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Retraction

Retracted: Risk Prediction Algorithm of Social Security Fund Operation Based on RBF Neural Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Manipulated or compromised peer review

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] L. Yang, "Risk Prediction Algorithm of Social Security Fund Operation Based on RBF Neural Network," *International Journal of Antennas and Propagation*, vol. 2021, Article ID 6525955, 8 pages, 2021.

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Research Article

Risk Prediction Algorithm of Social Security Fund Operation Based on RBF Neural Network

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In order to ensure the benign operation of the social security fund system, it is necessary to understand the social security fund facing all aspects of the risk, more importantly to know the relationship between different risks. Based on RBF, the interpretative structure model is applied to draw the risk correlation hierarchy diagram, which provides a scientific risk management method for the social security fund. RBF neural network is used to build the risk warning model of social security fund operation. Then, put forward the corresponding risk treatment scheme to the warning signal. Finally, the RBF neural network is used for comprehensive risk warning. In this paper, the risk warning of social security fund operation is the research object, and the corresponding risk treatment scheme is put forward for the warning signal. This paper uses an improved ant colony algorithm to optimize the parameters of the RBF neural network, which overcomes the shortcomings of the traditional RBF neural network such as slow convergence, ease of falling into local extremes, and low accuracy, and improves the generalization ability of the RBF neural network. It has the characteristics of good output stability and fast convergence speed. On this basis, the prediction model based on the improved ANT colony-RBF neural network is established, and the MATLAB software calculation tool is used for accurate calculation, which makes the prediction results of coal mine safety risk more accurate and provides more reliable decision basis for decision makers. The results show that the network has small calculation error, fast convergence, and good generalization ability.

1. Introduction

The elements of a system form a structure that determines the function and efficiency of the system. Interpretive structure model is a widely used method to analyze system structure in modern systems engineering. Interpretive structural models can be used to describe and analyze the interrelationships between system elements. It uses the known relationship between system elements to build the adjacencies matrix and then generate the reachability matrix and finally generate the hierarchy diagram [1]. It reveals the relationship between system elements through the form of hierarchy, including direct relationship, indirect relationship, membership relationship, and relative status. The operation of social security fund is a complex system, and various risks will be encountered in the operation. This paper tries to analyze the risk structure of social security fund operation from the perspective of system engineering by using the interpretive structure model [2].

China's insurance industry is in an unprecedented transition period. With the deepening of the reform of the national economic system, the living environment of China's insurance companies has undergone drastic changes, and some deep-level problems previously hidden have gradually been exposed. According to Standard & Poor's 2003 assessment of China's insurance market, the main risk facing China's property and casualty insurance industry is inadequate solvency, mainly due to insufficient liability reserves drawn and large capital gaps due to rapid business growth. Therefore, it is necessary to establish a comprehensive risk early warning system for property insurance companies in China [3]. The research on the risk early warning system of property insurance company is relatively few, and it mainly draws lessons from the banking risk early warning method.

Only Zeng Zhongdong, a domestic scholar, has put forward an early warning system of property insurance company's business risk based on fuzzy optimization and neural network [4]. Whether starting from artificial neural network technology or other technologies, want to go to, or technically is a breakthrough and innovation of traditional early warning system, it solves the traditional model is difficult to deal with high degree of nonlinear model, adaptive ability, lack of access to information and knowledge of indirect, time consuming and low ability of difficulties, so as to lay the foundations for the early warning go to practical [5–8].

Small- and medium-sized enterprises are an indispensable part of my country's national economic structure. They are of great significance to the stable and sustainable development of my country's economy and are gradually becoming the main force in the development of social productive forces. In recent years, many high-tech SMEs have risen rapidly, which has played a role in optimizing my country's economic structure. However, small- and medium-sized enterprises have weak financial strength, poor antirisk ability, and low creditworthiness. This makes banks more inclined to invest funds in large enterprises, and they are not very enthusiastic about lending to small- and medium-sized enterprises [9]. In the case of unbalanced sample data, the prediction of traditional risk analysis model has tendentious defects, so [10] analyzes the factors affecting the financial crisis and establishes a preliminary financial early warning index system of listed manufacturing companies in China. Then, the particle swarm optimization algorithm is used to improve the parameters of support vector machine, and the optimal financial crisis warning index set is selected. Combined with the theory and algorithm of empirical research, determine the financial early warning indicators of listed companies in China, and use SVM and PSO optimization parameters to establish an effective early warning model.

At present, the multilayer feedforward network is based on back propagation (BP), but most of the learning algorithms of this network must be based on some nonlinear optimization technology. Therefore, its application is limited due to the large amount of computation and slow learning speed [11–13].

2. Explain the Overview of the Structural Model

Interpretive structure model was developed by the American Professor Walter in 1973 to analyze the problem of element structure in complex social and economic system. The characteristic of this model is that the complex system is decomposed into several subsystems first, and then a multistage hierarchical structure model is constructed according to the relationship of the system elements with the help of computer and people's practical experience and knowledge [14–16].

The analysis procedure is as follows. (1) Form an analysis team. The number of team members is generally about 10, and each member is required to have relevant professional background in the research system and try to absorb professionals with different views into the team. (2) Design the questionnaire [17]. Design problems according to the interrelationships between system elements. The questionnaire design should pay attention to neutrality and avoid guiding the answer. (3) Gather panelists' opinions. All responses will be summarized, and a second round of consultation will be conducted for those who have serious differences in the relationship between system elements until a more uniform list of system elements is formed. (4) On the basis of the relation table of elements, the adjacency matrix and reachability matrix are established. (5) The skeleton matrix was established after the interlevel division of the reachable matrix. (6) The interpretation structure model was established according to the skeleton matrix.

2.1. The Construction of Social Security Fund Risk Structure Steps. Social security fund refers to the funds set up in various ways to implement the social security system in accordance with national legislation. Safety is the number one thing in the social security fund [18]. The collection, management, and payment of social security fund are facing systemic and nonsystemic risks. If the operation of social Security fund is regarded as a financial activity of institutional investors in the capital market, then it is possible to identify the major risk factors affecting the operation of the social security fund and to find the interrelationships between these risk factors [19]. This will help strengthen risk management in the operation of social security funds.

2.1.1. The Main Risk Factors of Social Security Fund Operation. (1) Credit risk (A1): The operation link of social security fund not only has credit risk of entrusted financial institutions and investment managers, but also will face credit risk in financial markets. Credit risk is broadly defined. Refer to the process of a transaction defined by a credit relationship. The possibility that one party in a transaction fails to fulfill its payment promise and causes losses to the other party is mainly caused by two aspects: subjectively, the existence of moral hazard and adverse selection; objectively, the existence of business cycles or the occurrence of other special events.

(2) Liquidity risk (A2): The social security fund should maintain sufficient liquidity in the investment process. If you do not have enough money and a certain short-term investment set aside in advance to cover your expenses, this may cause social security fund capital turnover difficulty, thus affecting the social security fund function play.

(3) Inflation risk (A3): Due to inflation, the real purchasing power of the operation results of the social insurance fund decreases, causing the depreciation of the fund. For pension funds, because of the long-term nature of its operations, the cumulative effect of inflation on the quality of life of retirees can not be ignored.

(4) Market interest rate risk (A4): The use of social security funds to buy securities will face a variety of risks. Among them, market interest rate risk refers to the fluctuation of security price caused by the change of market interest rate. This brings uncertainty to the buyer's earnings. Interest rates and security prices generally move in opposite

directions. When interest rates generally rise in the market, security prices will fall (both stocks and bonds) and vice versa. The price of the security will go up. Interest rate risk is the main risk of fixed income securities and bonds. A country's interest rate policy is determined by the central bank. Market interest rates will move in response to policy. So, the social security fund must take into account fluctuations in market interest rates in its investment operations.

(5) Asset allocation risk (A5): The social security fund aims to maintain and increase its value. You have to choose a reasonable mix of different asset classes. Due to the limitations of individual and institutional investors' own investment ability, allocate between different asset classes according to investment needs.

(6) Bankruptcy risk (A6): The management institution and trustee institution of the social security fund will be liquidated due to insolvency, leading to the loss of social security funds if they are broken up for other reasons.

(7) Financial risk (A7): Due to the social security fund's main business income and profit fluctuations, unreasonable liability structure leads to the increase of liabilities beyond the fund manager and fund custodians' bearing capacity. Or the change of financing conditions and environment leads to the loss of financial cost control.

(8) Economic environmental risk (A8): National macroeconomic weather and domestic and foreign economic background (including the position of the business cycle, economic policy, and adjustment of industrial structure) will affect the asset allocation choice of social security fund investment. And that leads to risk.

(9) Policy and legal risks (A9): Due to changes in various relevant systems, policy adjustments, or imperfections in regulations, risks will arise directly. Because social security is at a critical time for reform, formal social security regulations have not yet been promulgated. The uncertainty of reform makes various systems and policies have relatively large space for change.

(10) Overseas investment risk (A10): Overseas investment risk refers to the possibility of losses caused by changes in national sovereignty, political fluctuations, or economic crises in international economic activities of the social security fund. Based on the above analysis, after comprehensively considering the special security points and the realistic influencing factors of the current capital market, finally, 10 risk factors affecting the operation fund are determined as the object of analysis and research. In this way, the risk factor matrix A of the social security fund is obtained.

2.2. Adjacencies Matrix of Risk Factors of Social Security Fund Operation. The function of the adjacency matrix is to describe the direct relationship between the elements. It is the result of one by one comparison of each element. The rows are the elements that exert influence and the columns are the elements that are affected: 1 if there is a direct relationship between the two elements, and 0 if there is no relationship [20].

The 10 risk factors of the operation of social security fund are organically linked together, and the relationship of mutual influence can be expressed by the adjacent matrix. After many discussions with the analysis team members, the following adjacency matrix is established (see Table 1).

2.3. Generate the Reachable Matrix from the Known Adjacent Matrix

2.3.1. After the Generation of the Adjacent Matrix A. You sum it with the identity matrix I, A plus I, and then you power the matrix A plus I over A whole number n. The reachable matrix can be used to describe all the influences between the elements. The element M_{ij} of the reachable matrix M is 1, which means that there is a one-step or one-step reachable path between element A_i and element A_j. The reachable matrix completely expresses the direct and interconnection relationship between elements.

2.3.2. Interstage Division. The so-called interstage division is to divide the risk factors into different levels according to the structure of the above calculation. The manager of the social security fund will have a theoretical framework for managing risks.

The following concepts are involved in the process of interlevel division:

(1) Reachable set: The set of elements affected by element a_i is defined as the reachable set $R(a_i)$ of element a_i.

(2) Antecedent set: The set of factors affecting factor a_i is defined as antecedent set $A(a_i)$ of factor a_i.

(3) Superlative factor: For $R(a)$ and $A(a)$, a_i is the superlative factor. The elements in question are the risk factors mentioned in this article.

According to the reachability matrix, you can find the reachability set of any risk factor in the system starting with the reachability matrix. Through the list, find its superlative set of elements, and then cross them out of the reachable matrix. Then make the table from there. Find the highest level prime set in the new matrix. In this way, the different risks can be divided into different levels.

In order to be more concise and beautiful, the hierarchical diagram drawn by the computer is optimized to get the optimization hierarchy as shown in Figures 1 and 2.

3. Structure of RBF Neural Network

The structure of RBF neural network is shown in Figure 3.

For the mapping relation of RBF neural network, consider

$$y_j = f_n(x) = \sum_{j=1}^{m} v_{jk} R_j(x), \quad k = 1, 2, \ldots, p, \tag{1}$$

where p is the number of nodes; m is number of hidden layer nodes; n indicates the number of layer nodes; $R_j(x)$is the action function of the j-th neuron in the hidden layer (radial basis function).

The basic idea of forming radial basis function is to realize the transformation from input layer to hidden layer by using hidden layer element. In this way, the vector maps directly to the hidden space without connecting weights. As long as the cluster center of RBF is determined, this nonlinear relationship will be determined accordingly. The Gaussian function is the most commonly used in the RBF neural network model:

$$R_j(x) = \exp\left(-\frac{\left\|x - c_j\right\|}{2\delta^2}\right), \quad j = 1, 2, \ldots, m, \tag{2}$$

where m is the number of nodes in the hidden layer; x-n is the dimension input vector; c is the center (vector) of the j-th basis function, which has the same dimension as x; δ is center radius or width of neuron node in the j-th hidden layer; $\|x - c_j\|$ is vector norm of $x - c_j$, usually said x with c_j distance; for $R_j(x)$, there is a maximum of only c_j; along with the $\|x - c_j\|$ increases, $R_j(x)$ decay to zero.

The advantages of using the Gaussian basis function are as follows:

(1) The representation form is simple and convenient, and the complexity of the algorithm will not be increased too much even if multiple variables are input

(2) radial symmetry

(3) There is strong smoothing performance and existence of arbitrary derivative

(4) The Expression of Gaussian basis function is simple and analytic, so it is conducive to theoretical analysis

3.1. Realization of RBF Neural Network Algorithm. Suppose there are P training sample sets $X = X^1, X^2, \ldots, X^p$; when the input vector of the P training sample is given as $X^p = x_1, x_2, \ldots, x_m^T$, the corresponding expected output is $Y^p = \{Y_1, Y_2, \ldots, Y_m\}$, and the excitation is "basis function" $\Phi(\|x - c_j\|)$, where $c_j = c_{j1}, c_{j2}, \ldots, c_{jm}^T$ represents the clustering center point (or center vector) of the hidden node base function, $y^p = \{y_1, y_2, \ldots, y_m\}$ represents the actual output of the system, and then the objective function of the total error of the system for P training samples is

$$J = \sum_{p=1}^{P} J^p = \frac{1}{2} \sum_{p=1}^{P} \sum_{n=1}^{N} \left(Y^p - y^p\right)^2. \tag{3}$$

RBF neural network is a nonlinear mapping relationship, which has the energy to cover the receiving domain, and the output layer is the weighted sum of the outputs of the basis function of the hidden layer. Therefore, as long as the number of nodes and basis functions of the scientific and reasonable hidden layer are determined, the problem to be solved before can be transformed into a classification problem. That is to say, the design process of RBF neural network can be transformed into a linearly separable mapping problem of high dimensional space.

In the application of RBF neural network, three kinds of adjustable parameters need to be determined: center vector c_j, connection weight v, and threshold θ of the network. The process of learning algorithm has two stages, that is, the stage of learning without teachers and the stage of learning with teachers. In the first stage, teacher-free learning is based on all input sample sets $X = X^1, X^2, \ldots, X^p$, and cluster analysis method is used to solve the center vector c_j.

Table 1: Adjacency matrix.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	1	1	0	0	1	1	1	0	0	0
A2	1	1	0	0	1	1	1	0	0	0
A3	1	1	1	0	0	0	1	0	0	0
A4	1	1	0	1	0	0	1	0	0	0
A5	0	0	0	0	1	1	1	0	0	0
A6	0	0	0	0	0	1	1	0	0	0
A7	0	0	0	0	0	1	1	0	0	0
A8	0	0	1	1	0	1	1	1	0	0
A9	0	0	1	1	0	1	1	0	1	0
A10	1	1	0	0	0	0	0	0	0	1

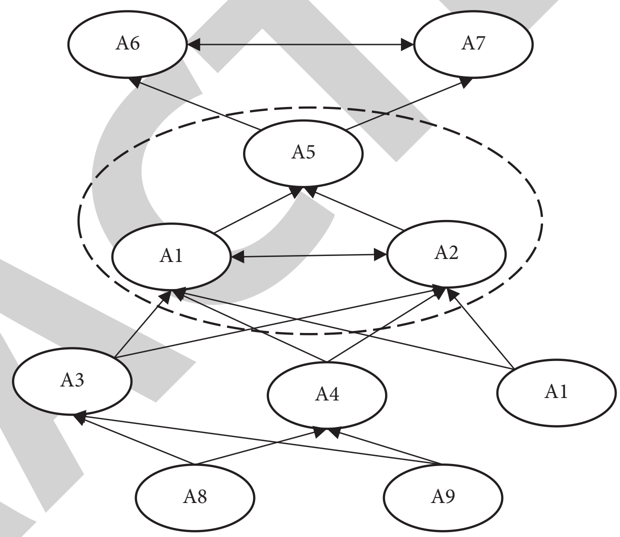

Figure 1: Optimization hierarchy.

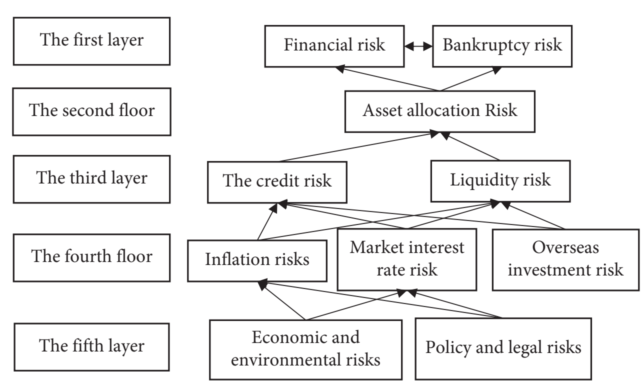

Figure 2: Optimization hierarchy.

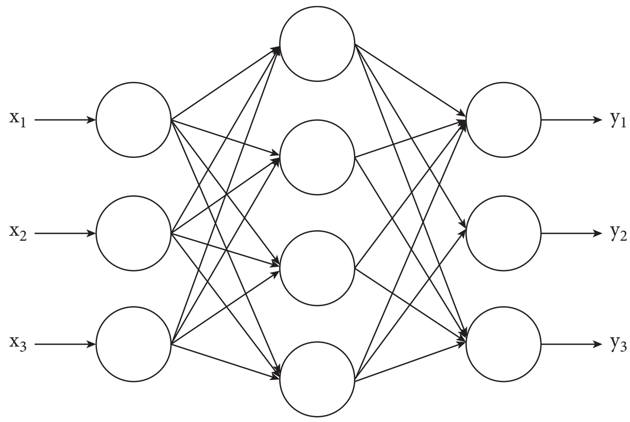

Figure 3: RBF neural network structure.

The second stage refers to the use of teacher learning algorithm to train and adjust the connection weight v_{jk} or threshold θ_k.

3.1.1. Learning without a Teacher. Teacher-free learning, also called unsupervised learning, is based on the clustering of all input sample sets to obtain the RBF center vector c_j of each hidden layer node. The k-means algorithm is a common clustering method, which is used to realize real-time adjustment of the center vector c_j. The training samples are clustered into several classes, and the center vector of the radial basis function is found by taking the minimum clustering distance as the index. The specific steps of the algorithm of k-means adjusting the central point are as follows:

(1) Consider the random initial value $c_j(0)$, $(j = 1, 2, \ldots, a)$, the initial value of the learning rate $\beta(0)$, and the limiting value of the error function of the total objective xx.

(2) Calculate the current Euclidean distance:

$$d_j(t) = \left\|x(t) - c_j(t-1)\right\|,$$
$$d_{\min}(t) = \min d_j(t) = d_r(t), \tag{4}$$

where r is the node with the smallest distance between input sample $x(t)$ and center vector $c_j(t-1)$.

(3) Center adjustment: the specific operation is

$$c_j(t) = c_j(t-1), \quad (j = 1, 2, \ldots, a),$$
$$c_j(t) = c_j(t-1) + \beta(t)\left[x(t) - c_r(t-1)\right]. \tag{5}$$

(4) After the operation of hidden layer nodes in a certain sample, the center vector and learning rate are modified according to the following formula:

$$\beta(t+1) = \frac{\beta(t)}{\sqrt{1 + \operatorname{int}(t/a)}}, \tag{6}$$

where $\beta(t)$ is the learning rate $(0 \le \beta(t) \le 1)$ and $\operatorname{int}(\cdot)$ is the integer function.

(5) For the next sample $p\,(p = 1, 2, \ldots, p)$, repeat the calculation of step 2. When the error function $J = \sum_{p=1}^{p} J^p \le \varepsilon$ of the total criterion is satisfied, the clustering is terminated.

3.1.2. There Are Teachers to Learn. When the center vector c_j of each node of the hidden layer is determined, the connection weight v or threshold θ is trained and adjusted. Since the output layer is similar to the basis function output of a hidden layer, and it belongs to the linear optimization operation, updating its weight is similar to solving the linear optimization problem, and various linear optimization algorithms can be used to achieve the purpose, without the existence of minimum problem in the BP neural network.

There are many methods to correct the weight, such as least mean square algorithm and least square algorithm. This paper takes the least square recursive method as an example to correct the weight. The objective function is defined as

$$J = \sum_{p=1}^{p} J^p = \frac{1}{2}\sum_{p=1}^{p} \Lambda(p)\left[Y^p - y^p\right]^2, \tag{7}$$

where $\Lambda(p)$ represents the weighted factor matrix.

In order to solve a set of weight estimation values v_{jk} and minimize the objective function, let

$$\frac{\partial J(t)}{\partial V} = 0^T. \tag{8}$$

Using the least squares recursive method, the recursive formula of weight is expressed as

$$v_{jk}(t) = v_{jk}(t-1) + K(t)\left\{Y^p - \left[\phi^p(t)\right]^T w_{jk}(t-1)\right\},$$
$$K(t) = P(t-1)\phi^p(t)\left\{\phi^p(t)P(t-1)\phi^p(t) + \frac{1}{\Lambda(p)}\right\}^{-1},$$
$$P(t) = \left\{I - K(t)\left[\phi^p(t)\right]^T\right\}P(t-1). \tag{9}$$

3.2. Characteristics of RBF Neural Network. RBF neural network has the following characteristics:

(1) Like BP neural network, I strong F neural network also belongs to feedforward neural network.

(2) In general, the activation function of the RBF neural network is a function with a local accepting domain; that is, the vector falls in a specified minimal region, and the hidden node will produce a meaningful nonzero response (the response value is (0,11)).Therefore, in general, we can call RBF divine network local receptive domain neural network.

(3) Influenced by the regional nature of localized acceptance, RBF neural network has taken the concept of distance into consideration when making decisions. That is to say, the vector is close to the

acceptance domain of RBF neural network, the Divine network will make a meaningful non-zero response to it. However, BP neural network has the characteristic of arbitrary partition caused by hyperplane segmentation. The advantage of this method is that it can avoid this shortcoming.

(4) Some experimental studies have proved, in general, the key factor affecting the performance of the neural network, rather than the form of the nonlinear activation function used by the neural network. Both RBF and BP belong to forward neural network, and the above description of the characteristics of RBF shows that the RBF avoids some defects of BP neural network in many aspects.

4. Experimental Analysis

The property insurance company can get the final warning result according to the warning signal of RBF neural network, take the corresponding risk management measures, and coordinate the solvency, reinsurance ability, and the temperature profit of the insurance company and other indicators.

(1) The green warning signal (1, 0, 0) indicates that the property insurance company operates in a good condition and there is basically no risk. On the one hand, the company can continue to consolidate its existing business and enhance its core competitiveness. On the other hand, it can actively expand new business and improve the efficiency of capital use through active asset and debt management, so as to constantly adapt to improve the solvency and reinsurance ability of the company.

(2) Yellow warning signals (0, 1, 0) indicate that there are problems in the operation of the property insurance company, but they are still under control and there are certain risks. On the one hand, the company should take measures to check all financial indicators as soon as possible, handle all capital outflow business carefully, and strengthen measures to ensure the capital return as soon as possible. On the other hand, we should strengthen the monitoring of business processes, find out the possible problems in the organizational structure, operation mechanism, and governance mechanism of the company, and actively prepare solutions to deal with the possible financial crisis in the future.

(3) Red warning signals (0, 0, 1) indicate that the property insurance company has made major mistakes in operation, faces huge risks, and may have an existential crisis. The company takes emergency measures to implement centralized control and dispatch of funds, integrates stability funds through various channels, sells assets such as national bonds and short-term bills, and actively recovers funds through various channels to reduce losses. At the same time, the China Insurance Regulatory Commission and other regulatory authorities should be notified as soon as possible to seek emergency financial assistance from regulatory authorities and the industry to prevent bankruptcy.

Table 2: Test results.

Company	Ideal output value	Actual output value
1	(1, 0, 0)	(0.995, 0.023, 0.008)
2	(1, 0, 0)	(0.987, 0.002, 0.009)
3	(1, 0, 0)	(0.993, 0.007, 0.001)
4	(0, 1, 0)	(0.002, 0.992, 0.027)
5	(0, 1, 0)	(0.002, 0.983, 0.0009)
6	(0, 1, 0)	(0.010, 0.979, 0.013)
7	(0, 0, 1)	(0.0001, 0.0006, 0.981)
8	(0, 0, 1)	(0.0005, 0.014, 0.984)
9	(0, 0, 1)	(0.0001, 0.0001, 0.9934)

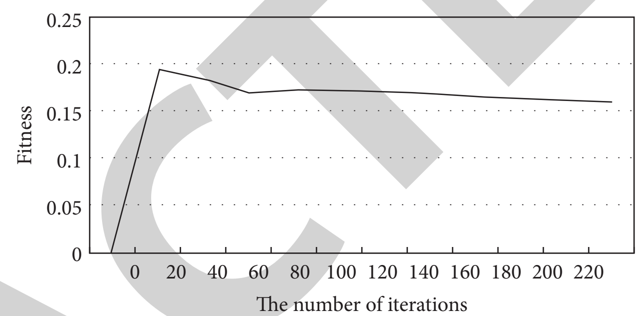

Figure 4: Improved ant colony algorithm optimization objective function convergence process.

First of all, the error index is err = 0.02; using the normalized data of the training set after 30 times of training, the error can meet the requirements. Secondly, the test is carried out using test set data, and the results are shown in Table 2. With a few exceptions, the actual output is very close to the expected output.

4.1. Simulation of Prediction Model. The parameters of RBF neural network are optimized by using the improved ant colony algorithm, and the convergence process is shown in Figure 4.

Figure 4 shows the adaptive convergence process of the objective function of RBF neural network optimized. It can be seen from the figure that the fitness rose in a straight line at the beginning, and the speed of rise was extremely fast. Although there were fluctuations when the iteration reached 34–95, it was difficult to decline after 130 generations when the fitness reached a certain value. After the iteration reached 210 generations, it was basically completely convergent, stabilized and finally reached the optimal.

4.2. Analysis of Experimental Results. In this paper, MATLAB software is selected for the analysis and design of RBF. According to the risk index data, samples 1–26 are selected as training samples to train the RBF neural network model optimized by ant colony algorithm. After the training is completed and the results meet the allowable error, samples

Table 3: The simulation results compared with the actual result.

Sample number	The actual results	RDF	Traditional ant colony algorithm	Traditional ant colony algorithm
27	0.6296	0.6220	0.6342	0.6318
28	0.6555	0.6619	0.6509	0.6574
29	0.8639	0.8754	0.8569	0.8612
30	0.4985	0.4937	0.5022	0.4970

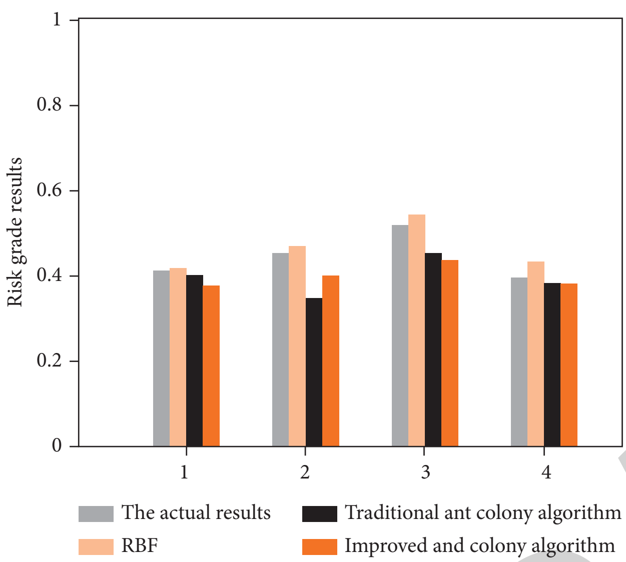

Figure 5: The actual value compared with the predicted results.

no. 27–30 are used to detect the RBF. The simulation results and actual results are shown in Table 3 and Figure 5.

As can be seen from Table 3 and Figure 5, the relative error between the predicted result of coal mine safety risk and the actual value through RBF neural network is 1.332% at most and 1.118% at least, and the average error is 0.746%. Through traditional ant colonies, the relative error between the prediction result of RBF neural network and the actual value of coal mine safety risk is the maximum 0.802% and minimum 0.735%, and the average error is 0.746%. By improving the ant colony, the maximum relative error result of RBF neural network, and the actual value of coal mine safety risk is 0.353%. The average error is 0.311%. So by improving the ant colony, RBF neural network model has a good prediction effect on the safety risk of coal mine, and the test has high accuracy and credibility, which can accurately reflect the overall safety situation of coal mine.

5. Conclusion

The nonsystemic risk and systemic risk of the social security fund investment operation: unsystematic risk (diversifiable risk) refers to the possibility that a particular cause will affect the return on a particular asset. It is a risk that can be eliminated with an efficient portfolio. Systemic risk (market risk, nondispersed risk) affects all assets (risks that cannot be eliminated by asset portfolio). This part of the risk is caused by risk factors that affect the market as a whole, for example, economic and environmental risks, policy and legal risks, foreign investment risks, market interest rate risk, and inflation risk. Therefore, systemic risk and nonsystemic risk form a whole and affect each other. Risk management theory and practice should not be separated from their internal relationship. By using RBF model method, a structural model of social security fund risk system with clear hierarchy and context is obtained, which provides a complete frame for the comprehensive risk management of social security fund investment. It provides theoretical basis for risk transformation model. Take bankruptcy risk and financial risk as the highest goal of risk management in the operation of social security fund. The interlinkage between risks requires the managers of the social security fund to manage the various risks under a comprehensive risk management. Attention should also be paid to the enterprise environment, market environment, economic environment, and policy laws that produce market risks in the operation of social security funds.

Data Availability

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

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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