

# Prediction of Enterprise Financial Crisis based on Improved Neural Network

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**Objectives:** Neural network is a very important research model in human brain research, and it has been cross researched and applied in many disciplines and fields. **Methods:** However, there are some shortcomings in the neural network, such as long learning cycle and slow convergence speed. **Results:** Therefore, in this paper, the enterprise financial crisis prediction based on improved neural network was proposed. Then in the light of the shortcomings of the neural network, the optimization and improvement were carried out. After that, the genetic algorithm was introduced to update the neural network structure and improve the prediction accuracy of the neural network. Finally, the improved neural network was applied to the financial crisis prediction, and good results were achieved. **Conclusion:** It is proved that the research has good application value and promotion prospect.

**Keywords:** improved neural network; enterprise finance; crisis prediction; research

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Neural network model, a complex network formed by the combination and connection of many simple neurons under certain rules, can take parallel and adaptive processing to the information with very obvious nonlinear characteristics, and has advantages over complex understanding operations<sup>1</sup>. By simulating the human brain nervous system, it stores and processes information, and has the function of simplifying, summarizing and simulating the information similar to the human brain<sup>2</sup>. The neural network can change the method of neural learning, and dynamically respond and process the external input information through its own neurons, which has the characteristics of storage and application of empirical knowledge. In addition, it can recognize and memorize the characteristics of some things, and so can recognize the objects according to the memory when it meets the information again<sup>3</sup>. In the 1940s, the study of neural networks began, mainly focused on the

physiology and psychology of brain function and the electrophysiological aspects of neurons<sup>4</sup>. In 1943, American psychologist Mika Rocco and mathematician Peters jointly established a mathematical model of formal neurons, which played a very important role in the study of neural networks<sup>5</sup>. Then, the development of neural network was affected by network defects and entered the low tide period. Until the 1980s, it was once again paid attention to, and then widely used in industrial control, economic research, engineering construction and other fields.

In the past 30 years of research on neural networks, the HNN model proposed by Hope Fede, an American physicist in 1982, is one of the most important research results that affect the development of neural networks<sup>6</sup>. Since then, scholars have successfully solved the problem of neural network stability based on the HNN model, and have made great achievements in the study of the ancient traveling salesman problem by using HNN's mathematical model. Neural

network is pushing forward breakthroughs in physics, computer science, mathematics, neuroscience and other interdisciplinary studies, and has played an important role in the study of artificial intelligence in recent years<sup>7</sup>. Neural network can simulate human knowledge learning, memory, reasoning, computing and other behaviors, and abstract mathematical model can keep human understanding abstract learning cognitive process<sup>8</sup>. In neural networks, a large number of neural nodes are used to represent the structure and function of human brain, and inductive learning method and large-scale empirical study are adopted for repeated learning. In the process of internal adaptation, the weights of each neuron are corrected, so that the mutual structure and connection weight distribution of neural networks are stable. The whole process is the learning process of acquiring knowledge<sup>9</sup>. The biggest advantage of neural network is its self-adaptability, nonlinearity, learning error correcting and relearning ability<sup>10</sup>. Therefore, in this paper, the research of enterprise financial crisis prediction based on improved neural network model was proposed.

For the improvement and optimization of neural network, it is mainly to improve the existing convergence cycle and prediction accuracy of the model. Neural network model can provide a simple nonlinear modeling method for complex systems, and achieve arbitrary nonlinear mapping at any precision. Through learning, the neural network model can automatically change the connection value of the internal network to adapt to the change of the system, has good fault tolerance and robustness, and can better use the multivariable system state. In the neural network, the sum of squared errors of the system is taken as the objective function, so that the convergence speed can be affected, and the local minimum value may occur. And the inaccurate prediction of the data model with a large number of numerical relations affects its popularization and application in practice. Therefore, in this paper, the optimization and improvement of the mathematical model were put forward, and the practice was verified in the prediction of enterprise financial crisis, so as to

test the improvement of the scientific and predictive accuracy of neural networks.

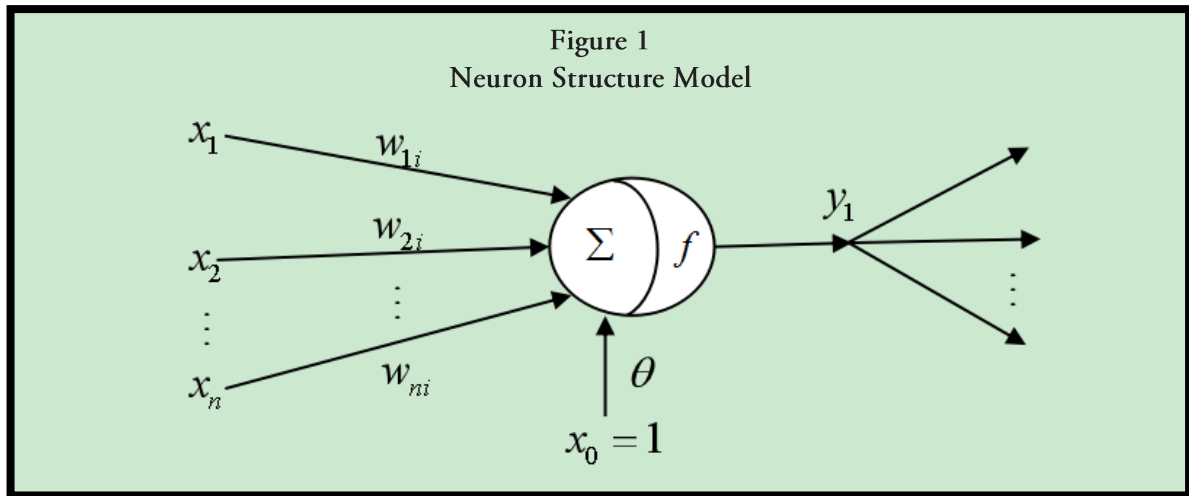
## METHODS

### Neural Network

Neural network mainly simulates the mode of human brain working, thinking and learning, which is the process of artificial neuron simulating biological neurons. Artificial neuron is the basic unit of the neural network, the function and characteristics of which are relatively simple when compared with the biological neuron. By combining a large number of artificial neurons to form a complex system of structure and function, all functions and properties of biological neurons can be fully replicated. The typical artificial neuron model structure is shown in figure 1, which is a nonlinear node form from multiple inputs to single output. The relationship between input and output can be represented by

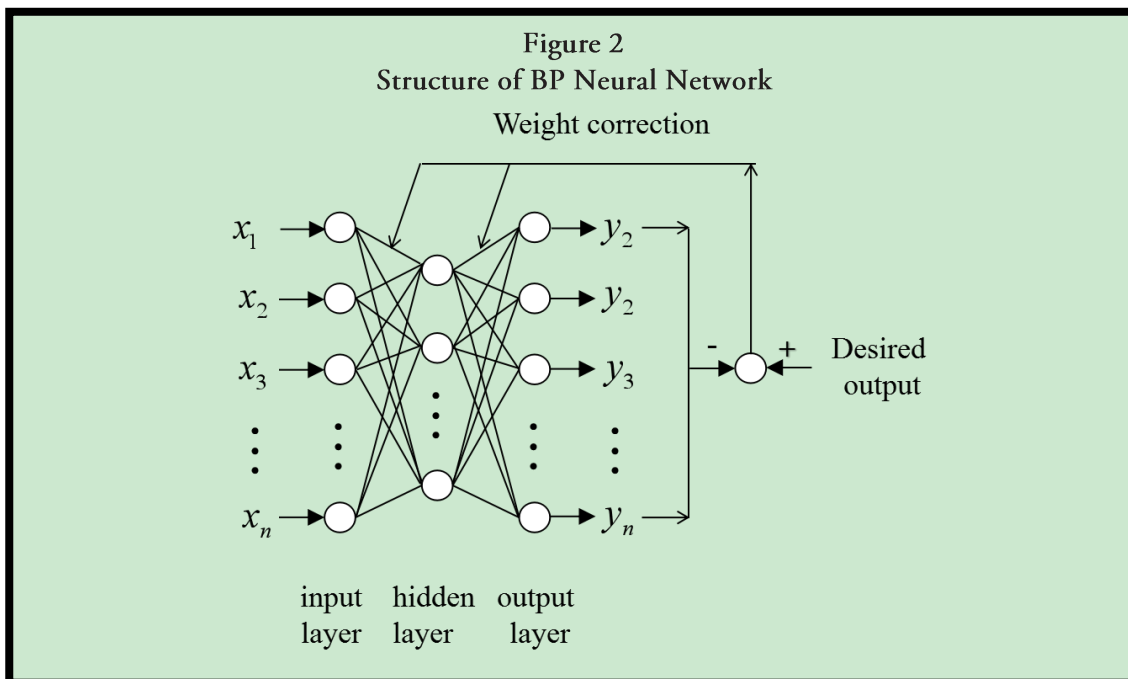
$$I_i = \sum_{j=1}^n w_{ji} x_j - \theta_i, y_i = f(I_i), \text{ where } x_j (j = 1, 2, \dots, n)$$

represents signals transmitted from other neurons.  $\theta_i$  represents the threshold, and  $w_{ji}$  represents the weight of the connection between the cell  $j$  and the cell  $i$ .



The structure of the neural network model is shown in figure 2. In a neural network, a signal is transmitted to the hidden layer after being inputted. After the excitation function is calculated, the information is transmitted to the output layer and changed to the output signal. The information feedforward layered neural network has the typical characteristics of error back propagation, and shows bidirectional propagation in the learning algorithm. The network structure is divided into input layer, output layer and hidden layer. The hidden layer may contain one layer or multiple layers, and each layer will link forward through the connection weights between nodes. The training process of neural networks is characterized by two kinds of propagation: forward and reverse. When the signal takes the process of "input layer-hidden layer-output layer", it shows the state of

forward propagation. When the hidden layer accepts the signal and produces an error that exceeds a certain range of expectation, the system corrects the weights and thresholds of the neurons in each layer based on this error, so as to make each layer more adaptive to each other, and to promote the performance of the system. This reflects the state of reverse transmission. In a network, a single node represents a neuron. There is no connection between neurons in the same layer, the nodes at each layer only accept the inputs from the upper layer, and the output of neurons in each layer only affects the nodes of the subsequent output layer. In practical applications, only one layer of the hidden layer can satisfy the need for use, and when the hidden layer reaches three, it can reflect the mapping of any continuous function.



$f(\cdot)$  is a transfer function in neural networks. It can be either a linear function or a nonlinear function with arbitrary order derivatives. The types of the corresponding functions are jump order function, sigmoid function, Gauss function, such as formula (1), (2), (3). And these three transfer functions also correspond to the 3 basic hierarchical structures of feedforward, feedback and self-organizing competition of artificial neural networks. At present, the most widely used three neural network models are BP network, Hopfield network and Kohonen network, among which, BP neural network is the most mature, widely used and stable.

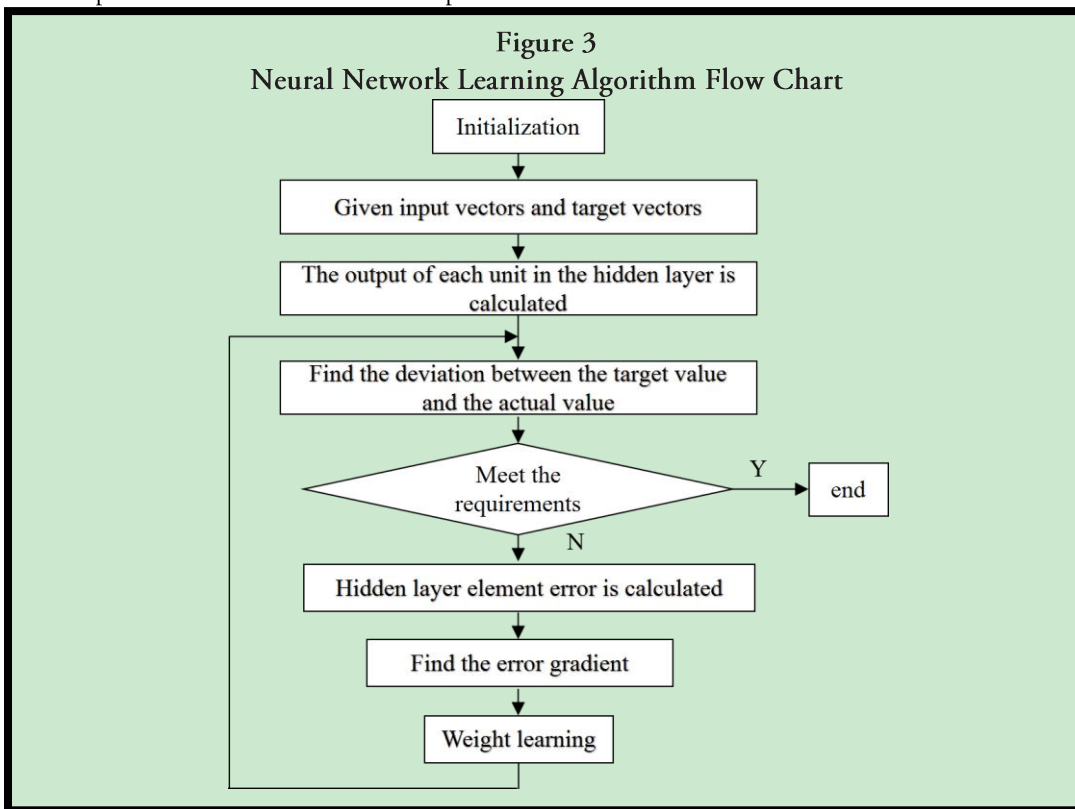
$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (1)$$

$$f(x) = th(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (2)$$

$$y_i = \exp\left(-\frac{1}{2\sigma_i^2} \sum_j (x_j - w_{ji})^2\right) \quad (3)$$

The basic algorithm of the neural network is the learning method of the tutor, and the main calculation steps of the basic learning algorithm are: (1) the weights  $w$  and  $\theta$  are initialized. The connec

tion weight of the input layer to the hidden layer neuron is determined as  $w_{ij}$ , the connection weight of the hidden layer to the output layer is  $w_{jk}$ , the threshold of the hidden layer is set to  $\theta_j$ , and the threshold  $\theta_k$  of the output layer neuron is given a smaller value between (0,1). (2) the input vector  $x_i = (x_1, x_2, \dots, x_m)$  of the input value and its corresponding expected output vector  $\hat{Y}_i = (\hat{Y}_1, \hat{Y}_2, \dots, \hat{Y}_n)$  are determined. The  $x_i$  value is input to the neuron node of the input layer, and the forward calculation is carried out according to the  $x_j^i = f\left(\sum_{i=0}^n W_{ij}x_i - \theta_j\right)$  ( $j=1,2,\dots,u$ ), or the reverse calculation is carried out according to the  $y_k = f\left(\sum_{k=0}^n V_{jk}x_j - \theta_k\right)$  ( $k=1,2,\dots,n$ ). (3) the error between output neuron output value and expected output value is calculated. If the error result is in line with expectation, the training is finished; if the gap is too large, the inverse calculation link of model calculation is again entered. After repeated correction function calculation, the weight of the required value is obtained, the model calculation is finished, and the signal is output. The flow of the BP neural network learning algorithm is shown in figure 3.



### Improvement of Neural Network

In this paper, the learning rate was optimized, and the dynamic learning rate was used to achieve the goal of decreasing convergence times and improving accuracy. The learning process of neural network is the key link, and the key problem is to solve the fixed learning rate and adjust the weight frequently. In order to

overcome the problems such as low learning rate, slow convergence speed and low learning rate, the learning rate formula is optimized to help the network reduce the amount of correction and avoid the weight exceeding the optimal value on the gradient. The optimization formula of learning rate is shown in formula (4).

$$\eta(n) = \begin{cases} a \times \eta(n-1) & E(n) < E(n-1) \\ a \times \eta(n-1) & E(n) > c \times E(n-1) \end{cases} \quad (4)$$

$$w(n) = w(n-1) - \eta(n) \times \frac{\partial E(n)}{\partial W(n)}$$

$\eta(n)$  is the learning rate of N iterations,  $E(n)$  and  $E(n+1)$  are the values of the two error functions before and after. Constant value  $a = (1, 2)$ ,  $b = (0, 1)$ ,  $c = [1, 1.1]$ . When  $E(n) < E(n+1)$ , the expression error is decreasing, the learning rate will increase to a times of the past, and the

convergence rate will accelerate. When  $E(n) > E(n+1)$ , the error is increasing, and the weight is over adjusted in the iteration. It is necessary to reduce the learning rate to b times, so as to avoid crossing the gradient direction, resulting in the local optimum weight.

$$\begin{aligned}
 E(w(n) + \eta_n d(n)) &= \min E(w(n+1)) \\
 w(n+1) &= w(n) + \eta_n d(n) \\
 d(n) &= -g(n) + \beta_n d(n-1), d(0) = -g(o)
 \end{aligned}
 \tag{5}$$

In order to reduce the error in the training of BP neural network, the value of the directivity function of the direction of search can be reduced continuously. However, under this principle, the network convergence speed is too slow, and it is easy to enter the local minimum search. At the same time, conjugate gradient algorithm is introduced to provide direction vector for search. This algorithm takes the error function of the weight setting range as the two line function, and can calculate the accurate approximation at one time. The implementation process is as follows: firstly, the objective function is set to  $\min E(w) \quad w \in R$ . When the minimum value of the error function is searched in the gradient direction, the formula (5) can be obtained, and the network can be corrected.

The application range of neural network is affected by network structure, which leads to local minimum and so on. Therefore, in this paper, genetic algorithm was introduced to improve the performance of the neural network. Genetic algorithm has great advantages in global search. It is based on population, and uses individual fitness as a criterion to judge the following operations, thus which not only has good global searching ability, but also improves the local search ability in the presence of mutation operator. The main forms of genetic algorithm for neural network optimization are as follows: firstly, the topology and network parameters of the neural network are optimized. In order to solve the problem that the hidden layer and node number of neural network can't be accurately determined, the genetic algorithm is used to optimize the topology structure, and then the network parameters are optimized. Secondly, after determining the structure of the neural network, the genetic algorithm is used to optimize the threshold and weight of the neural network. The parameters include the number of nodes in the input and output, the number of layers

and the number of nodes in the hidden layer. The algorithm flow chart of optimizing BP neural network structure by using genetic algorithm is shown in figure 4. The algorithm steps of optimizing BP neural network structure by using genetic algorithm are as follows. Firstly, preprocessing of encoding and decoding is carried out. After determining the number of hidden layers and the number of nodes in the network, the chromosomes are generated randomly and decoded respectively to form the corresponding neural network. The initial weight of the neural network is set to 1 for learning and training. The difference between the expected output value and the actual output value of the corresponding network under each coding is calculated, and the individual with the smallest error is composed of the first generation male parent. The crossover, mutation and other genetic algorithms are used to manipulate the current population and generate the next generation population. The above steps are carried out until the optimal individual is found, and the corresponding network is the optimal neural network structure.

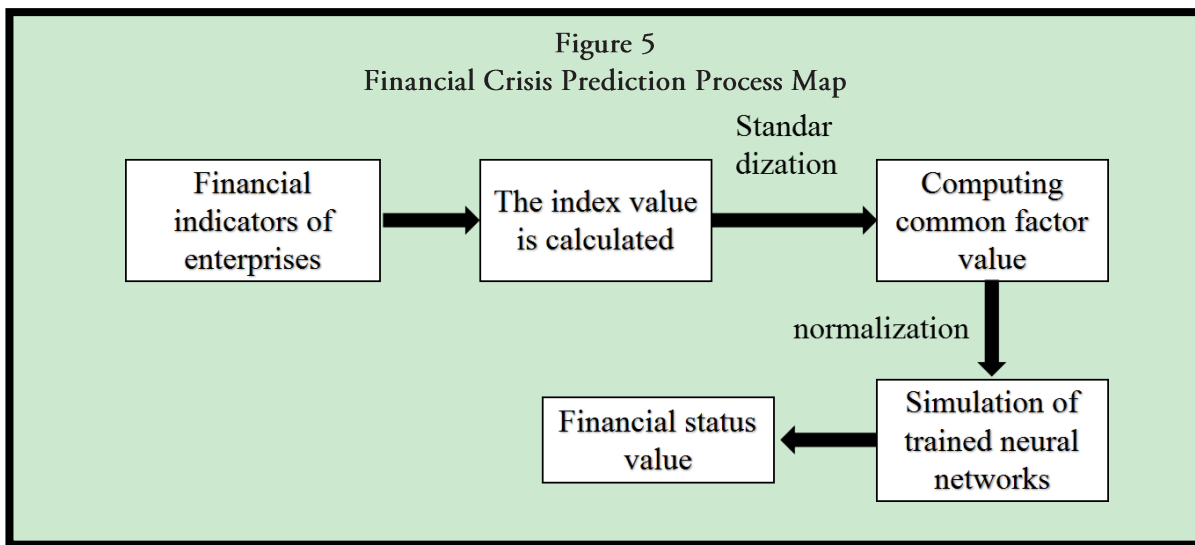
## RESULTS

In this paper, the enterprise financial crisis prediction based on the improved neural network was studied and demonstrated. The financial status of the enterprise was set to three states, namely, financial health (1, 0, 0), financial grey state (0, 1, 0) and financial risk state (0, 0, 1). When the results of neural model output were corresponding (1, 0, 0), (0, 1, 0), (0, 0, 1), the financial crisis of enterprises can be visually observed. Firstly, the basic parameters of neural network were set. (1) Parameter setting of the input layer and the hidden layer. The number of nodes in the input layer was consistent with the principal component analysis of the enterprise. In this paper, 7 factors of principal component were used as input variables to establish the neural network model of enterprise financial crisis prediction, and so the node in the input layer of

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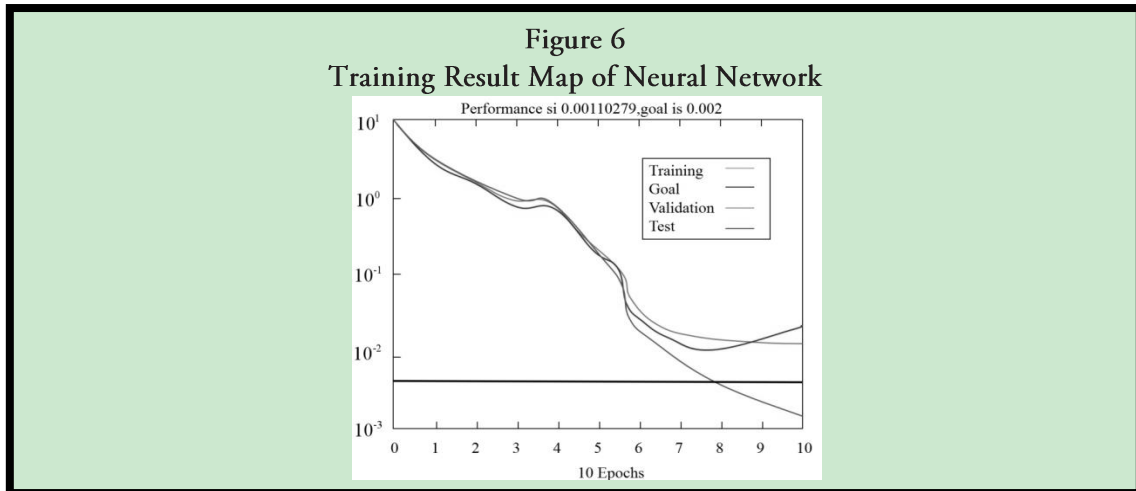
the neural network was set to 7, and the number of nodes in the output layer was 3. Through the corresponding formula, there were 6 layers of hidden layer. (2) Setting the training parameters of the neural network. In this paper, the TRAINLM function was adopted, with the characteristics of short convergence period and small error, being suitable for the fitting problem of small and medium scale function. The LEARNNGDM function was used to adjust the weight value. And the threshold and weight can be dynamically adjusted by using the method of

momentum gradient descent. In performance, the MSE function was selected to calculate the vector error between the output and the target. The transfer function was TANSIG, in which the number of network layers was 2, the number of nodes in hidden layer was 6, and the number of nodes in output layer was 6. The expected error of the judgment was 0.001, and MATLAB neural network toolbox was used to learn and train neural network. The process chart of enterprise financial distress prediction is shown in figure 5.



According to the requirements of improved neural network model for parameter input, in order to make the original data not affect the model evaluation, the data of 7 input factors were normalized and transformed into the results of the index between [0,1], and the neural network of 7\*6\*3 was established. Neural input data was the 7 factor data of the enterprise, and the corresponding financial index data was regarded as the target and expected output. In this paper, 150 samples collected from enterprises were taken as learning samples and trained into neural network algorithm to train 7\*6\*3 structure. The final set of iterations was 500 times, and the training error target was 0.001. When the number of iterations was more than 500 and the training error was not reached, the training program will automatically stop. The

elements of the weight matrix were random data with normal distribution. Finally, the training index diagram of the improved neural network model was obtained, as shown in figure 6. In this experiment, the network training reached 15 steps, the network performance was up to standard, the training error was 0.00045, less than 0.001, and so the neural network training was completed. After the standardized processing of the index value, the processing result was substituted into the neural network. The actual output of the enterprise was (0, 1, 0), and the enterprise finance was in the gray area, there was a potential crisis in the financial situation, and it was necessary to find hidden dangers and rectify them.



The trained neural network model was used to test the enterprise sample data set, and the variance contribution rate and the score matrix were calculated by using the formula. After that, the proportion of the scores of the comprehensive factors was obtained. The analysis of the composition of enterprise crisis is shown in table 1. From the table, it can be seen the first shareholder shareholding, external guarantee,

management transactions, net profit, the board of supervisors scale, P / E ratio, equity concentration and other factors account for a larger proportion. According to this structure, the financial indicators are improved and managed to help enterprises out of the financial crisis. It also proves that the enterprise financial crisis prediction based on the improved neural network has a good effect and application value in enterprise crisis prediction, and has practical applicability.

**Table1**  
**Analysis of the Composition of Enterprise Crisis**

Index	Return on net assets	Return on assets	Net profit margin	Current ratio
proportion	0.0401	0.0192	0.0416	0.0185
index	quick ratio	Debt asset ratio	Growth rate of net assets	Capital turnover rate
proportion	0.0167	0.0089	0.317	0.0291
index	Cash flow liabilities ratio	Shareholder equity ratio	Price earnings ratio	City net rate
proportion	0.0316	0.0143	0.0865	0.0345
index	The first shareholder shareholding rate	Ownership concentration	Board size	Board of supervisors scale
proportion	0.0765	0.712	0.0275	0.0879
index	Related party transactions	agency cost	External guarantee	audit opinion
proportion	0.0511	0.0281	0.0571	0.0273

**DISCUSSION**

As an efficient mathematical model, Neural network can help human beings go from traditional qualitative evaluation to scientific quantitative evaluation, and can provide great technical support for people in economic management, engineering construction, practical technology modeling and so on. In the algorithm, there are some shortcomings in the standard neural network, such as too long learning time, too many iterations and low learning rate, and it is often necessary to improve the model algorithm in practice. Therefore, in this paper, the research of enterprise financial crisis prediction based on improved neural network was proposed. Firstly, the characteristics of standard neural network structure were expounded. Then aiming at the deficiency of the structure of network algorithm, the improved method was studied to help neural network avoid the possible defects in learning and improve the

prediction accuracy of the model. The optimization of learning rate was proposed, and the convergence rate was decreased and the accuracy was improved through dynamic learning rate; conjugate gradient algorithm was used to provide direction vector for search and reduce search cycle; and genetic algorithm was introduced to solve the problem that the network structure was not easy to determine and the local minimum was easy to appear in the application scope of neural network. After the optimization and improvement of the neural network model, the research of enterprise financial crisis prediction was successful. From the results of the study, the optimization algorithm can improve the accuracy of the interpretation of the crisis prediction. However, there are some improvements in this study. The next step is to improve the prediction accuracy of the model, which is the direction of further research.

### **Human Subjects Approval Statement**

This paper did not include human subjects.

### **Conflict of Interest Disclosure Statement**

None declared.

### **References**

1. Harbi S, Guesmi F, Tabassi D, et al. Application of response surface methodology and artificial neural network: modeling and optimization of Cr(VI) adsorption process using Dowex 1X8 anion exchange resin. *Water Science & Technology A Journal of the International Association on Water Pollution Research*, 2016, 73(10):2402.
2. Kannan T D B, Ramesh T, Sathiya P. Application of Artificial Neural Network Modelling for Optimization of Yb: YAG Laser Welding of Nitinol. *Transactions of the Indian Institute of Metals*, 2016:1-9.
3. Lin C H. Hybrid recurrent Laguerre-orthogonal-polynomials neural network control with modified particle swarm optimization application for V-belt continuously variable transmission system. *Neural Computing & Applications*, 2017, 28(2):1-20.
4. Long J, Zhang Y. Discrete-Time Zhang Neural Network for Online Time-Varying Nonlinear Optimization With Application to Manipulator Motion Generation. *IEEE Transactions on Neural Networks & Learning Systems*, 2017, 26(7):1525-1531.
5. Ma C, Wu L, Zhou Y, et al. Analysis and Optimization of the Application of RS-BP Neural Network in Prediction of Deep Subway Foundation Excavation Monitoring. *Construction Technology*, 2016., 80:91-43.
6. Moorthi N S V, Franco P A, Ramesh K. Application of design of experiments and artificial neural network in optimization of ultrasonic energy-assisted transesterification of Sardinella longiceps fish oil to biodiesel. *Journal of the Chinese Institute of Engineers*, 2015, 38(6):731-741.
7. Nazemi A. A Capable Neural Network Framework for Solving Degenerate Quadratic Optimization Problems with an Application in Image Fusion. *Neural Processing Letters*, 2017:1-26.
8. Rangaiah G P. Application of Artificial Neural Network and Genetic Programming in Modeling and Optimization of Ultra-Violet Water Disinfection Reactors. *Chemical Engineering Communications*, 2015, 202(11):1415-1424.
9. Xu X S, Zhou F, Zhang T, et al. Application of neural network by genetic algorithm optimization in SINS/GPS. *Journal of Chinese Inertial Technology*, 2015, 23(3):322-327.
10. Zhang H, Yan G Y, Wang T. Application of Genetic Optimization Neural Network in Modeling of Platform Temperature Control System. *Navigation & Control*, 2016.57-26.