogorov-Smirnov value and test the normal distribution of each index variable. Secondly, if the variable conforms to the normal distribution, the Levene test of the variance equation and the *t*-test of the mean equation are carried out. If the variable does not conform to the normal distribution, the Wilcoxon rank is calculated and the nonparametric test is carried out. Finally, the correlation analysis of each variable is carried out to eliminate the significantly interrelated variables and determine the final prediction index system. Data processing software includes Excel, Spss19, and MATLAB.

K-S test is used to check whether the experimental data conform to the normal distribution, while Kolmogorov-Smirnov value reflects the probability that the distribution function $f(y)$ meets the normal distribution standard in a specific range. The criterion for determining the significance level of the test is 0.05 (the same below), according to the results of K-S test and significance test. It can be seen that the *P* values of the seven indicators of operating gross profit margin, growth rate of total assets, growth rate of basic earnings per share, turnover rate of current assets, shareholding proportion of the largest shareholder, equity concentration, and number of senior executives are greater than the significance level of 0.05 and obey the normal distribution, while the *P* values of other indicators are less than 0.05, which does not meet the normal distribution.

For variables that do not fit into the normal distribution, count the Wilcoxon measurement and make the measurement nonparametric. The test results are shown in Table 5. The earnings analysis shows that real estate is stable, revenue growth, property growth rate, commodity exchanges, stock exchanges, fairness, management comparisons, business associations, business owners, the separation of the two rules, the president and the appointment, ride wide of directors,

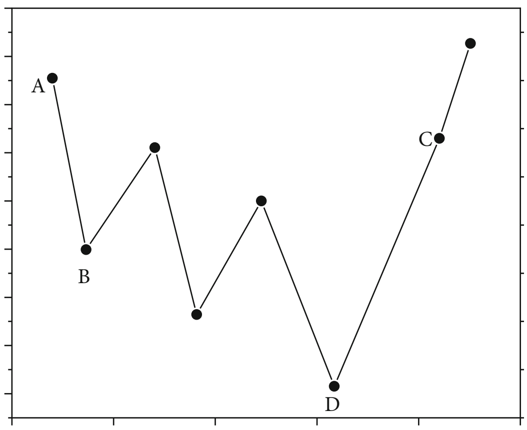

Figure 6: Local minima and global minima.

financial index prediction model for ST company and non-ST company is 66.3% and 72.7%, respectively. The discrimination accuracy of the comprehensive early warning model for the financial crisis early warning of ST companies and non-ST companies is 81.3% and 83.9%, respectively. Compared with the pure financial index model, the comprehensive index model improves the crisis early warning ability of ST companies and non-ST companies by 14.27% and 8.76%, respectively. It can be concluded that the integration of nonfinancial indicators into the prediction model can significantly improve the prediction accuracy of the model. At the same time, the study also found that ST companies and non-ST companies have differences in financial indicators, ownership structure, and management structure. In practical application, corporate controllers, managers, investors, and other stakeholders can focus on the changes of these indicators and then make judgments and take measures in time in combination with other factors that should be considered, so as to reduce or even avoid losses. Specific differences are as follows:

Table 5: Network link weight and threshold of each layer.

Weight and threshold from hidden layer to output layer				Weight and threshold from hidden layer to output layer			
W_{X1Y1}	W_{X1Y1}	W_{X1Y1}	W_{XiYj}	W_{Y1Z1}	W_{Y1Zp}	W_{YjZ1}	W_{YjZp}
	...				...		
Θ_{Y1}			Θ_{Yj}	Θ_{Z1}			Θ_{Zp}
Y_1			Y_j	Z_1			Z_p

numberof directors, and all supervisors. The result p of Mann-Whitney *U*'s test for 11 negative ions was greater than the value of 0.05; i.e., there was no significant difference between the "ST" and "non-ST" groups of 11 negative values. They are excluded from the study. The remaining 19 measures ($P < 0.05$) reject the initial assumption and assume that there is a significant difference between the two groups, so that the severity is maintained as an estimate of the difference between the two groups.

5.3.2. Correlation Analysis. After the above screening, 14 indicators were eliminated from the 37 alternative indicators, and now, 23 indicators are retained for correlation test. After inspection, the financial prediction model is constructed by retaining 8 financial indicators: net profit margin of total assets (X3), operating gross profit margin (X4), return on investment (X5), current ratio (X6), asset liability ratio (X8), receivables turnover rate (X12), fixed assets turnover rate (X14), and EVA (X21). There are also five nonfinancial indicators, namely, the largest investor fairness (Y1), the largest market share (Y2), real manager fairness (Y3), valuation and equity (Y8), and the president and the appointment of the CEO (Y9), selected as the input indicators of the comprehensive prediction model together with the above eight financial indicators.

The financial LM-BP neural network model constructed in this paper has good predictive power for enterprise financial crisis. From the calculation results of experimental samples, it can be seen that the discrimination accuracy of pure

(1) In terms of financial indicators, ST company generally has negative profitability indicators such as operating gross profit margin and net profit, serious losses and continuous insufficient return on investment, high asset liability ratio, poor solvency, and high risk

(2) The operating turnover capacity is poor, which is reflected in the significantly low turnover rate of accounts receivable and other indicators

(3) Compared with traditional financial indicators, EVA indicators can more objectively and completely reflect the long-term operating results of listed companies. The average EVA of ST enterprises is negative, far behind the normal operating enterprises, showing negative growth

(4) In terms of ownership structure, ST companies are more likely to occur in listed companies not controlled by the state. The reason is that there are different degrees of agency contradictions between the controlling shareholders and external investors of non-state-owned listed companies, which will undoubtedly hinder the improvement of corporate performance

6. Conclusion

Based on the standard BP-NN prediction model, this paper uses three different training functions as the technical route to improve the BP network algorithm, namely, additional momentum method, conjugate gradient method, and L-M (Levenberg-Marquardt) optimization method, to make an empirical analysis on the sample data of nonfinancial listed companies. By comparing the training process and simulation and regression results of the three improved algorithms, it is found that LM-BP is significantly better than the additional momentum improvement method and conjugate gradient improvement method in terms of network convergence speed, training error, and satisfaction of output results. By comparing the financial index prediction model and the comprehensive prediction model, the prediction results show that the introduction of nonfinancial indicators significantly improves the diagnosis efficiency and prediction accuracy of the model and can better meet the purpose of financial crisis early warning in practical application. Based on the findings of the study and the current situation of early warning of emergencies of some listed companies, the following recommendations are made in this paper:

(1) Improve the crisis awareness of listed companies and improve the crisis early warning system. When a listed company has financial abnormalities, the early warning system can give timely warning before the enterprise falls into financial crisis and assist the company controller to take effective measures in advance, so as to avoid the further deterioration of potential financial problems. The premise is to establish and improve an effective early warning system and enhance crisis awareness. At the same time, we should constantly improve the prediction index system, optimize the prediction model, timely collect information and make prediction, find the problems existing in the production and operation process of the company and apply the remedy to the case, prevent the occurrence of financial crisis in time, and maintain the normal operation of the enterprise

(2) Correctly understand EVA and strengthen its application in crisis prediction. The traditional financial system does not deduct the opportunity cost when calculating the company's profit, which may lead to the serious consequence that the profit is overestimated. Correspondingly, EVA index just makes up for the shortcomings of the traditional financial index system. When calculating the economic value of the company, we fully consider debt capital and equity capital and deduct them as the cost of net profit. Therefore, the introduction of EVA index system in financial early warning can strengthen the prediction ability of the early warning system and enable listed companies to better prevent financial problems

(3) Strengthen the internal management of the company and optimize the equity allocation. Listed companies need to select financing methods in combination with their own reality, optimize the equity allocation, actively guide major shareholders to play a positive role, and prevent the rupture of cash flow in a certain link due to excessive debt and reducing their ability to pay, which affect the payment of due debts and lead to the possibility of financial crisis. In addition, a perfect internal management system can provide a solid internal foundation for listed companies and take timely measures in the face of financial problems, so as to quickly get rid of the crisis

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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