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Retraction

Retracted: Application of Optimized BP Neural Network In Financial Alert System

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Q. Gao, "Application of Optimized BP Neural Network In Financial Alert System," *Journal of Function Spaces*, vol. 2022, Article ID 1816315, 10 pages, 2022.

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Research Article

Application of Optimized BP Neural Network In Financial Alert System

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The development of economic globalization not only brings development opportunities for enterprise development but also causes the rapid changes of economic environment. Global enterprises are facing many development challenges. It is very significant to implement financial alert. However, most of the existing financial alert systems are based on traditional quantitative analysis and cannot face the demand of big data growth. Based on this, main body of a book studies and analyzes the request of optimized BP neural network in financial alert system. Based on the financial early warning and a brief analysis of the development requirements of BP neural network, this paper establishes a financial early warning model for BP neural network. Considering the shortcomings of BP neural network, genetic algorithm is used to optimize the specification. Finally, a new reference scheme is provided for economic early warning. And use the following steps to create a list, taking into account the volume analysis in the conceptual design. The emulation results indicates that the optimized BP neural network can accelerate the convergence, has strong stability, and has higher accuracy in financial alert.

1. Introduction

The concept of financial alert first appeared in western countries. At present, the theory of financial crisis is constantly improving, and there are many research results in the research and analysis of financial distress [1]. From the perspective of fiscal forewarning, early research mainly depends on personal development experience, and there will always be some deviation in financial alert [2]. With the development of financial alert theory and the introduction of statistical theory, development of big data technology provides new research methods for risk warning in various fields [3, 4]. Although there are many researches on enterprise financial alert at home and abroad at this stage, there are still no good migration request research results. Many methods immediately refer to a certain early warning model for analysis, which is not reliable [5]. Therefore, it is required to optimize the request of BP neural network in financial alert system.

Under this background, the main body of a book studies the request of BP neural network in financial alert system. The first chapter briefly introduces the situation of financial alert, the commonly used pattern, and the chapter arrangement of this study. Chapter 2 introduces the request and improved algorithm of financial alert algorithm and BP neural network at home and abroad and summarizes the shortcomings of the current research. In Chapter 3, the disadvantages of BP neural network research are combined, and a BP neural network model is established. A new network structure is proposed to optimize the stability and learning of BP neural network by using real coding method on initial gravities and thresholds. In Chapter 4, financial alert model is in view of BP neural network. The performance of optimized BP neural network is judged by analyzing the convergence speed, stability, and early warning accuracy under different algorithms. The experimental results indicate that compared with the traditional BP neural network, the optimized BP neural network proposed in main body of a book has faster convergence speed and shorter running time and has better request attributes in financial alert.

The innovation of this paper is to establish the maximum number of hidden layer nodes in BP neural network optimization. The application requirements of optimized BP neural network in financial early warning system are studied and analyzed. Considering the shortcomings of BP neural network, genetic algorithm is used to optimize the specification and finally provides a new reference for economic early warning, using the nonuniform characteristics of the initial population space randomly generated by GA. Using equidistant sampling method, it is easier to find individuals and accelerate the convergence speed. The simulation results show that the optimized BP neural network can accelerate the convergence speed, has strong stability, and has high accuracy in financial early warning.

2. State of the Art

With the development of enterprises, the harm caused by financial risks is also deepening, which has a significant impact on the survival and development of enterprises. Considering the prevention of the losses caused by financial risks, it is very indispensable to take financial alert analysis. At present, there are many researches in financial alert analysis, which have completely shifted from qualitative research to quantitative research. For example, Huang and Guo established a new financial risk evaluation system in the research. In the research, fuzzy analysis method is adopted. For noise data and contour graph, virtual set processing method is adopted to analyze the unstable factors in the market and form fuzzy matrix, which helps fuzzy method to obtain more valuable fuzzy membership degree and further improve the request performance of risk assessment system [6]. In their research, in financial risk assessment, Tang et al. measured report data, introduced decision tree C4.0 algorithm for research and mining data rules, and built report detection system to find fraud. Through this model, the error information in finance could either be found in time and the potential knowledge could either be mined [7]. Wang and Xie used BP neural network to implement early warning analysis on the financial affairs of enterprises in coastal areas [8]. In the design of the early warning system, Sun and Lei chose textile enterprises being the study subject to sort out the data characteristics of textile enterprises. Leading textile companies in the A-share textile sector have listed mining companies being their research targets [9]. Deng et al. proposed the kpca-mpso-bp model in the financial alert analysis of e-commerce, constructed it using KPCA, IPSO, and BP neural network and Credit Risk Index of cross-border e-commerce in view of KCA, used MPSO to search the inertia gravity and threshold of BP neural network, and used BP neural network to train the credit risk data of 13 cross-border e-commerce enterprises [10]. Zhao used ARMA model, two types of neural networks (back propagation), and MLP to quantitatively analyze the portfolio in his research [11]. In gas detection, Zhou et al. used BP neural network to optimize the specifications of KF, introduced differences reimbursement to track the system state, and eliminate the changes of dynamic system specifications. The do-akf algorithm indicated the best performance [12]. On the basis of the 2 π periodicity of angle measurement under static temperature and the complexity of the influence of ambient temperature change, Jia et al. proposed a method to improve the angle measurement accuracy of rotary encoder in view of Fourier expansion BP neural network (fe-gabpnn) optimized by GA, which has good fitting performance [13].

To sum up, it could either be seen that in the relevant research of financial alert, in addition to qualitative research, quantitative research is widely used, but there are many factors causing enterprises to get caught up in financial crisis, and some indicators are difficult to be analyzed quantitatively by traditional quantitative research methods. In the request of data mining algorithms in financial alert, most of them are analyzed on the basis of foreign pattern. There are many requests of BP neural network, but they are not localized and lack of practical request. In the request research of BP neural network, in addition to traditional algorithms, BP neural network optimization algorithms continue to emerge, but they are rarely applied to financial alert analysis. Therefore, it is of great practical significance to implement the request research of optimized BP neural network in financial alert.

3. Methodology

3.1. Design of Financial Alert Model. Mature enterprises are relatively mature in the management and development system, especially in the financial alert system. The daily operation and management of enterprises must be disturbed by many factors, but these factors could either be divided into external factors and internal factors in essence. Enterprise operation management is the key element of enterprise survival and profit and the logical relationship between the elements. It determines the market operation results of an enterprise. In the long run, whether an enterprise can find an enterprise operation mode suitable for its business needs and continuously improve it determines whether an enterprise can have a future. The causes of problems in management are nothing more than organizational structure problems; for example, the structure is chaotic. The enterprise goal is not clear, and the enterprise must first have clear goals and plans to make steady progress. We must make clear what the problem is and then find a solution. Through the calculation and analysis of financial alert data, we can realize the supervision of finance and find problems in time. From the perspective of investment, financial alert can provide more information on enterprise operation and management and realize the rationalization of investment. For the regulatory authorities, the use of financial alert model can analyze the potential risks in the market and implement risk control in time. Considering that financial early warning needs to adopt more scientific and accurate evaluation methods. Because of its self-learning, recognition, and judgment ability, BP neural network can process large-scale data in parallel and has the ability of logical thinking emulation. Compared with the early system, BP neural network has great advantages [14].

BP neural network has great advantages in financial alert and has the characteristics of information processing parallelism. Each neuron can calculate on the basis of the obtained information and then output the results, which improves the information processing ability of financial alert [15]. BP neural network has the characteristics of high fault

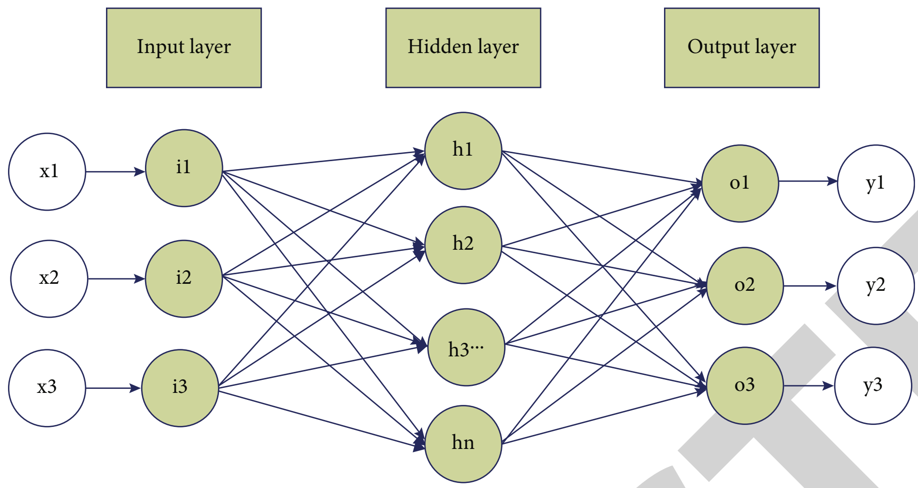

Figure 1: Basic structure of BP neural network.

tolerance and inaccurate calculation. In the financial alert indicators, it does not strictly require the enterprise sample data, nor does it need to assume the data situation independently. It can deal with discontinuous and incomplete information and improve the ability of using financial alert data [16]. New model has strong adaptive ability. It can not rely on external coercive forces but also achieve balance on the basis of information exchange and feedback. It can improve the time variability of financial alert and meet the needs of different enterprises [17]. With the accumulation of sample size, financial alert can continuously update knowledge and realize dynamic financial alert. In view of the advantages of new model in financial alert, new model is used to realize financial alert. The basic structure is indicated in Figure 1.

In the financial alert analysis, the selection of financial indicators is very significant. Financial indicators should be sensitive, have timely warning information, and can reflect the real situation of the enterprise. The financial indicators should be comparable and able to conduct comparative analysis among industries and enterprises. Financial indicators should be easy to obtain and highly operable, which can systematically reflect the financial situation of the enterprise and avoid one-sided amplification of the partial financial situation of the enterprise. Therefore, in the financial alert analysis, the financial indicators select the data closely related to finance, including market sales rate, net interest rate, cash sales rate, average return on net assets, amount of accounts receivable, asset cash rate, asset return, current ratio, quick ratio, asset liability ratio, asset turnover rate, accounts receivable collection and transfer rate, current asset turnover rate, operating income growth rate, tangible asset liability ratio Growth rate of total assets, price to book ratio, cash flow liability ratio, and inventory turnover rate.

As an artificial neural network model, new model simulates human neural network, which is divided into input, output, and implicit layers. It has strong nonlinear mapping ability, but new model also has its own shortcomings in request [18]. BP neural network requires little learning efficiency, but it is not fast enough in practical request, so it can only use incremental exercise. The emulation of any function is close to and can deal with all kinds of network problems, but in fact, BP neural network does not always have a solution [19]. In nonlinear systems, it is difficult to choose a good learning rate, and the lack of parameter attributes impacts the exercise performance. Therefore, BP neural network needs to be optimized.

3.2. BP Neural Network Optimized by Genetic Algorithm. In this paper, GA is used to optimize BP neural network. Suppose that the input layer of new model is represented by M and the output layer is represented by P. The linking gravity between the implicit layer and the input layer is W_{ij}, and the linking gravity between the implicit layer and the output layer is W_{jp}. The sigmoid function is selected as the excitation function, and the input sample is represented by X, the output sample is represented by Y, and the expected attributes is represented by d. Forward propagation could either be expressed as

$$\begin{aligned} u_j^J &= \sum_{m=1}^{m} w_{mj} x_m, \\ v_j^J &= f \sum_{m=1}^{m} w_{mj} x_m, \quad j = 1, 2, \cdots, J. \end{aligned} \tag{1}$$

The total error of the network output layer could either be expressed as

$$E = \frac{1}{2} \sum_{p=1}^{p} e_p^2(n), \tag{2}$$

where $e_p(n)$ represents the single error of the node. When the output layer propagates forward, the error signal will be transmitted. After modifying the linking gravity layer by layer, the error back propagation will change. New model uses the gradient descent method to modify the network gravity. The selection of excitation function is

$$f(x) = \frac{1}{1 + \exp\,(-ax)}. \tag{3}$$

Then, the n gravity adjustment amount could either be expressed as

$$\Delta w_{jp}(n) = \eta\left[y_p(n)\left(1 - y_p(n)\right)\right]\left(d_p(n) - y_p(n)\right). \tag{4}$$

Using the same reasoning and assuming that the gradient is expressed as $\delta_j^{J}(n) = -\delta E(n)/\delta u_j^{J}(n)$, we can get

$$\Delta w_{mj}(n) = \eta \delta_j^{J}(n) x_m^{M}(n). \tag{5}$$

Determine the quantities of network input layer nodes, implicit layer nodes and output nodes on the basis of the set input and output sequences, and initialize the linking gravities of the input layer and implicit layer, and a is for initial threshold of implicit layer, and b is for the threshold attributes of the output layer. Calculate the output of the implicit layer on the basis of the input vector, and the given threshold of the initial gravity, the formula is

$$H_j = f\left(\sum_{j=1}^{n} w_{ij}x_i - a_j\right), \tag{6}$$

where H is for calculation result of implicit layer, and the attribute range of j is 1~l. The expected results are calculated on the basis of the actual output of the new model. The formula is

$$O_k = f\left(\sum_{i=1}^{l} w_{jk}H_f - b_k\right), \tag{7}$$

where k is a natural quantities, with an attribute of 1~m. Calculate the error result on the basis of the formula.

BP neural network is widely used, in which the quantities of implicit layer nodes need to be reasonably selected. In the selection, the main body of a book takes an implicit layer as the study subject, determines the input layer and output layer in combination with the actual demand, and selects the optimal quantities of implicit layer nodes on the basis of the formula

$$l = \log_2^n \le \sqrt{m + n} + a, \tag{8}$$

where l represents the quantities of implicit layers, m represents the quantities of access nodes, n represents the quantities of output nodes, and a ranges from 0 to 10.

The introduction of GA can give full play to the advantages of the two algorithms. The exercise of new model is in view of the principle of gradient descent, and the threshold attributes of gravity are constantly revised to avoid falling into local minimum attributes. GA can realize global search [20]. Through global search, the gravity and threshold of new model could either be redetermined without impacting the nodes, implicit layers, and other specifications of new model [21]. In the optimization, the GA encodes the linking gravities to form the initial population and then calculates and screens each individual through crossover and mutation until the optimal gravity and threshold are obtained [22]. Then, adjust the adaptability on the basis of the output error results to ensure the minimum error attributes. The specific process is indicated in Figure 2.

When using GA, we first need to solve the problem of coding. The encoding operation does not impact the convergence performance. In the operation, the individual is encoded, and the individual is composed of input layer, implicit layer, linking gravity, and output threshold [23]. In new model, the most significant feature is the sum of squares of the error between the output attributes and the expected attributes. The more the error is, the smaller the performance of new model is. In the process of sample propagation, if the error attributes are large, the BP network needs to be corrected [24]. The introduction of GA can search the network gravity, introduce the gravity and threshold of chromosome into it, and reduce the error function. The objective function could either be expressed as

$$\min E(\xi) = \frac{1}{2}\sum_{i=1}^{U} (y^* - y)^2, \tag{9}$$

where E represents the error. Considering the improvement of the adaptability of chromosome, adaptability function is introduced. Adaptability function is not only an significant standard to distinguish individuals but also a standard of natural selection. Use the degree function to check whether the individual has reached the optimal solution in the calculation [25]. If the adaptability function is not selected properly, abnormal individuals may be produced in the early stage of genetic evolution. These individual experiences impact the performance of the algorithm because they are too prominent. In the later stage of genetic evolution, when the algorithm converges, due to the small difference between individuals, there may be a local optimal solution. Even improper adaptability function will lead to genetic stop. In the selection of adaptability function, the function cannot be negative, and it should be as simple as possible to reduce the computational complexity. The adaptability should have strong universality, and there is no need to revise the specifications of the adaptability function. Fitness of an individual refers to the measure of the degree of dominance of an individual in the survival of a population, which is used to distinguish the "good" and "bad" of an individual. Fitness is calculated using fitness function. Fitness function is also called evaluation function, which mainly judges individual fitness through individual characteristics. The general process of evaluating the fitness of an individual. After decoding the individual coding string, the individual phenotype 2 can be obtained. The objective function value of the corresponding individual can be calculated from the individual's phenotype. According to the type of optimization problem, the

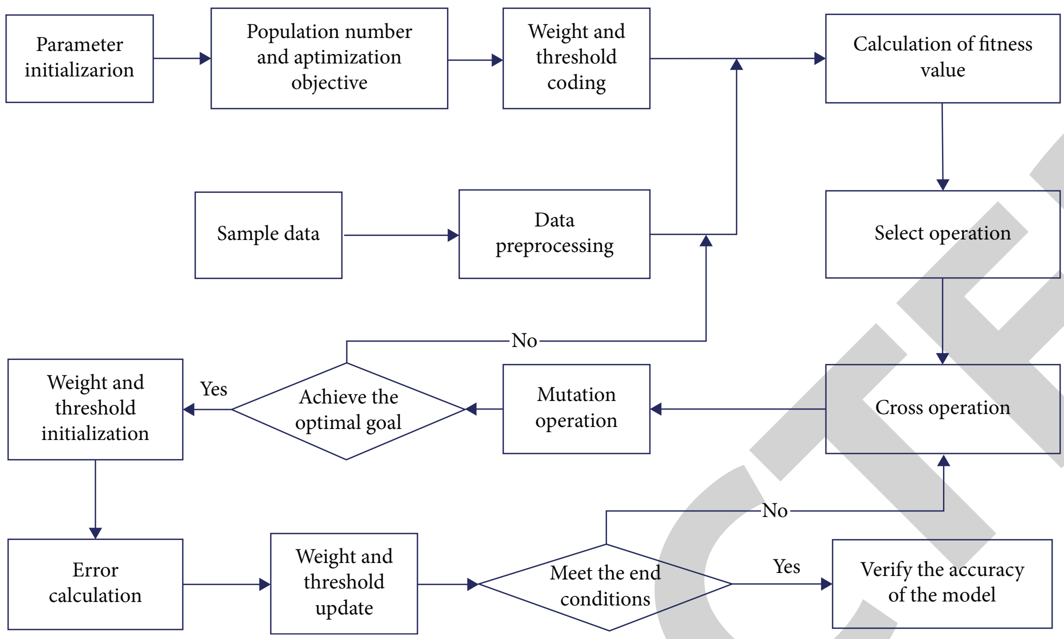

Figure 2: GA optimization neural network.

individual fitness is calculated from the value of the objective function according to certain conversion rules. In this paper, the selection of adaptability function is in view of the total error of new model, so the selection of individual adaptability function is

$$f = \frac{2}{2 + \sum_{k=1}^{k} \sum_{j=1}^{n} \left(T_j^k - Y_j^k \right)^2}, \tag{10}$$

where k represents the quantities of sample sets, T represents the ideal output, and Y represents the real output result.

GA is used to optimize BP neural network. When selecting, the best individual is saved, and the proportion of adaptability is used at the same time. Select the individual with the highest adaptability attributes in the population and immediately enter the next generation without crossover and mutation. This method can ensure that the optimal solution is not impacted by crossover and mutation, but the quantities of optimal individuals may increase sharply and get caught up in local optimal solution. Therefore, it is also indispensable to combine the adaptability ratio method to save the best individual. Assuming that the population size is n, the likelihood of individual selection is expressed as

$$P_{s_i} = \frac{f_i}{\sum_{j=1}^{n} f_i}, \tag{11}$$

where f_i represents the adaptability function attributes and p_{si} represents the likelihood of being selected, which reflects the proportion of individual adaptability in the sum of individual adaptability. The combination of these two methods can select individuals with large adaptability function attributes to enter the next generation with the greatest likelihood and also provide a certain likelihood for individuals with small adaptability attributes to prevent the problem of local optimal solution.

In GA, compared with other algorithms, the most obvious feature is crossover operation, which is the most common method to generate new individuals. Using GA to optimize BP neural network also needs to go through chromosome cross mutation. Different ways are used in coding connecting genes and parameter genes, and the two parts need to be cross operated, respectively. Among them, the coding of connecting genes adopts one-point crossover operation, and the parameter genes adopt arithmetic crossover. The linear combination of two individuals belongs to arithmetic crossing. Assuming that the individual is represented by x and the crossed individual is represented by x', the formula could either be expressed as

$$\begin{cases} x_1' = a x_1 + (1 - a) x_2, \\ x_2' = a x_2 + (1 - a) x_1. \end{cases} \tag{12}$$

In the formula, the attributes of a ranges from 0 to 1. The mutation operation of the algorithm adopts different compilation methods to adjust the connecting genes and specifications. The basic mutation method is used to change the gravity que gene of the connecting gene, and the nonuniform mutation method is used to change the rate gene. Specifically, the likelihood of the individual is specified as the variation point, and then, the genetic attributes of the variation point is inversely calculated to generate a new individual. The mean variation operation can ensure the free movement of individuals, but it is difficult to search the key areas. Therefore, in the nonuniform variation, the random attributes with uniform distribution are not used for

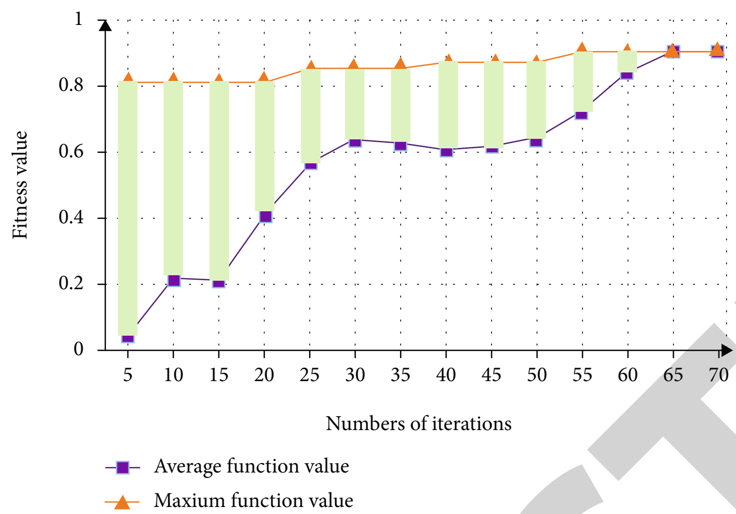

FIGURE 3: Relationship between test function 1 and evolution times.

attributes selection, and the random disturbance results are used as new gene attributes. Each gene is mutated with the same likelihood, and the whole solution vector will change slightly.

$$P_c = \begin{cases} \dfrac{f_{\max} - f}{f_{\max} - f_v}, & \left(f^{/} \geq f_v\right), \\ 1, 0, & \left(f^{/} < f_v\right), \end{cases}$$
$$P_m = \begin{cases} 0.5 \times \left(\dfrac{f_{\max} - f}{f_{\max} - f_v}\right), & (f \geq f_v)m \\ \dfrac{f_v - f}{f_v - f_{\min}}, & (f < f_v), \end{cases} \tag{13}$$

where P_c is for represents the intersection likelihood, P_m is for represents the sudden change likelihood, $f_{\max}$ and $f_{\min}$ represent the maximum and minimum adaptability attributes, respectively, f_v represents the average adaptability attributes, and $f^{/}$ represents the larger adaptability attributes of the two crossed chromosomes. When the individual adaptability tends to be the same, the intersection likelihood and sudden change likelihood could either be the largest, and the adaptability is relatively scattered; the likelihood is the smallest. For individuals whose adaptability attributes are higher than the average attributes, they can enter the next generation, and individuals whose adaptability attributes are lower than the average attributes will be eliminated. The adaptive likelihood can provide the individual optimal attributes and ensure the convergence of the algorithm on the basis of ensuring the diversity of the population.

4. Result Analysis and Discussion

4.1. Emulation Analysis of Optimized BP Neural Network. Establish BP neural network, including 5 input neurons, 4 output neurons, and 6 implicit layer neurons. Optimize the neural network model in view of GA for network learning, store the result gravities, and establish the neural subnetwork knowledge base. The algorithm can only be realized by using MATLAB changes.

Using the real quantity coding method, the population size is set to 100, the initial attribute of variation likelihood is set to 0.05, the initial attribute of intersection likelihood is set to 0.6, and the initial attribute of B is set to 0.01. Then, the test function is optimized, and the same transformation rules are used to translate the test function upward to obtain the evolutionary adaptability function. The measurement results are indicated in Figures 3 and 4.

The data in figure indicates that, compared with the unimproved algorithm, in terms of optimizing the test function, the new model can achieve faster convergence and perform well, can reduce the quantities of iterations, and has high accuracy. The average running time of the traditional algorithm is 0.704 s, and the running time of the optimized new model algorithm is 0.604 s, which indicates that the optimized new model algorithm can shorten the running time at the same time. The improved algorithm can implement genetic optimization on many points at the same time and then search on the basis of the direction of negative gradient, so as to avoid the problems of local minimum points and slow convergence speed.

The algorithm of optimizing new model is used to optimize the maximum upper bound network. Considering the reduction of computational complexity, the amount of network exercise is 30, and the mean square error function is used as the adaptability function. The optimal quantities of implicit layer nodes are 12. The change of adaptability function in the optimization process is indicated in Figure 5. It could either be seen from the figure that after 60 iterations, the optimal individual adaptability will not change, and the average adaptability is still changing.

After determining the optimal quantities of implicit layers, the input layer node is 24 and the output layer node is 4. GA is used to optimize the gravity and threshold of new model. The quantities of network exercise are still 30. The mean square error function is used as the adaptability

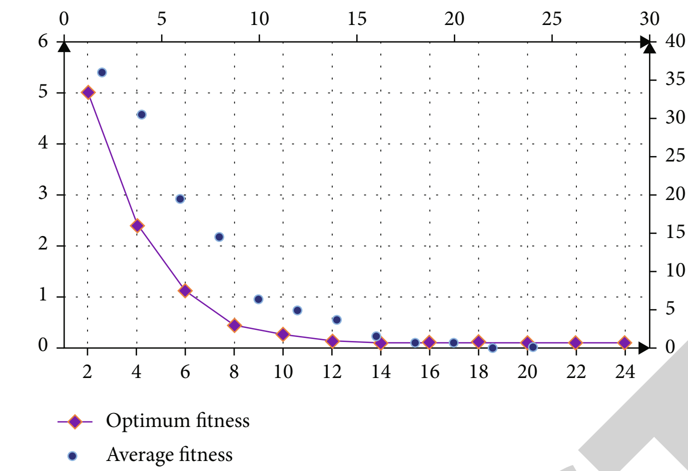

Figure 4: Relationship between adaptability of test function 2 and evolutionary algebra.

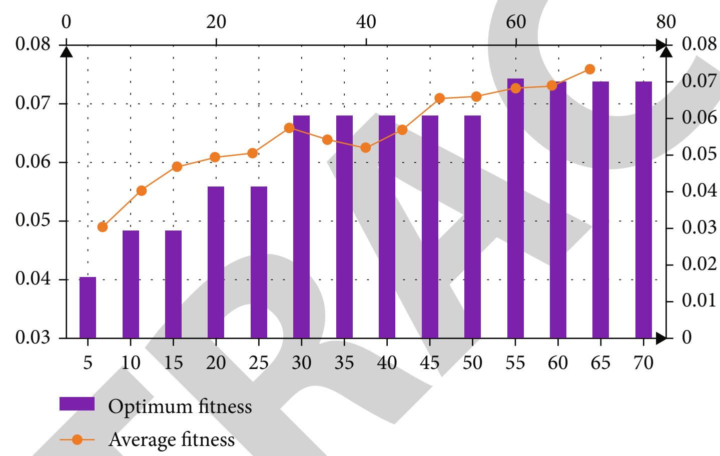

Figure 5: Adaptability function optimization process.

function. After 65 times of evolution, the optimal individual adaptability is gradually stable.

The GA is used to find the maximum attributes of the nonlinear function globally, as indicated in Figure 6. After the maximum attributes is obtained, the objective function and binary transcoding are calculated through initialization coding, and then, the maximum adaptability attributes and the optimal individual are found through genetic variation. The results are indicated in Figure 7. The learning error rate of nonlinear function in view of GA is within 3%.

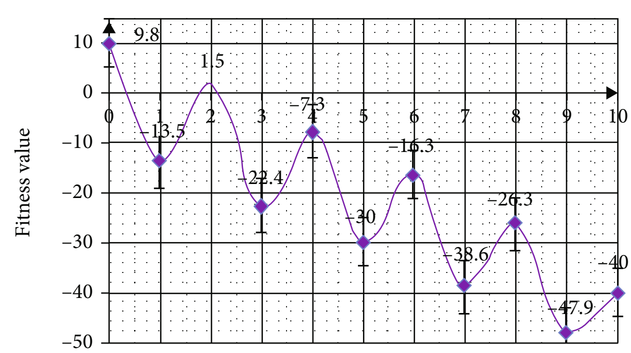

Figure 6: Global optimization of nonlinear function.

4.2. Financial Alert Analysis. The optimized BP neural network model is used to analyze the financial alert of enterprises. Under the environment of MATLAB, the programming language and the collected data samples are input into the model for analysis. Although the optimized BP neural network has no high requirements for the original data, the amount of data selected is too large. SPSS software is used to analyze the sample factors, and all sample data are input to obtain the significance likelihood, which is 0~1 If the ratio reaches 0.9, it is considered that the factor has great influence, and if it is lower than 0.6, it is considered that it is not indispensable to analyze. Implement correlation analysis on the selected financial index data to select the factors with great influence. The selected indicators include quick ratio, turnover rate of current assets, asset cash ratio, growth rate of total assets, return on net assets, sales expense ratio, and price to book ratio. The current ratio, the turnover rate of current assets, and the cash ratio of assets all reflect the solvency of the enterprise. The growth rate of total assets reflects the growth ability of the enterprise, the return on net assets reflects the profitability, the proportion

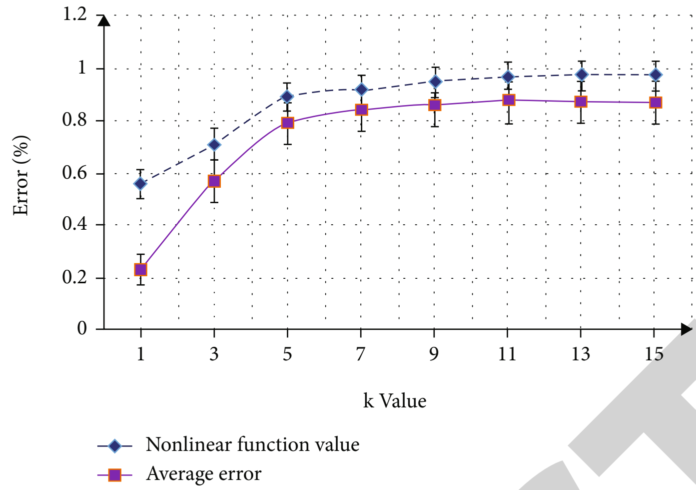

Figure 7: Error analysis of nonlinear function emulation.

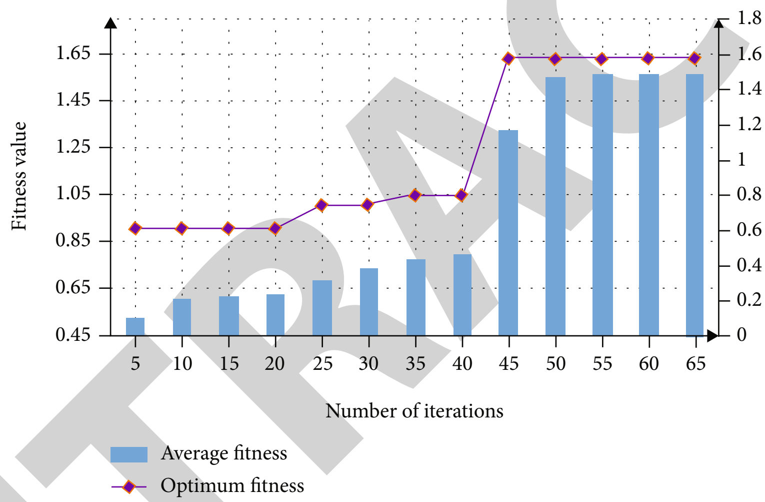

Figure 8: Adaptability evolution curve of experimental data.

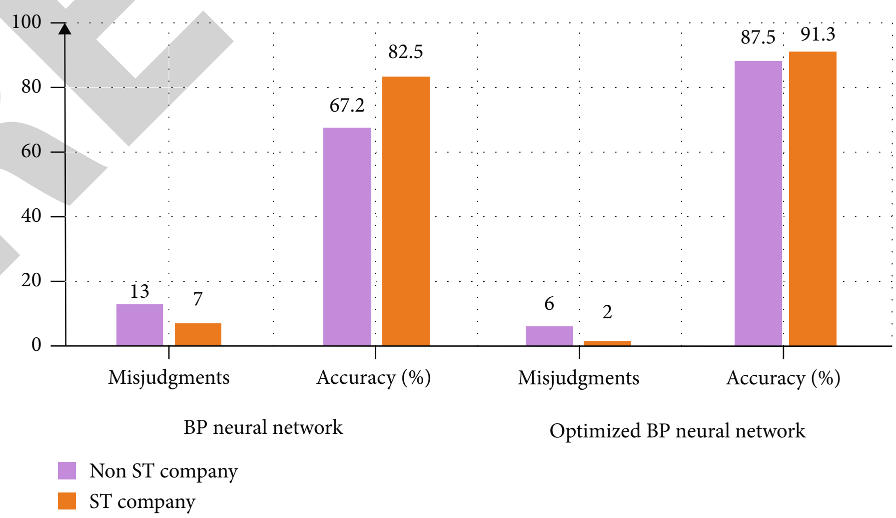

Figure 9: Accuracy of financial alert before and after new model optimization.

of sales expenses reflects the market sales ability, and the price to book ratio reflects the stock attributes of the enterprise.

The input layer reflects the neurons of the data, and the financial indicators included are enterprises. Therefore, the input layer sets seven nodes, and the data of nearly five years is brought into the optimized new model for experimental analysis. 60% of the data is used as sample data and 40% of the data is used as test data, which is compared with the real crisis situation of the enterprise to calculate the accuracy. In the optimization design of new model, GA is used to search through adaptability. Therefore, the best adaptability and adaptability function will be inconsistent in request. Considering the analysis results, continuous iteration is required until the requirements are met. Figure 8 is the adaptability evolution curve of experimental data. St refers to special treatment. The stock represented by ST Company is st stock, which has relatively large investment risks.

The accuracy of financial alert before and after new model optimization is indicated in Figure 9. From the figure, it could either be seen that the early warning accuracy of optimized new model has been significantly improved, which proves the superiority of the algorithm.

5. Conclusion

This paper studies the requirements of optimizing BP neural network in financial early warning and constructs a financial early warning analysis model. The stability of the algorithm is improved, and the maximum upper bound model of the number of hidden layer nodes is proposed. GA is used to optimize the design of the new model, and roulette selection is carried out on the basis of population grouping to maintain population diversity. The running time of the algorithm is mainly used to calculate the adaptability function. The simulation results show that compared with the traditional algorithm, the optimized model can give full play to the mapping ability of the new model. It should be pointed out that when optimizing the new network, the reference of GA can only improve the prediction accuracy. It has better learning ability and faster convergence speed and improves the accuracy of financial early warning. In the case of small sample size or uneven distribution, it may affect the prediction results, which needs further research. In this paper, the use of financial early warning can better monitor and diagnose finance, timely discover crises, and better promote the development of enterprises. In the business activities of enterprises, finance is at the core stage. This paper provides reference value for good financial operation and enterprise development.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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