

Retraction

Retracted: Risk Assessment Method of Agricultural Management Investment Based on Genetic Neural Network

Security and Communication Networks

Received 27 June 2023; Accepted 27 June 2023; Published 28 June 2023

Copyright © 2023 Security and Communication Networks. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets 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 own 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] J. Zhao, "Risk Assessment Method of Agricultural Management Investment Based on Genetic Neural Network," *Security and Communication Networks*, vol. 2022, Article ID 2373363, 10 pages, 2022.

Research Article

Risk Assessment Method of Agricultural Management Investment Based on Genetic Neural Network

JingJing Zhao 

Changchun University of Finance and Economics, Jilin, Changchun 130122, China

Correspondence should be addressed to JingJing Zhao; xqb@nuc.edu.cn

Received 18 November 2021; Revised 22 December 2021; Accepted 21 January 2022; Published 29 April 2022

Academic Editor: Chin-Ling Chen

Copyright © 2022 JingJing Zhao. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

At present, the economy has entered the new normal. In the environment of economic slowdown, agricultural operation and investment risk management is of great significance in investment activities. In order to avoid the related risks of the agricultural operation and investment, improve the stability of agricultural operation and investment risk assessment, and ensure the effect of the agricultural operation and investment risk assessment, an agricultural operation and investment risk assessment method based on genetic neural network is proposed. This method fully considers the global optimization capability of the genetic algorithm and optimizes the weights and thresholds of the BP neural network. According to the construction principle of the index system, from the perspective of systemic risk and nonsystematic risk, a risk assessment index system for agricultural business investment has been established. Based on the establishment of risk evaluation index system, using the genetic neural network method, the agricultural operation investment risk evaluation model is established to realize the agricultural operation investment risk evaluation. The experimental results show that the proposed method has a good effect on the risk assessment of the agricultural operation and investment and can effectively improve the stability of the risk assessment of agricultural operation and investment.

1. Introduction

In the market economic environment, agricultural business enterprises are gradually emerging, which promote the development of the agricultural economy, and the real realization of modern agriculture also requires them to play a greater role [1–3]. Agricultural management enterprise is an enterprise integrating development, production, operation, and service. It can change the current situation of the economy and science and technology and organically combine economy and science and technology. Therefore, it plays a role of link [4, 5]. However, with the rapid economic development, the international competition of agricultural enterprises is becoming increasingly fierce, which increases various uncertain factors, and various risks faced by agricultural operation and investment are also complex. At present, the risk decision-making methods used by agricultural operations and investment managers for complex investment projects cannot accurately evaluate the size of

their risks, so if they cannot carry out effective risk prevention, enterprises will inevitably suffer losses. Agricultural operation investment is a significant sign of great progress in agricultural development. Only with the good development of agricultural operation and investment, we can solve a series of problems related to farmers, such as employment pressure, low income, and rural urbanization, and stabilize the healthy development of other economic and related industrial sectors [6, 7]. Therefore, studying the risk management of agricultural operation and investment is of great and far-reaching significance to promoting the upgrading of the agricultural industry and reducing the project investment risk of agricultural enterprises.

At present, scholars in related fields have studied the risk assessment of operation and investment. Reference [8] proposes one belt, one road country risk assessment method for renewable energy investment under uncertainty. Using the TODIM method, they determine the risk factors of renewable energy investment and divide them into five categories:

economic, technological, environmental, social, and political. The fuzzy analysis network method is used to weight the identified factors, and the COPRAS, MABAC, and GRA methods are used to sort different renewable energy sources under uncertain conditions to realize the risk assessment of renewable energy investment. Finally, the sensitivity analysis of investment decision is carried out, focusing on the tradability of renewable energy projects. This method is helpful to evaluate investment projects and expand the international market. Reference [9] proposed the investment risk assessment of coal-fired power plants in the Belt and Road countries based on the ANP-Entropy-ToDIM method. An evaluation criteria system is established from eight dimensions, and the weights of these criteria are determined by the combinatorial analysis network process entropy method. Considering the psychological characteristics of decision-makers, the TODIM method is used to rank the overall risk level of CFPP investment in 23 countries to realize the investment risk evaluation of coal-fired power plants. This method has the maximum weight of the economic basis standard.

Based on the above analysis, this paper proposes a risk assessment method for agricultural operation and investment based on genetic neural network. Based on the analysis of the principle of BP neural network and genetic algorithm, and according to the construction principle of the index system, the risk evaluation index system of agricultural operation and investment is established. The genetic neural network method is used to construct the risk assessment model of agricultural operation and investment, so as to realize the risk assessment of agricultural operation and investment. Finally, it is verified that the proposed method has a better risk assessment effect and can effectively improve the stability of risk assessment.

2. Genetic Neural Network

2.1. Principle of BP Neural Network. BP (backpropagation) neural network takes the network error square as the objective function and uses the gradient descent method to calculate the minimum value of the objective function [10–12]. BP neural network has strong pattern recognition ability and nonlinear mapping ability, which is suitable for solving the problems of function approximation, pattern recognition, classification, and so on. The typical topology of the BP neural network is shown in Figure 1.

The information processing process of the BP neural network can be divided into two parts: forward propagation and back propagation.

- (1) Forward propagation: By calculating the output of the previous layer of neurons as the input of the next layer of neurons, it is calculated by layer. For a labeled sample set $\{(x^i, y^i)\}_{i=1}^m$, where x^i, y^i represents the i training sample and label, respectively, and m is the sample dimension. Suppose the neural network model is $h_{w,b}(x)$, where w and b are the connection weights and biases between each layer of the model. Assuming that s^k is the input value of the k layer, the output of the $k + 1$ layer neuron is expressed as follows:

$$s^{k+1} = w^k a^k + b^k, \quad (1)$$

$$a^{k+1} = f(s^{k+1}). \quad (2)$$

In formulas (1) and (2), w^k and b^k are, respectively, expressed as the weight and bias of layer k network, a^k is the output value of layer k neuron, and $f(\cdot)$ is the activation function of neuron, usually sigmoid function or tanh function [13–15]. The forward propagation of the network can be completed by successively calculating from the input layer to the output layer.

- (2) Back propagation: Back propagation refers to the process of optimizing the loss function of the neural network with algorithms such as random gradient descent [16]. In order to make the learning results of the network model on the training samples more consistent with the label data, that is, to minimize the difference between the network output value and the label data, the loss function is defined as

$$J(w, b) = \frac{1}{m} \sum_{i=1}^m \frac{1}{2} \|y^i - \hat{y}^i\|_2^2 + \frac{\lambda}{2} \sum_i \sum_j w_{ij}^2. \quad (3)$$

The above formula consists of two parts. The first half represents the mean square error between the output value and label value of the network model on the training sample set. The latter half represents the weight attenuation term, which is used to reduce the weight amplitude value and prevent overfitting. In order to minimize formula (3), the following steps are usually carried out:

Step 1. The weight w and bias b are randomly initialized, the training samples are inputted into the network for calculation, and the output value is obtained.

Step 2. Optimization algorithms are used such as stochastic gradient descent to update w^k and b^k as follows:

$$w^k = w^k - \alpha \frac{\partial J(w, b)}{\partial w^k}, \quad (4)$$

$$b^k = b^k - \alpha \frac{\partial J(w, b)}{\partial b^k}. \quad (5)$$

In formulas (4) and (5), α is the learning rate, usually the value [0–0.1], adjusted according to the actual situation. It can be seen from the above formula that the key to the backpropagation algorithm is to calculate the partial derivative of the loss function $J(w, b)$ to the weight w and the bias b . Its partial derivative is expressed as

$$\frac{\partial J(w, b)}{\partial w^k} = \beta^{k+1} (a^l)^T, \quad (6)$$

$$\frac{\partial J(w, b)}{\partial b^k} = \beta^{k+1}. \quad (7)$$

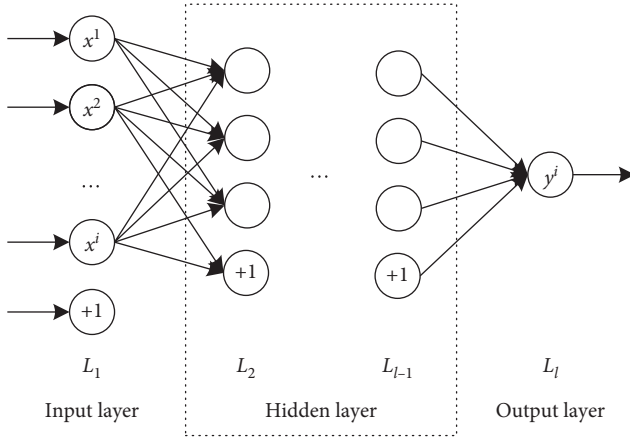


FIGURE 1: Typical topology of BP neural network.

In formulas (6) and (7), β^k is the residual value of neurons in the k layer of the network. On this basis, the difference between the output value of the output layer and the sample label is first calculated to obtain the residual value β^l of the output layer, then calculate the residual β^{l-1} of the previous layer in the reverse direction, and calculate all the residuals as follows:

$$\begin{aligned}\beta^l &= -(\bar{y}^i - y^i) f'(s^l), \\ \beta^k &= w^k \beta^{k+1} f'(s^k).\end{aligned}\quad (8)$$

Step 3. Iterate until the minimum value is obtained. The backpropagation algorithm searches the weight of the model in the high-dimensional space through the random gradient descent algorithm and continuously iterates the training process to minimize the loss function as much as possible. However, for multihidden layer networks, this algorithm often converges at the local minimum rather than the global minimum. The mathematical space of the error function of multilayer neural network is high dimensional, there are many gradient descent routes, and there are many routes including local extremum convergence. Random initialization of weights and offsets often leads to a loss function, resulting in falling into a local minimum of a certain dimension.

2.2. Principles of Genetic Algorithm. Based on the theory of evolution and genetic genetics, the genetic algorithm finds the optimal solution rather than the local solution of the actual problem by simulating the species selection and evolution in nature [17–19]. The optimization is based on the individual fitness obtained by the algorithm. The optimization method is mathematical iteration, and finally, the optimal solution of the problem to be solved is obtained. The specific process of the genetic algorithm is shown in Figure 2.

It can be seen from Figure 2 that the effect of the genetic algorithm in the actual optimization process is determined by the following five key factors:

- (1) Coding of parameters to be optimized: Genetic algorithm first encodes the parameters of the problem; that is, the problem is encoded into a string. The simplest coding method is binary coding. The problem can be represented by a binary array. Another method is real number coding.
- (2) Initial population setting: The population size will directly affect the optimization efficiency and running times of the genetic algorithm. The population size can be set according to the actual situation, and the general value range is [20, 200].
- (3) Individual fitness calculation: Fitness is the standard for evaluating the quality of chromosome individuals in the population and the basis for selecting genetic operation [20–22]. In the specific application, the design of the fitness function should be combined with the requirements of solving the problem itself. In this paper,

$$f(E) = \frac{1}{1+E} \quad (E \geq 0). \quad (9)$$

- (4) Genetic optimization operator setting: Genetic operation can gradually optimize the solution of the problem and approach the optimal solution. Genetic manipulation includes selection, crossover, and variation [23–25]. Selection and crossover basically complete most of the search function of the genetic algorithm, and mutation increases the ability of the genetic algorithm to find near-optimal solution.

Selection: The selection process is the premise of cross mutation. The first step is to select the chromosomes that can produce the next generation population. The commonly used selection method is the roulette algorithm [26–28]. The probability of an individual being selected is positively correlated with the value of its fitness function. The probability of an individual $f(x_i)$ being selected can be expressed as follows:

$$f(x_i) = \frac{f(x_i)}{f(x_1) + f(x_2) + \dots + f(x_n)}. \quad (10)$$

Crossover: Two chromosomes randomly A, B select a position to exchange some genes to produce two new chromosomes. The probability of chromosome crossing can be expressed by P_c .

Before chromosome crossing,

$$\begin{aligned}A: & 00000|011100000000|10000, \\ B: & 11100|000001111110|00101.\end{aligned}\quad (11)$$

After chromosome crossing,

$$\begin{aligned}A': & 00000|000001111110|10000, \\ B': & 11100|011100000000|00101.\end{aligned}\quad (12)$$

Variation: In the process of chromosome evolution, variation will occur with a certain probability, which is expressed by P_m .

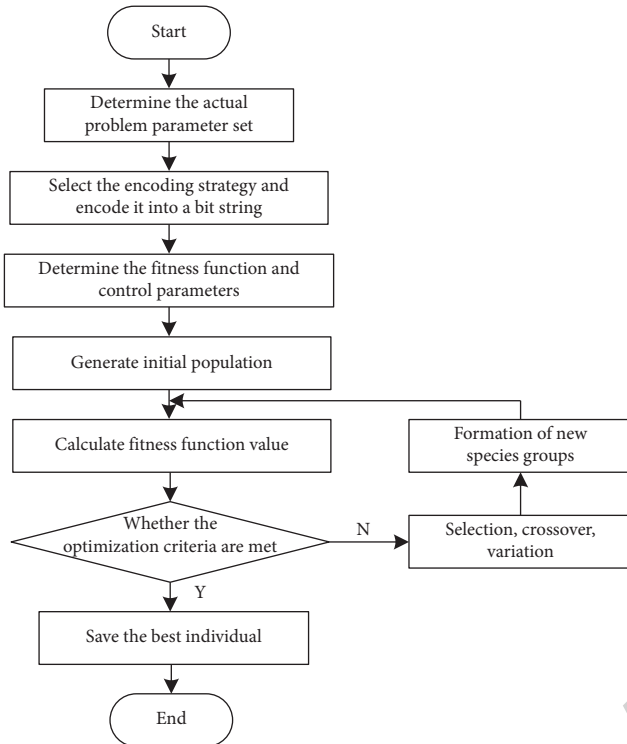


FIGURE 2: Specific process of genetic algorithm.

Before chromosome variation,

$$000001110000000010000. \quad (13)$$

After chromosome variation,

$$000001110000100010000. \quad (14)$$

- (5) Genetic control operator setting: It mainly sets the algebra of genetic evolution. For the optimization with a small population number, the evolutionary algebra range should be [50, 100].

2.3. Construction of Genetic Neural Network. This paper uses a genetic algorithm to optimize the weights and thresholds of the BP neural network, constructs a genetic neural network, and achieves the purpose of obtaining the optimal solution [29, 30]. The basic principle of the genetic neural network is to solve it by a genetic algorithm. Because a genetic algorithm searches a group of points in the solution space at the same time and forms an evolving population sequence, some global good points can be obtained at the same time after evolving a certain algebra. Starting from these good points, the neural network is used to solve them, respectively, and then, the global optimization solution is obtained. The flowchart of the genetic neural network is shown in Figure 3.

The steps of using a genetic algorithm to assist in optimizing the weight of a neural network are as follows:

- (1) A part from the total sample is randomly extracted, which is a set of weight thresholds, and effective

coding methods are used to encode the group. A gene string represents a weight threshold distribution state of the network, and a chromosome represents a set of weight thresholds of the neural network.

- (2) By calculating the error function of each chromosome in the neural network, the fitness function value of the population is further determined, and the constituent population in line with the target value is selected.
- (3) The population with high fitness in line with the target is taken as the parent, and the next step is passed on to the offspring.
- (4) To process and calculate the parents to get the next generation, crossover operator and mutation operator are used.
- (5) Whether the obtained results meet the termination goal is determined. If it is satisfied, it will terminate and enter the next stage. If there are still deficiencies, it will repeat the cycle until satisfactory results are obtained.

3. Construction of a Risk Evaluation Index System for Agricultural Business Investment

3.1. Construction Principle of Index System. In order to fully consider the influencing factors of agricultural operation investment risk and strive to obtain scientific and objective evaluation results, the following principles should be observed when constructing the risk evaluation system:

- (1) Scientific principle: The design of the risk evaluation index of agricultural operation investment must comply with relevant economic theories [31]. The selection of indicators should cover all risk factors as much as possible, and the concept and significance of indicators should be clear, which can accurately reflect the characteristics of the agricultural operation and investment risks, meet the requirements of risk evaluation, and ensure the comprehensiveness and objectivity of the results.
- (2) Systematic principle: The risk assessment of agricultural operation and investment is a systematic problem. When selecting indicators, the indicators should be closely linked with the evaluation object, and the essential characteristics of the evaluation object should be systematically analyzed. The index system should not only reflect the overall logic but also highlight the hierarchy and relevance.
- (3) Accuracy principle: Accuracy is reflected in two aspects: first, the evaluation index must accurately reflect the state of the evaluation object, and second, the index data must accurately meet the needs of the model; that is, the caliber of the data and the model must be consistent.
- (4) Comparability principle: The design of indicators must comply with unified and general accounting

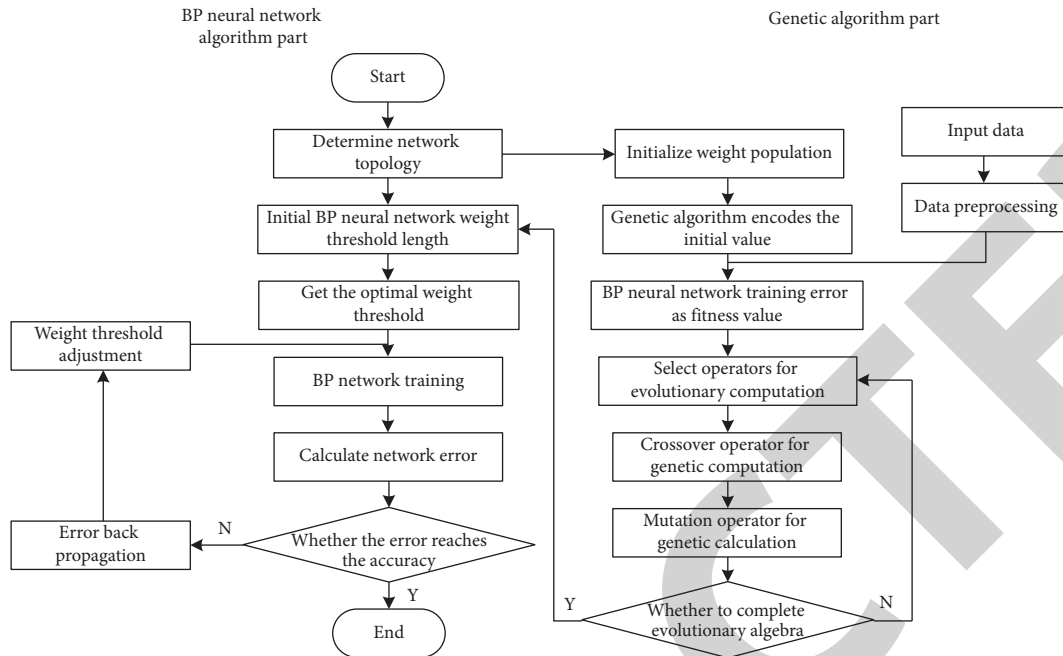


FIGURE 3: Flowchart of the genetic neural network.

methods and can be compared between different countries, regions, and projects. At the same time, attention should be paid to the measurement range and unit of measurement of indicator data, so as to facilitate horizontal or vertical comparison.

- (5) Feasibility principle: The quantitative standard of indicators and the difficulty of obtaining relevant data shall be considered in the selection of indicators. The selected indicators shall be convenient for statistics, analysis, and acquisition. Indicators whose data are difficult to obtain or cannot be quantified may not be included in the index system for the time being.

3.2. Risk Evaluation Index System of Agricultural Operation Investment. Following the construction principle of the index system and integrating the opinions of technical authorities, senior experts, and agricultural risk investment experts are integrated. On this basis, systematic and non-systematic risks are integrated to construct an index system for agricultural business investment risk assessment. Details are as follows.

Systemic risks mainly include the following:

- (1) Policy and regulation risk: This risk refers to the unexpected negative impact on venture capital caused by imperfect policies and regulations or frequent adjustments and changes. Among them, the imperfect policies and regulations on venture capital are one of the most prominent potential risks.
- (2) Macroeconomic fluctuation risk: This risk refers to the risk generated in the process of macroeconomic trend and fluctuation, such as economic recession, economic crisis, inflation, and deflation.

- (3) Social factor risk: This risk refers to the investment risk caused by social unrest or social factors such as cultural customs, investment philosophy, and mass consumption tendency.

Nonsystematic risks mainly include the following:

- (1) Technical risk: The advanced nature, maturity, practicality, matching, technological innovation, and scientific research talent resources are the key to winning the technological superiority and market advantage in the knowledge economy era and also the foundation for venture capital to gain high profits.
- (2) Production risk: This risk refers to the risk caused by defects in production equipment status, organization system, operation and management mode, quality of production personnel, supply of raw materials, and intermediates.
- (3) R & D risk: This risk is the core of the high-tech investment project and the key embodiment of the technical advantages. The R & D risk closely related to the project will affect each investment stage, and it is also the most direct embodiment of the project risk.
- (4) Market risk: This risk mainly refers to the risk caused by the uncertainty of product market competitiveness, such as the degree of market demand and adverse factors in product substitutability, cost performance, marketing network, and life cycle, which may lead to market risk.
- (5) Management risk: This risk refers to the risk caused by uncertain factors such as the quality and experience of managers, scientific decision-making,

rationality of enterprise management, selection of investment tools, size of investment scale, phased dynamic portfolio investment strategy, evaluation and screening of investment projects, capital structure of enterprises.

4. Construction of Risk Assessment Model of Agricultural Operation and Investment

4.1. Establish Network Topology. Based on the established risk evaluation system, according to the number of known risk measurement indicators, the number of different neurons in the input layer, hidden layer, and output layer is determined, so as to build a complete BP neural network structure model. The number of neurons in the input layer is the number of evaluation indexes, the result of the output layer is a single neuron, and the hidden layer can be obtained by model algorithm.

- (1) Construct a set of risk evaluation factors: Let $U = \{u_1, u_2, \dots, u_m\}$ be M risk indicators for evaluating agricultural investment. There are 21 evaluation indicators, and then, $M = 21$.
- (2) Determination of decision rating: According to the management evaluation of agricultural operation and investment risk, the evaluation status of the agricultural operation and investment risk is obtained, as shown in Table 1.
- (3) Sample training: According to the measurement indicators in the index system, data collection is combined with the actual qualitative data scoring situation, and the data are preprocessed to obtain the primary training sample set, sample set $M = \{m_1, m_2, \dots, m_p\}$.
- (4) Determination of the number of hidden layer neurons: According to the calculation formula of hidden layer neurons,

$$s = \sqrt{M + N} + \gamma. \quad (15)$$

In formula (15), M is the number of input neurons, N is the number of output results, and γ is a constant value between 0 and 1.

4.2. Genetic Algorithm Optimizes the Weights and Thresholds of Neural Networks. In terms of initial coefficient value selection and optimization, it is mainly composed of three parts: the threshold of hidden layer and output layer, the connection weight of input layer and hidden layer, and the connection weight of hidden layer and output layer [32, 33]. Each sample in the population set, as an individual, will reflect the ownership value and threshold between neurons in each layer of the BP neural network. The coding length of the sample individual for the genetic algorithm is equal to the sum of the number of thresholds and weights connected between all layers of the trained neural network of all samples in the population, which is

$$l = m \times n + s \times n + n. \quad (16)$$

In formula (16), s and m are the number of neurons in the hidden layer and input layer, respectively, and n is the number of neurons in the output layer. The weight matrix from the input layer to the hidden layer is as follows:

$$W = |w_{jr}|_{n \times s}. \quad (17)$$

The weight matrix from the hidden layer to the output layer is as follows:

$$V = |v_{rk}|_{s \times m}. \quad (18)$$

The threshold of hidden layer neurons is as follows:

$$B = |b_1, b_2, \dots, b_s|. \quad (19)$$

The threshold of the output layer neuron is as follows:

$$C = |c_1, c_2, \dots, c_m|. \quad (20)$$

The input vector of the genetic algorithm is as follows:

$$X = |w_{11}, w_{12}, \dots, w_{13}, b_1, b_2, \dots, b_s, v_{11}, v_{12}, \dots, v_{13}, c_1, c_2, \dots, c_m|. \quad (21)$$

4.3. Determination of Fitness Function. Assuming that P is selected to train the sample data, different training samples in the neural network get different training errors E^p . Based on the calculation basis of the sample output error square $(E^p)^2$, the total output error of the network for the overall training of the sample is

$$E_{\min}(k) = \frac{1}{2} \sum_{k=1}^P (d_k^p - o_k^p)^2, \quad p = 1, 2, \dots, k. \quad (22)$$

In formula (22), o_k is the result vector of the output layer of the network, and d_k is the expected output vector obtained through sample training. According to the principle of model combination, the target search for the optimal solution is to select the weight threshold with the smallest error square and E performance by training in the neural network in the evolutionary generation of the sample. According to the evolution direction, the fitness function of the genetic algorithm can only increase continuously, so the fitness function combines the characteristics of the two as follows:

$$f(E_{\min}(k)) = \frac{1}{E_{\min}(k)}. \quad (23)$$

4.4. Parameter Setting of Genetic Operation. Based on the application principle of the genetic algorithm, the parameter value of the genetic operator in the genetic algorithm is set. According to the characteristics of the research subject and the core operating principle of the genetic algorithm, the parameters are effectively analyzed and set.

- (1) Selection operator Φ : According to the selection strategy of the adaptation proportion of the fitness

TABLE 1: Risk assessment of agricultural operation investment.

Risk intervals	Risk status	Risk description
0–0.2	Safety	Network operation security
0.2–0.5	Relatively safe	Occasionally minor effects
0.5–0.67	Commonly	Cause small impact loss
0.67–0.85	More dangerous	Cause great difficulties
0.85–1	Danger	Causing serious losses or business interruption

value in the genetic algorithm, assuming that the fitness value of the i sample in the M sample individuals in the genetic algorithm is f_i , the selection probability of each sample individual i selected by the selection operator in the genetic operator is

$$\Phi_i = \frac{f_i}{\sum_i^M f_i}. \quad (24)$$

- (2) Crossover operator P_r : Based on the principle comparison, the model in this paper chooses the arithmetic crossover method [34–36]. Arithmetic crossover assumes that Γ_A^t, Γ_B^t is the arithmetic crossover between two sample individuals. To execute the algorithm, it is necessary to determine the value of the coefficient α in a reasonable linear combination of each sample individual. If and only if α is a constant, the algorithm is uniform arithmetic crossover. An arithmetic crossover algorithm is a method to obtain new sample individuals by the pairwise linear combination of samples. Then, the new sample individuals are

$$\begin{aligned} X_A^{t+1} &= \alpha X_B^t + (1 - \alpha) X_A^t, \\ X_B^{t+1} &= \alpha X_A^t + (1 - \alpha) X_B^t. \end{aligned} \quad (25)$$

- (3) Mutation operator P_Ψ : The genes carried by each sample individual are arranged on its chromosome, the corresponding gene is selected from the chromosome of the sample individual with the mutation probability Ψ , and the value is randomly replaced within the value range. If x_k is the mutation point of the gene, the value range is $[U_{\min}^k, U_{\max}^k]$, and h is randomly selected in accordance with $[0, 1]$, and then,

$$x_k = U_{\min}^k + h \times (U_{\max}^k - U_{\min}^k). \quad (26)$$

- (4) Selection of control parameters: The actual operation of the genetic algorithm needs to preset the following 4 algorithm operating parameters, which is T, M, P_r, P_Ψ . T represents the evolutionary algebra of the genetic algorithm, which is generally between 100 and 500 generations according to the research subject. M represents the size of the sample group, which is selected between 20 and 50 according to the sample size. P_r represents the crossover probability of the genetic algorithm, and the value ranges from $[0.4–0.99]$. P_Ψ represents the mutation probability of the genetic algorithm, and the value ranges from $[0.0001–0.1]$.

4.5. *Execute BP Algorithm.* First, the genetic operation is performed. After continuous crossover, variation, heredity, and other generations of reproduction in the sample population, the target sample individual with the largest fitness is searched; that is, the initial weight and threshold of each layer connection of the optimized neural network are obtained, and the optimization results are assigned to the neural network to obtain the optimized neural network structure model and then train the sample data.

The data values of various risk measurement indicators of agricultural operation and investment are brought into the model for training. The data samples are used to learn the nonlinear function relationship, and then, the control samples are used to verify, and the final output value of agricultural operation and investment risk evaluation is obtained, which is the risk of agricultural operation and investment of the example. According to the grade range of each risk rating in the model, the risk grade of agricultural operation investment risk is determined by comparing it with the final agricultural operation investment risk value.

5. Experimental Analysis

5.1. *Sample Data Acquisition and Analysis.* In order to verify the effectiveness of the risk assessment method of agricultural operation and investment based on the genetic neural network, the project leader and some staff of an enterprise were selected to cooperate, and a total of 21 indicators and 23 groups of data were collected. Due to the different data types of the index data, the input data are processed for data standardization in order to be effective and reasonable. On this basis, a risk assessment model for agricultural business investment is established. In this paper, MATLAB is used for experimental analysis, and the BP network structure is determined according to known conditions. The number of input nodes corresponding to the number of risk indicators in the article is 21, and the number of output layer nodes is 1, which is the comprehensive risk value of the final risk evaluation of the method. According to the data sample size, the number of sample training is selected to be 2000 times, the training target is 0.0001, and the learning rate is 0.01. After experimental adjustments, the initial population size is set $M = 50$, then the encoding method is selected to encode the weight threshold, encoding length $l = 18 \times 9 + 9 \times 1 + 9 + 1 = 180$, genetic algebra $T = 150$, crossover probability $P_r = 0.7$, mutation probability $P_\Psi = 0.05$, and the number of iterations is 100.

5.2. *Effect Analysis of Risk Assessment of Agricultural Operation Investment.* After genetic optimization, according to the conditions that the optimal sample individual meets, the

sample individual with the best fitness is searched, and the optimal decoding value is obtained and applied to the established neural network structure to provide the initial weight threshold between the connections of each layer of the network and train. After the network training, any part of the samples is selected to predict their risk decision-making comments by the network, and regression fit the other training labels. The training fitting of the genetic neural network is shown in Figure 4.

It can be seen from Figure 4 that the training label corresponding to the training sample is basically consistent with the prediction risk decision-making comments obtained by the trained model judging the training data. It can be seen that the genetic neural network risk assessment effect obtained by the training of the proposed method is good and can be used for agricultural operation and investment risk assessment.

5.3. Stability Analysis of Agricultural Management Investment Risk Assessment. In order to further verify the stability of the agricultural operation investment risk assessment of the proposed method, the correlation coefficient δ is used to carry out the stability analysis of the agricultural operation investment risk assessment. The higher the value of δ , and the higher the overall stability of the risk assessment. The calculation formula is as follows:

$$\delta = \frac{\sum_{i=1}^{\sigma} (y(i) - \bar{y})(y'(i) - \bar{y}')}{\sqrt{\sum_{i=1}^{\sigma} (y(i) - \bar{y})^2 \sum_{i=1}^{\sigma} (y'(i) - \bar{y}')^2}} \quad (27)$$

In formula (27), σ is the number of test samples, $y(i)$ is the test label, $y'(i)$ is the prediction result, \bar{y} is the average value of the test labels, and \bar{y}' is the average value of the prediction results. Through the above experiment, according to formula (27), the fit between the prediction result of the proposed method and the label of the test sample is calculated as shown in Figure 5.

It can be seen from Figure 5 that the prediction result has a linear relationship with the test sample label. The correlation coefficient $\delta = 0.9908$ is calculated between the two. It can be seen that the agricultural management investment risk assessment model of the proposed method has high stability.

5.4. Analysis of Key Indicators for Risk Assessment of Agricultural Operation Investment. The risk evaluation of agricultural operation investment is of great significance to the actual agricultural operation. In order to enable managers to better grasp the focus of work, the experiment uses the increase and decrease component method as an analysis tool to measure the key degree of various indicators to the risk of agricultural operation and investment. The calculation formula is as follows:

$$\omega = \frac{1}{n} \left[\sum_{j>i} (p(i, j) - p(i+1, j)) + \sum_{j>i} (p(j, i) - p(j, i-1)) \right] \quad (28)$$

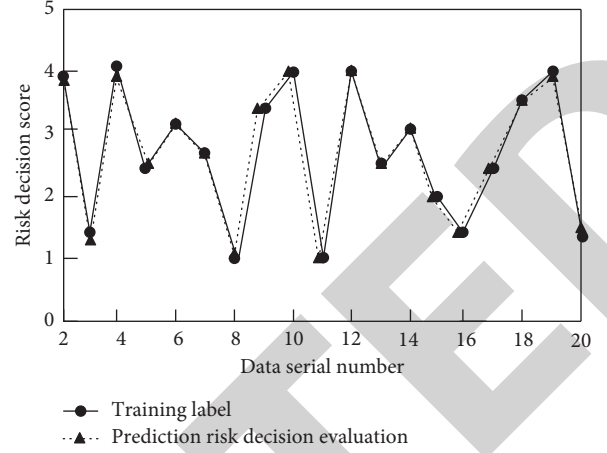


FIGURE 4: Training output results of the proposed method.

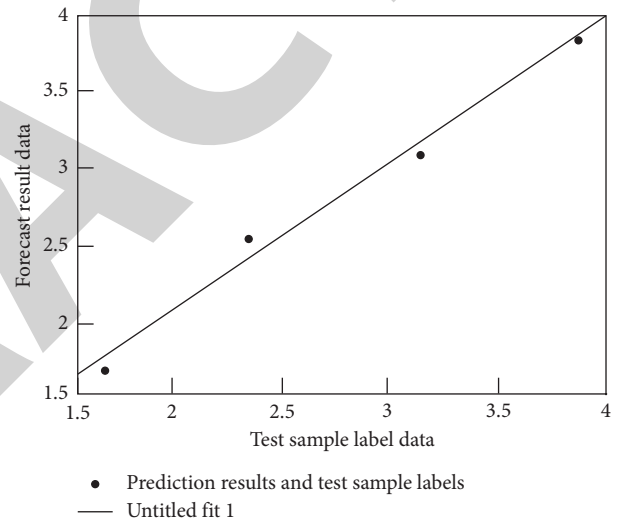


FIGURE 5: Fit between the prediction results of the proposed method and the labels of test samples.

In formula (28), $p(i, j)$ represents the evaluation relevance obtained from the i to j risk evaluation index which is used in the evaluation of agricultural business investment risk. ω represents the contribution of the i risk evaluation index to the risk evaluation of agricultural business investment. Among them, the larger the ω , the greater the contribution of the indicator, that is, the more critical the indicator. Through the above experiments, the contribution distribution of indicators in the risk assessment system of the proposed method is calculated according to formula (28), as shown in Figure 6.

It can be seen from Figure 6 that in the whole risk evaluation index system, the production risk index is the most important for the risk evaluation of the whole agricultural operation and investment and should be the focus of agricultural operation and investment. In the production risk, the operation and management mode should be taken as the core evaluation index, and the rest of the work should be carried out together. The management risk index is of

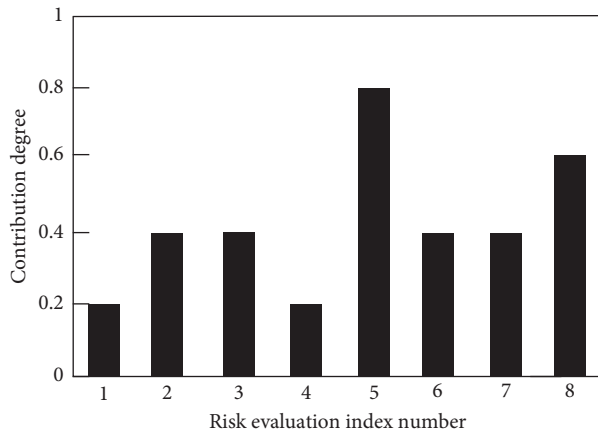


FIGURE 6: Contribution degree distribution of indicators in the risk evaluation system of the proposed method.

secondary importance to the risk evaluation of agricultural operation and investment and should be paid more attention to after the production risk. The contribution of each subindex in risk management is equal, and equal attention should be paid to it.

From the above analysis, it can be seen that the BP neural network optimized by genetic algorithm in this method evaluates the risk assessment of agricultural operation and investment, the fitting degree of the output results is high, and the assessment effect is good. Therefore, this method can be used as an effective technical means to determine the risk of agricultural operation and investment. At the same time, the overall stability of this method is high, and the contribution of each index can be determined accurately.

6. Conclusion

The risk assessment of agricultural operation investment proposed in this paper has a good effect and has high stability in the risk assessment of agricultural operation and investment. In the risk assessment index system, production risk and management risk have a great impact on the whole evaluation results, which should be the focus of agricultural operation and investment management. However, this method only considers the actual situation of an enterprise and a single enterprise in the process of the agricultural operation and investment risk assessment. Therefore, in the next research, we need to study the risk evaluation of agricultural operation and investment from the perspective of multienterprise cases, there is a large amount of enterprise data support, and the effect of the risk evaluation model will be better.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

References

- [1] X. Xi and J. Zhang, "Complexity analysis of a decision-making game concerning governments and heterogeneous agricultural enterprises with bounded rationality," *Chaos, Solitons & Fractals*, vol. 140, no. 11, Article ID 110220, 2020.
- [2] O. Bezpatochna, "Forecasting the state of agricultural enterprises based on the results of economic diagnostics," *Journal Of Scientific Papers*, vol. 6, no. 1, pp. 3–11, 2021.
- [3] D. C. Monckton, "Economic impacts of coal seam water for agricultural enterprises, lessons for efficient water management," *Sustainable Water Resources Management*, vol. 5, no. 1, pp. 333–346, 2019.
- [4] H. Godlewska-Majkowska and A. Komor, "Energy as a factor of investment attractiveness of regions for agricultural enterprises," *Energies*, vol. 14, no. 9, pp. 2731–2738, 2021.
- [5] O. Kovalenko, L. Yashchenko, and V. Zhuk, "Diagnostics of the state of agricultural enterprises financial security," *Accounting and Finance*, vol. 1, pp. 52–60, 2021.
- [6] Q. Huang, Y. Xu, and C. Courcoubetis, "Financial incentives for joint storage planning and operation in energy and regulation markets," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 3326–3339, 2019.
- [7] M. F. Bellemare, K. Chua, J. Santamaria, and K. Vu, "Tenurial security and agricultural investment: evidence from Vietnam," *Food Policy*, vol. 94, no. 7, Article ID 101839, 2020.
- [8] A. Hashemizadeh, Y. Ju, B. Smhb, and H. Phong, "Renewable energy investment risk assessment in belt and road initiative countries under uncertainty conditions," *Energy*, vol. 214, no. 1, Article ID 118923, 2020.
- [9] J. Yuan, X. Li, C. Xu, C. Zhao, and Y. Liu, "Investment risk assessment of coal-fired power plants in countries along the Belt and Road initiative based on ANP-Entropy-TODIM method," *Energy*, vol. 176, no. 1, pp. 623–640, 2019.
- [10] S. Tang and F. Yu, "Construction and verification of retinal vessel segmentation algorithm for color fundus image under BP neural network model," *The Journal of Supercomputing*, vol. 77, no. 1, pp. 1–15, 2021.
- [11] M. Tsukada, M. Kondo, and H. Matsutani, "A neural network-based on-device learning anomaly detector for edge devices," *IEEE Transactions on Computers*, vol. 69, no. 7, pp. 1027–1044, 2020.
- [12] Z. Liu, "Construction and verification of color fundus image retinal vessels segmentation algorithm under BP neural network," *The Journal of Supercomputing*, vol. 77, no. 7, pp. 7171–7183, 2021.
- [13] J. Liu, X. Yang, Y. Feng, and P. Cui, "New fractional derivative with sigmoid function as the kernel and its models," *Chinese Journal of Physics*, vol. 68, no. 12, pp. 533–541, 2020.
- [14] M. Tripathy, S. R. Chiluveru, and B. Mohapatra, "An accuracy controlled iterative method for efficient sigmoid function approximation," *Electronics Letters*, vol. 56, no. 18, pp. 854–859, 2020.
- [15] A. Darwish, H. M. Ahmed, A. H. Arnous, and M. F. Shehab, "Optical solitons of Biswas–Arshed equation in birefringent fibers using improved modified extended tanh-function method," *Optik - International Journal for Light and Electron Optics*, vol. 227, no. 23, Article ID 165378, 2020.
- [16] E. Yan, J. Song, C. Liu, J. Luan, and W. Hong, "Comparison of support vector machine, back propagation neural network and extreme learning machine for syndrome element differentiation," *Artificial Intelligence Review*, vol. 53, no. 4, pp. 2453–2481, 2020.

- [17] L. Abualigah and M. Alkhrabsheh, "Amended hybrid multi-verse optimizer with genetic algorithm for solving task scheduling problem in cloud computing," *The Journal of Supercomputing*, vol. 78, no. 1, pp. 740–765, 2021.
- [18] L. Wang, Y. Guo, B. Dalip, Y. Xiao, and Y. Lin, "An experimental study of objective pain measurement using pupillary response based on genetic algorithm and artificial neural network," *Applied Intelligence*, vol. 242, no. 2, Article ID s10489, 2021.
- [19] Y. Sun, B. Xue, M. Zhang, G. G. Yen, and J. Lv, "Automatically designing CNN architectures using the genetic algorithm for image classification," *IEEE Transactions on Cybernetics*, vol. 50, no. 9, pp. 3840–3854, 2020.
- [20] M. Mahato, S. Gedam, J. Joglekar, and K. M. Buddhiraju, "Dense stereo matching based on multiobjective fitness function—a genetic algorithm optimization approach for stereo correspondence," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 6, pp. 3341–3353, 2019.
- [21] V. K. Ivanov, D. S. Dumina, and N. A. Semenov, "Determination of weight coefficients for additive fitness function of genetic algorithm," *Software & Systems*, vol. 33, no. 1, Article ID 14833, 2021.
- [22] M. Feng and Y. Cheng, "Solving truck-cargo matching for drop-and-pull transport with genetic algorithm based on demand-capacity fitness," *AEJ - Alexandria Engineering Journal*, vol. 60, no. 1, pp. 61–72, 2020.
- [23] A. K. Das and D. K. Pratihar, "Solving engineering optimization problems using an improved real-coded genetic algorithm (IRGA) with directional mutation and crossover," *Soft Computing*, vol. 25, no. 1, pp. 5455–5481, 2021.
- [24] J. Too and A. R. Abdullah, "A new and fast rival genetic algorithm for feature selection," *The Journal of Supercomputing*, vol. 77, no. 7, pp. 2844–2874, 2020.
- [25] S. Cao and Q. Yao, "Simulation of multi-user power line communication resource optimization scheduling strategy," *Computer Simulation*, vol. 36, no. 4, pp. 61–64+82, 2019.
- [26] G. Cao and X. Wang, "Image encryption based on the combination of roulette wheel selection with linear congruence pixel transformation," *Multimedia Tools and Applications*, vol. 78, no. 8, pp. 10625–10647, 2019.
- [27] M. Bekirli, "Solving continuous optimization problems using the tree seed algorithm developed with the roulette wheel strategy," *Expert Systems with Applications*, vol. 170, no. 15, Article ID 114579, 2021.
- [28] X. Wang and P. Liu, "Image encryption based on roulette cascaded chaotic system and alienated image library," *The Visual Computer*, vol. 38, no. 9, pp. 1–17, 2021.
- [29] W. Dai and P. Hu, "Application of BP neural network in the analytic hierarchy process of person-post evaluation model," *The Journal of Supercomputing*, vol. 76, no. 9, pp. 1–18, 2019.
- [30] S. Wang, T. H. Wu, T. Shao, and Z. X. Peng, "Integrated model of BP neural network and CNN algorithm for automatic wear debris classification," *Wear*, vol. 426, no. 4, pp. 1761–1770, 2019.
- [31] L. Mcgrath, "Linking sustainable development assessment in Ireland and the European union with economic theory," *Working Papers*, vol. 51, no. 2, pp. 327–355, 2020.
- [32] J. Fei and Y. Chu, "Double hidden layer output feedback neural adaptive global sliding mode control of active power filter," *IEEE Transactions on Power Electronics*, vol. 35, no. 3, pp. 3069–3084, 2019.
- [33] J. Fei, Y. Chen, L. Liu, and Y. Fang, "Fuzzy multiple hidden layer recurrent neural control of nonlinear system using terminal sliding-mode controller," *IEEE Transactions on Cybernetics*, vol. 3, no. 12, pp. 1–16, 2021.
- [34] Q. Zhang, S. Yang, M. Liu, J. Liu, and L. Jiang, "A new crossover mechanism for genetic algorithms for steiner tree optimization," *IEEE Transactions on Cybernetics*, vol. 3, no. 7, pp. 1–12, 2020.
- [35] Y. Xue, H. Zhu, J. Liang, and A. Sowik, "Adaptive crossover operator based multi-objective binary genetic algorithm for feature selection in classification," *Knowledge-Based Systems*, vol. 227, no. 5, Article ID 107218, 2021.
- [36] K. Wang, Y. Gong, Y. Peng, C. Hu, and C. Chen, "An improved fusion crossover genetic algorithm for a time-weighted maximal covering location problem for sensor siting under satellite-borne monitoring," *Computers & Geosciences*, vol. 136, Article ID 104406, 2020.