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Research Article

Research on Credit Evaluation of Financial Enterprises Based on the Genetic Backpropagation Neural Network

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In this paper, an improved neural network enterprise credit rating model, which is grounded on a genetic algorithm, is suggested. With the characteristics of self-adaptiveness and self-learning, the genetic algorithm is utilized to adjust and enhance the thresholds and weights of the neural network connections. The potential problems of the backpropagation (BP) neural network with slothful speed of convergence and the possibility of falling into the local minimum point are solved to a convinced degree using the genetic algorithm in combination. The hybrid technique of the genetic BP neural network is applied to a credit rating system. Using commercial banks' datasets, our experimental evaluations suggest that, using a combination of the BP neural network and the genetic algorithm, the proposed model has high accuracy in enterprise credit rating and has good application value. Moreover, the proposed model is approximately 15.9% more accurate than the classical BP neural network approach.

1. Introduction

At present, the traditional method of proportional analysis is still mainly used to evaluate the credit of enterprises in the Republic of China. The biggest disadvantage of this method is that the determination of indicators and weights in credit evaluation has great subjectivity, which is bound to increase the credit risks of commercial banks. In this paper, a credit rating model based on the BP neural network, which is further enhanced and optimized, by a genetic algorithm is proposed. The proposed model could significantly reduce the inaccuracy of credit rating caused by human factors to a certain extent. Using genetic algorithm, the initial weight and threshold of the backpropagation (BP) neural network are optimized, and the range of weight is increased to solve the two shortcomings of the BP neural network, which are (i) slow convergence speed and (ii) falling into the local minimum. Through combining the BP neural network with the genetic algorithm, the advantages of both are complementary.

The chief technique for commercial banks to investigate enterprise credit risk is using linear combination methods to complete the credit rating of all enterprises according to certain evaluation indexes. However, subject to the one-sidedness and randomness have always been the fatal drawbacks of these rating methods. Therefore, it is essential to look for alternative methods such as machine learning and artificial intelligence to improve the optimization of current credit rating systems in China. To evaluate the enterprise credit rating widely, competently, quantitatively, precisely, and suitably, this paper uses the classical genetic algorithm, one of the widely used optimization algorithms, to enhance the thresholds and weights of the classical BP neural network (NN) to establish a credit rating model for an enterprise, which is grounded on the new genetic algorithm integrated into the BP neural network. The main characteristics of the proposed model are (i) fast convergence speed, (ii) global optimization, and (iii) accurate evaluation of the credit rating. The credit rating model well adapts dynamically to the work of enterprise credit rating and has certain

application value. The following are the main innovation points of this paper:

(1) This paper proposes a credit rating approach grounded on the BP neural network that uses the classical genetic algorithm to increase the model accuracy and generate reasonable rating recommendations

(2) Characteristics such as self-adaptiveness and self-learning of the classical genetic algorithm are utilized to modify, enhance, and improve the thresholds and weights of the neural network connections

(3) Experimental results and our evaluations on real datasets show that the suggested hybrid genetic BP neural network model has higher accuracy as compared to the classical BP neural network

The structure of the remaining part of this paper is as follows. Section 2 describes the details of the background and state-of-the-art-related works. In Section 3, we discuss the methodology used to establish a credit rating system. Section 4 builds a BP neural network model. In Section 5, we integrate the genetic algorithm into the BP neural network and illustrate the experiments and results. Finally, Section 6 concludes this paper along with several key directions for further research and investigation.

2. Related Work

Artificial neural network (ANN) is an intelligent information processing technology that reproduces the information processing procedure of the human brain. It has strong robustness, self-adaptability, and self-organization and and is good at association, synthesis, and promotion [1]. These models illustrate and mimic diverse stages of the biological neural system with respect to various angles. The BP neural network model discussed in this paper is one of them. The idea of the BP neural network algorithm is as follows. First, a small random number is used to represent the connection weight and bias weight of each unit, and then, secondly, a group of training sample data is selected. The calculation process is mainly divided into two processes: (i) the forward process, which transfers the input to each unit and (ii) finally obtains the output at the output node of the network [2]. In the reverse process, the error between the actual output of the network and the expected output of the network is returned to the input layer from the output layer through the middle layer. Note that the offset weight and the connection weight are continuously adjusted in this process. Finally, the error between the actual output and the expected output of the training sample is less than the expected error given in advance [3].

Genetic algorithm is a computational model that illustrates and simulates the natural selection and genetic approach of the biological development and evolution process. Genetic algorithm is an approach for the exploration of the optimum solution through mimicking the process of natural evolution [4]. Moreover, genetic algorithm views the problem space in the way of coding space, with the coding population as the basis of evolution and the fitness function as the basis of evaluation. The individual bit string in the whole population is selected, crossed, and mutated to simulate the biological evolution and complete an iterative process. After multiple iterations, the individual evolution in the population will be completed, and the optimal solution is finally obtained [5, 6].

3. Establishment of the Credit Rating Model

3.1. Index Selection of the Rating Model. At present, the main method for commercial banks to analyze enterprise credit risk is to use linear combination methods to complete the credit rating of all enterprises according to the four key evaluation indexes of enterprise credit [7, 8]. However, subjective one-sidedness and randomness have always been the fatal drawbacks of these rating methods [9]. Therefore, to establish a comprehensive and scientific index evaluation system, it must be based on appropriate financial regulations and must follow the overall requirements of easy access, concise and reasonable, comprehensive, complete, strong operability, and stability. Based on referring to the credit rating system structure of foreign enterprises and combining it with the actual situation of domestic enterprises, according to the basic principle of combining qualitative indexes with quantitative indexes and potential abilities with practical abilities, the following enterprise credit rating index system structure is established. The index system is composed of approximately 26 indexes. Moreover, the network structure of this enterprise credit rating model depends on these 26 indexes. The rating index system is shown in Table 1.

3.2. Index Data Normalization. Among the 26 indicators, as shown in Table 1, eight secondary indicators of external environment enterprise quality are discrete nonnumerical data. Therefore, to speed up the learning speed, we need to scale the discrete nonnumerical data in equal proportion so that the scaled results fall into a certain range. Moreover, to prevent the large numerical information from drowning the small numerical information in the scaling process, we need to use the normalization method to deal with each input item. For the input vector set $X = \{x_1, x_2, \ldots, x_n\}$, the following formula, as illustrated by equation (1), is used to normalize and scale the input data (where x_i' is the result of x_i' normalization processing) [10, 11].

$$x_i' = \frac{x_i - \min(X)}{\max(X) - \min(X)}. \tag{1}$$

Let us assume the operator quality, nonnumerical discrete data, as an example to illustrate the normalization method. For example, if the value of the operator quality attribute is that the enterprise leaders have rich field knowledge and management experience, then the score is defined as 4 [12]. Note that 6 is the maximum value of the attribute score, while 0 is the minimum value. Thus, according to equation (1), the normalized attribute value v is given by

Table 1: Enterprise credit rating index system.

First-level indicators	Secondary indicators	Method
External environment and enterprise quality	Development prospects	Qualitative
	Policy and regulation environment	Qualitative
	Business order and credit environment	Qualitative
	Quality of leaders	Qualitative
	Enterprise performance	Qualitative
	Management decision	Qualitative
	Production layout	Qualitative
	Credit record	Qualitative
Economic strength	Asset ratio	Qualitative
	Return on cash flow of total assets	Qualitative
	Interest cover	Ration
Operating efficiency	Sales profit margin	Ration
	Net interest rate of assets	Ration
Solvency	Asset liability ratio	Ration
	Current ratio	Ration
	Quick ratio	Ration
	Contingent negative ratio	Ration
	Ratio of cash flow to current liabilities	Ration
Operating capacity	Product sales rate	Ration
	Turnover of current assets	Ration
	Turnover of the whole assets	Ration
Profitability	Net profit rate of sales	Ration
	Gross profit margin of sales	Ration
	Profit rate of net assets	Ration
	Return on the whole assets	Ration
	Growth rate of net assets	Ration

$$v = \frac{4-0}{6-0} = 0.67. \tag{2}$$

For qualitative data, with given maximum and minimum values, the above method can also be used for normalization and scaling purposes.

4. Construction of the BP Neural Network Model

4.1. Selection of the Hidden Layer Number. Previous research has shown and proved for a long time that this does not account for in what way how much complex the function of mapping is; indeed, one hidden layer is potentially adequate to encounter the requirements [5, 7, 13]. Therefore, this paper also assumes the previous findings of researchers and scholars and chooses just a solitary hidden layer architecture to shape and design the BP neural network approach for the proposed enterprise credit rating system [14].

4.2. Determination of the Number of Hidden Layer Neurons. The same sample dataset is used to train the network with a different number of hidden layer neurons while waiting for the weight to be altered. Finally, the quantity of hidden layer neurons is estimated using the principle of minimum error. In order to obtain faster error reduction speed, one or two neurons can be added on the premise of solving the problem. Therefore, six is determined as the number of hidden layer neurons.

4.3. Determination of the Transfer Function. Due to the fact that, among the input and the output vector set $X = \{x_1, x_2, \ldots, x_n\}$, there is no linear relationship, therefore, we assume that the neuron transfer function of the classical or optimized BP neural network must be differentiable all over the place. This paper determines the sigmoid function as the transfer function. The sigmoid function is expressed as

$$f(x_i) = \frac{1}{1+e^{-x_i}}. \tag{3}$$

The function is a nondecreasing continuous function representing the state continuous neuron model in the real number field [0, 1].

4.4. Determination of the Training Times. After a period of the training, the error of the testing model ought to be obtained at this moment in time. It should be noted that the weight value at this time should be kept synchronously updated every time the test error is extracted. If the test error rises, then it means that the network has reached the best training times. Usually, it is well understood that, at the best training time, the weight value of the model currently has the best generalization capability [15].

4.5. Design of the Output Layer. In this paper, to keep everything simple, we assume that the output layer of the proposed credit rating system just wants to imitate the enterprise credit rating; therefore, only and at most only one

output layer node is set, which is divided into 10 levels, i.e., scope of the credit rating [16]. The details are shown in Table 2.

4.6. Model Establishment. According to the previous analysis, this paper plans a three-layer, combination of the genetic and BP neural network, model to mimic various credit ratings of the enterprises. The suggested model comprises approximately, or more precisely, exactly twenty-six input layer nodes; that is, the input vector $X = \{x_1, x_2, \ldots, x_n\}$. These input layer nodes correspond to 26 indicators in the enterprise credit rating system. Note that the hidden layer of the proposed model comprises a maximum of six nodes; that is, the hidden layer vector $Y = \{y_1, y_2, \ldots, y_6\}$. There is a node in the output layer, that is, variable O. The value of O represents the actual output credit rating of the enterprise [17].

According to this paper, the output value "O" of the neural network should be in the range of [0, 1]; mathematically, this is illustrated as $O \in \{0, 1\}$. The expected output is the result of transforming the actual output of the training sample into [0, 1], expressed as the vector $D = (d_1)$. Furthermore, the weight values amongst the input and the hidden layers are expressed by the vector $V = \{v_{1,1}, v_{1,2}, \ldots, x_{26,6}\}$, and from the hidden layers to the output layers, they are represented by the vector $W = \{w_{1,1}, w_{2,1}, \ldots, x_{6,1}\}$, respectively. The hidden layer is given by [18]

$$y = f\left(\sum_{i=1}^{26} v_{ij} x_j\right). \tag{4}$$

The output layer is given by

$$O = f\left(\sum_{i=1}^{6} w_{j,1} y_j\right). \tag{5}$$

Note that $f(x)$ is the unipolar sigmoid transfer function selected in this paper, i.e., equation (2). The genetic algorithm-grounded BP neural network architecture of the credit rating model of the enterprise that is established by the above principles is shown in Figure 1.

5. Application Analysis of the BP Neural Network Optimized by the Genetic Algorithm in Enterprise Credit Rating

5.1. BP Neural Network Optimized by the Genetic Algorithm. The calculation of the threshold value and connection weight value of the neurons is the core idea of neural network operation. Genetic algorithm can be utilized to improve and enhance the threshold value and connection weight value between neurons. The global optimization method of the suggested BP neural network using a genetic algorithm is as follows. The genetic algorithm is utilized to improve and enhance the initial threshold value and connection weight value between neurons of the BP neural network. Then, the BP algorithm is applied to modify the threshold value and connection weight value between neurons according to the negative gradient direction, and the network is trained. The major reasons of why this method is utilized to improve and enhance the establishment of the BP neural network include the following: (i) the genetic algorithm can effectively avoid the disadvantage that the search range falls into the local minimum; (ii) it can also reduce the training times of the threshold value and weight value; and (iii) it can advance the speed of convergence of the model. The operation of the BP neural network optimized by the genetic algorithm is described in two steps as follows:

Table 2: Scope of the credit rating.

Output	Credit rating
$0 \geq 0.95$	AAA
$0.95 > 0 \geq 0.85$	AA
$0.85 > 0 \geq 0.74$	A
$0.74 > 0 \geq 0.62$	BBB
$0.62 > 0 \geq 0.48$	BB
$0.48 > 0 \geq 0.36$	B
$0.36 > 0 \geq 0.21$	CCC
$0.21 > 0 \geq 0.12$	CC
$0.12 > 0 \geq 0.09$	C
$0.09 \geq 0$	D

(1) Chromosome coding: because the threshold and weight values of the neural network are continuous parameters and the coding method of the floating-point number is characterized by continuous parameter optimization, therefore, the steps of coding and decoding are omitted. To a certain extent, it can improve the speed of the genetic algorithm operation and the accuracy of the feasible solution. Therefore, this paper chooses the floating-point coding method to encode chromosomes. The threshold and weight values are cascaded according to the input layer node to the hidden layer node and, subsequently, from the hidden layer node to the output layer node. It should be noted that a chromosome in the population is a cascaded output array.

(2) Fitness function: the fitness function value determines the evaluation result of the genetic algorithm for the viability of chromosomes. The larger the fitness function value of the chromosomes is, the easier it is to be selected for genetic operation and, furthermore, the smaller the square sum of the error between the actual output value and the expected output value of the output layer neurons. This shows that the accuracy of the BP neural network is higher. In this paper, the mean square error function of the BP algorithm is selected as the fitness evaluation function. The optimization algorithm of the BP neural network, in terms of the flowchart, is shown in Figure 2.

5.2. Application Analysis of the BP Neural Network in Enterprise Credit Rating. According to the previous analysis, the input layer of the enterprise credit rating model established in this paper has approximately 26 nodes. There

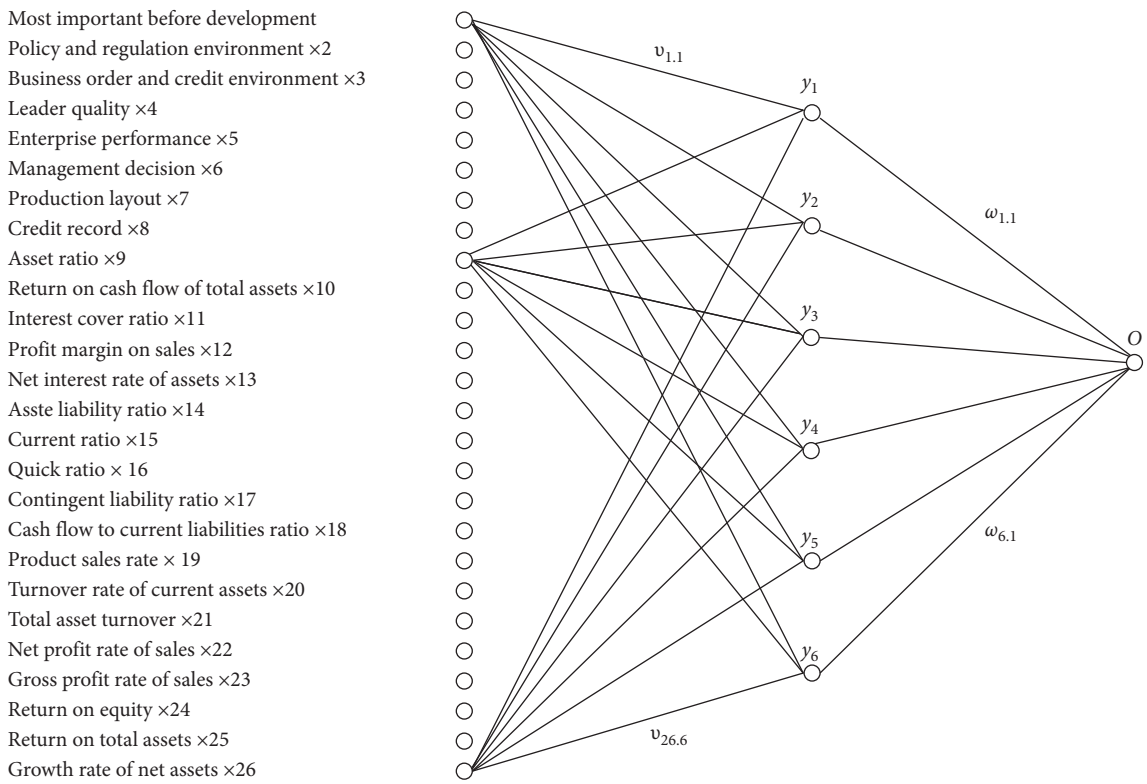

Figure 1: The credit rating model.

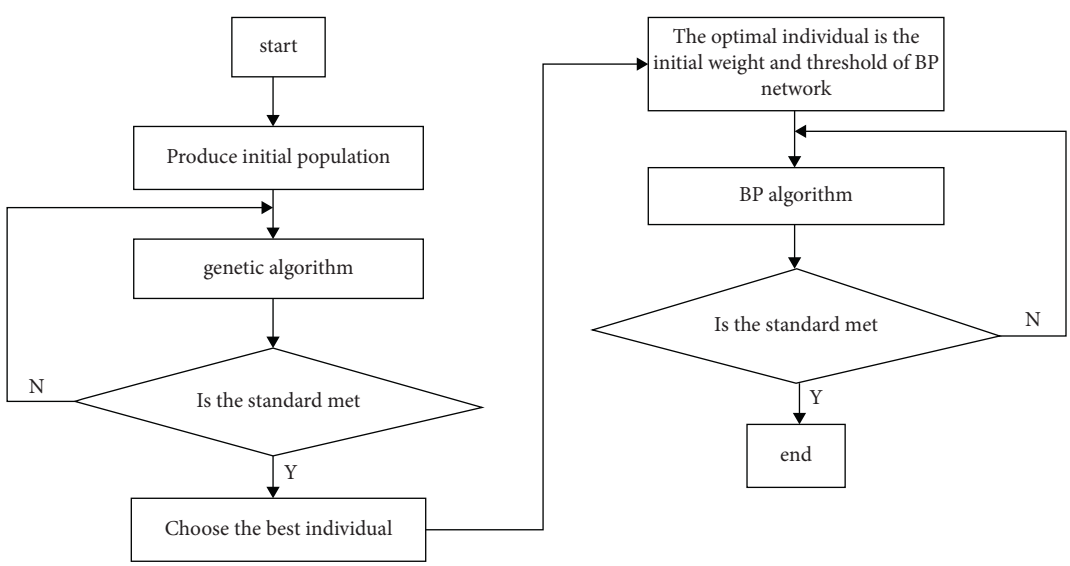

Figure 2: Flowchart of the genetic BP neural network optimization algorithm.

are six nodes in the hidden layer and one node in the output layer. The rating model is nonlinear, and the question whether the model can converge and reach the local minimum or not essentially depends on the initial weights to a large extent. Therefore, this is very important to make the state value of each neuron close to zero when the initial weights are added. At the same time, the experimental results of Stornetta and Huberman show that when the weights are adjusted in the range of [−0.5, 0.5], the state value of each neuron is close to zero. As a result, the convergence time will be shortened by approximately 30% to 50% [19].

The test parameters are as follows: the expected error is 0.005, the unipolar sigmoid function is the transfer function, the initialization of network weights is limited in the [−0.5, 0.5] interval, the selection probability is 0.05, the crossover rate is 0.1, the variation rate is 0.05, and the population size is 300. Moreover, the maximum evolutionary algebra is 1500. The sample learning data used in this paper come from

Table 3: Connection weights of the input layer and hidden layer after training.

Input layer	Hidden layer					
	1	2	3	4	5	6
1	−0.5349	0.6554	0.3255	0.091	−1.0189	1.1820
2	0.8526	−0.4313	1.2015	−1.0425	0.4017	−0.1709
3	1.1856	1.1660	0.2807	−0.4031	−02354	1.126
4	1.1660	0.2807	−0.3892	0.556	−1.0425	0.8050
5	−0.1402	−0.3642	0.9511	1.2881	0.0406	−0.3059
6	0.1369	0.8786	−1.171	−0.30559	0.2082	0.8186
7	0.5556	0.9290	1.0406	0.1569	1.1369	−0.8414
8	−0.5714	1.2881	0.7082	−0.3678	−0.9727	−0.8135
9	−0.4274	0.4695	0.5004	0.7118	0.9667	1.2990
10	−0.9711	0.1421	1.3295	−0.2142	0.0731	1.0525
11	1.2646	−0.7481	0.774	−0.3154	−0.0107	−0.8469
12	1.0484	−0.9704	1.668	−0.5349	1.2822	−0.4742
13	1.1615	−0.8296	−0.5125	−1.0189	1.4454	0.0091
14	0.6554	0.3255	−0.4586	0.6942	0.8477	−0.4313
15	−0.1584	−0.8720	1.820	0.6670	0.8526	0.8651
16	−0.6971	0.2784	0.5465	−0.6697	0.4232	0.5555
17	0.0552	1.3068	−0.3870	0.3055	−0.6873	0.8310
18	0.4686	0.7038	−0.6208	−0.5677	0.4911	−0.2349

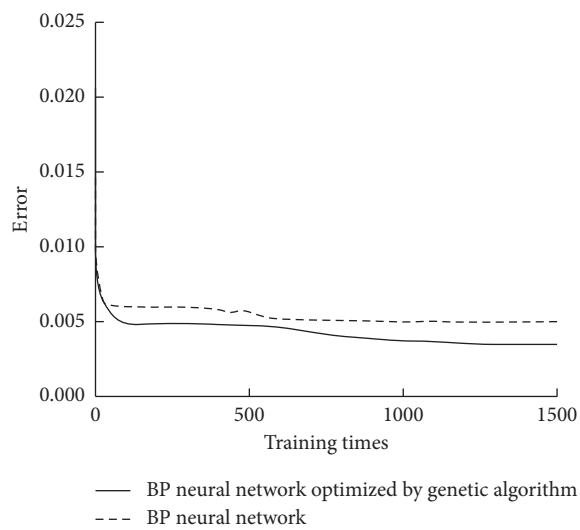

Figure 3: Training results of two kinds of neural networks (genetic algorithm-integrated BP neural network for the credit rating system).

approximately 189 enterprise credit evaluation data samples provided by a bank. When all the training data are input into the network, the input order of each training sample is randomly sorted first and then fed as the input into the model for training. The connection weights of the input layer and hidden layer after the training are shown in Table 3. Our evaluation with these assumptions shows that the BP neural network enhanced through integrating the genetic algorithm can meet the requirements of the training, and the speed of the error is higher than that of the general BP neural network, as shown in Figure 3.

5.3. Model Testing. After completing the training, 78 groups of the enterprise data of a commercial bank are selected and input into (i) the BP neural network and (ii) the BP neural network model optimized by the genetic algorithm for testing, respectively. Simultaneously, the results of the suggested network outcomes are compared with the actual credit rating outcomes. The outcomes of the proposed model testing are illustrated in Table 4.

The prediction accurateness of the credit rating assessment model is measured by the proportion of two kinds of errors: (i) the first kind is that the company's credit rating is wrongly estimated high (for example, the company's actual credit rating is B, and the model misjudged BB) and (ii) the second type of error is that the company's credit rating is underestimated (for example, the company's actual credit rating is A, and the model's misjudgment is BBB). The misjudgment rates of the traditional BP neural network (NN) model and the suggested BP neural network (NN) model optimized and enhanced by the genetic algorithm for the test samples are shown in Table 5. It can be observed from outcomes shown in Table 5 that the proposed BP

Table 4: Model testing results.

Serial number	Expert rating results	BP neural network	Optimization of the BP neural network model by genetic algorithm
1	BB	A	BB
2	A	BBB	A
3	BBB	AAA	BBB
4	AA	A	AA
5	A	B	A
6	BB	BB	B
7	B	BBB	B
8	BBB	BB	BBB
9	BB	A	BB
10	A	A	A

Table 5: Misclassification rate of two models for test samples.

Model	Type 1 error	Type 2 error	Total miscarriage of justice
BP neural network	3 (3.85)	3 (3.85)	6 (7.70)
BP neural network optimized by genetic algorithm	0 (0)	2 (2.56)	2 (2.56)

The rate of misjudgment is in brackets, and the unit is %; the number of misjudgments is outside the brackets.

neural network improved by integrating the genetic algorithm can obtain a high accuracy rate in the enterprise's credit rating [20, 21].

6. Conclusions and Future Work

To evaluate the enterprise credit rating comprehensively, efficiently, objectively, accurately, and conveniently, this paper practices the integration of a genetic algorithm to improve and enhance the thresholds and weights of the BP neural network model. Furthermore, the proposed work finds a credit rating model for the enterprise that is grounded on the classical genetic algorithm. The main characteristics of the proposed model are fast convergence, global optimization, and accurate evaluation of credit rating systems. Our evaluation over certain plausible assumptions demonstrates that the credit rating model can well adapt to the work of enterprise credit rating and has certain application value. The proposed model is approximately 15.9% more accurate than the classical BP neural network approach.

Compared with the classical genetic algorithm, the BP neural network algorithm has significantly enhanced the diversity of new generations, and the performance of the optimized genetic BP neural network has been improved. The enhancement of the mutation possibility boosts the aptitude and speediness of the genetic algorithm for the exploration of the global optimal solution, and the credit rating model has effectual convergence proficiency and accurate prediction accuracy. In the future, we will consider swarm evolutionary algorithms such as PSO and its various variants for integrating into the BP neural network for more robust enterprise credit rating systems [22, 23]. Furthermore, large datasets should be considered to evaluate and generalize the findings of our proposed research and investigation. Other aspects such as security, supply chain, and accurateness of the credit rating system are also of utmost importance to ensure correct and appropriate rating for various enterprises. Researchers at academia and industries are developing blockchain, supply chain management-based approaches to secure and make such systems more robust, accurate, precise, and secure [24, 25].

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest.

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