Received: 9 August 2017 | Revised: 30 August 2017 | Accepted: 4 September 2017
DOI: 10.1002/cpe.4343

WILEY

SPECIAL ISSUE PAPER

Financial early warning of non–life insurance company based on RBF neural network optimized by genetic algorithm

Chun Yan[1] | Lin Wang[1] | Wei Liu[2,3] | Man Qi[4]

[1] College of Mathematics and System Sciences, Shandong University of Science and Technology, Qingdao 266590, China
[2] Shandong Province Key Laboratory of Wisdom Mine Information Technology, Shandong University of Science and Technology, Qingdao 266590, China
[3] College of Computer Science and Engineering, Shandong University of Science and Technology, Qingdao 266590, China
[4] Computing, Digital Forensics and Cybersecurity, Canterbury Christ Church University, Canterbury, Kent CT1 1QU, UK

Correspondence
Wei Liu, Shandong Province Key Laboratory of Wisdom Mine Information Technology, Shandong University of Science and Technology, Qingdao 266590, China.
Email: liuwei_doctor@yeah.net

Funding information
National Natural Science Foundation of China, Grant/Award Number: 61502280 and 61472228

Summary
Due to the characteristic of risk diversification in non–life insurance industry, the company's financial risk early warning is very important. In order to reasonably predict the financial status of non–life insurance company, the evaluation system of financial risk indicator is constructed from the aspects of solvency, profitability, and growth ability. Taking data of non–life insurance companies in past years as sample, the evaluation indicators are weighted objectively using the entropy method. The RBF neural network model is improved with the genetic algorithm, and the early warning model is established. The empirical results show that the prediction accurate rate of RBF neural network model based on genetic algorithm is increased.

KEYWORDS
entropy method, genetic algorithm, RBF neural network, risk early warning

1 | INTRODUCTION

At present, the development of non–life insurance industry in China shows the coexistence of growth and low profit, and the industry structure gradually merges with the international mature market.[1] However, the development of non–life insurance industry presents a polarization phenomenon. Most non–life insurance companies face development dilemmas of single business source and lack of premium growth point. They also face with six risks including investment, underwriting, fees, surrender, liquidity, and misleading sales. Meanwhile, a new normal state of China's economy has come into being. The slowdown in economic growth has a certain effect on non–life insurance industry. The needs and business growth of non–life insurance are declining. All these factors determine that the non–life insurance industry will inevitably face a huge financial risk. It is necessary and has practical significance to study how to improve the risk early warning management of non–life insurance industry, to construct the risk early warning system, which is suitable for non–life insurance industry in China, and to enhance the ability of non–life insurance industry to resist risks.[2]

From the existing literature, statistical methods and artificial intelligence neural network methods are the two main methods of non–life insurance companies for financial risk early warning. So far, statistical methods such as univariate analysis, multivariate discriminant analysis, nonparametric analysis, logistic regression models, and probabilistic regression model analysis have been widely used. The risks of insurance companies are predicted using logit, discriminant analysis, and regression analysis in Gulsun and Umit.[3] The financial statements of 45 Turkish insurance companies were analyzed. Forty-five related and 17 unrelated data were used as independent variables to improve the statistical discriminant model. The results show that this model has high prediction rate and applicability. The first arrival time and early warning area distribution under Erlang risk model are studied in Dickson and Li.[4] However, they ignored multiple warning problems. CFaR model and logistic financial distress early warning model for ST and non-ST companies in China's securities market are constructed in Xie et al.[5] The successful prediction rate of this early warning model is high. The concept of financial early warning system for insurance companies is proposed in Bai and Li.[6] They numerically simulated the bankruptcy distribution density and warning time of insurance companies by Monte Carlo method. However, taking into account the problems that the assumptions of traditional statistical method are not easy to meet, and the traditional statistical method is subject to more restrictions, the advantages of neural network model represented by RBF are more obvious. It has less restrictions and has good performance in the approximation ability, classification learning, and learning speed. It also has the learning adaptability, self-organization ability, can deal with complex nonlinear problems quickly and effectively, and has better fault tolerance and robustness. The relevant research works in domestic and foreign countries are as follows. Empirical research on data from British companies is conducted in Tseng and Hu.[7] They predicted the accuracy rates of the secondary interval regression model, the regression model, the back propagation neural network, and the radial basis neural network. The empirical results show that the radial basis neural network has the highest accuracy. Research on financial early warning of 40 non–life insurance companies using the variation coefficient method and radial basis neural network model is conducted in Deng and Wen.[8] The results show that the RBF neural network model is a good prediction mechanism. Eighty-eight companies that are specially treated for the first time between 2010 and 2013 are taken as the samples of financial crisis companies in Luo and Niu.[9] They achieved successful prediction rate that is close to 90% using the neural network model as a financial early warning method. Two hundred sixty-three industry financial indicators are taken as the training set of neural network training, 76 industry financial indicators are taken as the test samples, and the early warning model of financial crisis based on the RBF neural network is established in Xu.[10] The model results show that the RBF neural network model is superior to the user-defined model through model simulation and result analysis, and the RBF neural network model can provide accurate and reliable suggestions for decision makers.

However, RBF also has some shortcomings; for example, the RBF node center is not adjustable, and the node center and width are not easy to determine. Therefore, we used the genetic algorithm to optimize the RBF neural network. The genetic algorithm has a strong global search ability; therefore, the RBF network has a significant improvement in the approximation performance after the optimization of genetic algorithm. The relevant research work on risk prediction by constructing GA-RBF model at home and abroad is done. Genetic algorithms are used to optimize the parameters of the RBF network and predicted the stock using the obtained genetic algorithm network after the optimization in Du and Luo.[11] This method has good generalization ability and learning speed. It overcomes the shortcomings of BP network and solves the problem that the selection of RBF network parameters lack of uniform standard. The stock price trend using optimized RBF neural network with genetic algorithm is predicted in Wang et al.[12] The results show that the structure and the approximation performance of neural network improved significantly, and the accuracy rate is improved compared with the traditional RBF.

In the study of financial risk early warning of non–life insurance companies, this paper, for the first time, attempts to determine the weights based on the entropy method and conducted training and prediction on the selected samples with the RBF neural network model. The entropy method overcomes the problem that the weight determination is not rigorous, which is caused by the strong subjectivity in the analytic hierarchy process and fuzzy evaluation method. The entropy method can objectively reflect the indicator weight and its evaluation value and reflects the financial risks of non–life insurance companies quantitatively through the training and prediction data of RBF neural network model reducing the impact of fuzzy randomness. On this basis, the genetic algorithm is introduced to improve the RBF neural network, which provides a feasible and effective method for financial risk early warning of non–life insurance companies.

The rest of this paper is organized as follows. Section 2 reviews entropy method, RBF neural network model, and genetic algorithms. Section 3 establishes evaluation indicator system. Empirical analysis is done in Section 4. Concluding remarks are made in Section 5.

2 | RESEARCH METHODS

2.1 | Entropy method

In order to obtain a more objective indicator weight, in the study of this paper, the indicator objective weight is calculated by the entropy method. The entropy method can solve the problem that the evaluation is not objective due to the subjective judgment and make the weight coefficient more reasonable. The calculation theory of the entropy method is as follows:

First, use the gravity method to make the data dimensionless:

$$y_{ij} = \frac{x_{ij}}{\sum\limits_{i=1}^{n} x_{ij}} \tag{1}$$

Then, calculate the entropy value of the *j*th indicator:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} y_{ij} \ln y_{ij} \tag{2}$$

Then, the difference coefficient of the jth indicator is

$$g_j = 1 - e_j \quad j = 1, 2, \ldots, P \tag{3}$$

Finally, the weight of the jth indicator is

$$\omega_j = \frac{g_j}{\sum_{j=1}^{p} g_j} \quad j = 1, 2, \ldots, P \tag{4}$$

2.2 | RBF neural network model

The basic idea of RBF network is as follows: First, the RBF network uses the units in hidden layer to transform the nonlinear separable input space into linear separable feature space (usually high dimension space). Then, the output layer is used for linear classification, and the classification is completed. The RBF neural network is a single hidden layer forward network, which consists of three layers, as shown in Figure 1.

The first layer is input layer. The nodes of the input layer pass the signal to the hidden layer; the number of nodes is equal to the input dimension.

The second layer is hidden layer, whose nodes are composed of radial basis function. The number of nodes depends on the complexity of the problem. The inversion S-type function, fitted quadratic function, and the Gaussian function are common functions in the radial basis functions. This paper uses the Gaussian function, whose specific form is

$$\varphi(x) = \exp\left(-\frac{\|X_k - X_i\|^2}{2\sigma_i^2}\right) \quad i = 1, 2, \ldots, M \tag{5}$$

where $X_i = [x_{i1}, x_{i2}, \ldots, x_{iM}]$ is the center of the Gauss function and σ_i is the width parameter of the kernel function.

The third layer is the output layer, which uses linear activation function, and the number of nodes is equal to the dimension of the output data.

In Figure 1, the input layer contains M neurons, and $m$denotes any neuron. The hidden layer contains N neurons, and any neurons are represented by i. The "basis function" is $\phi(X, X_i)$, which is the excitation output of the ith hidden element. The output layer contains J neurons, and j represents any neuron. The synaptic weights of hidden layer and output layer are represented by w_{ij},($i = 1, 2, \ldots, N, j = 1, 2, \ldots, J$).

The training sample set is assumed as $X = [X_1, X_2, \ldots, X_k, \ldots, X_N]^T$. Any of the training sample is $X_k = [x_{k1}, x_{k2}, \ldots, x_{km}, \ldots, x_{kM}]$, ($k = 1, 2, \ldots, N$), the actual output is $Y_k = [y_{k1}, y_{k2}, \ldots y_{kj}, \ldots, y_{kJ}]$, ($k = 1, 2, \ldots, N$), and the expected output is $d = [d_{k1}, d_{k2}, \ldots, d_{kj}, \ldots, d_{kJ}]$, ($k = 1, 2, \ldots, N$).

When the input training sample of network is X_k, the actual output of the jth output neuron in the network is

$$y_{kj}(X_k) = \sum_{i=1}^{N} w_{ij}\varphi(X_k, X_i), \quad j = (1, \ 2, \ldots, N) \tag{6}$$

2.3 | Genetic algorithm

Genetic algorithm is a parallel processing algorithm proposed in the 1960s to simulate the natural genetic mechanism and natural selection in the evolutionary theory. In this paper, the genetic algorithm is used to optimize the RBF neural network model. When optimizing the RBF with genetic algorithm, it is necessary to determine the coding form, population initialization, fitness function construction, operation selection, cross operation, and mutation operation. The flow chart of genetic algorithm is shown in Figure 2.

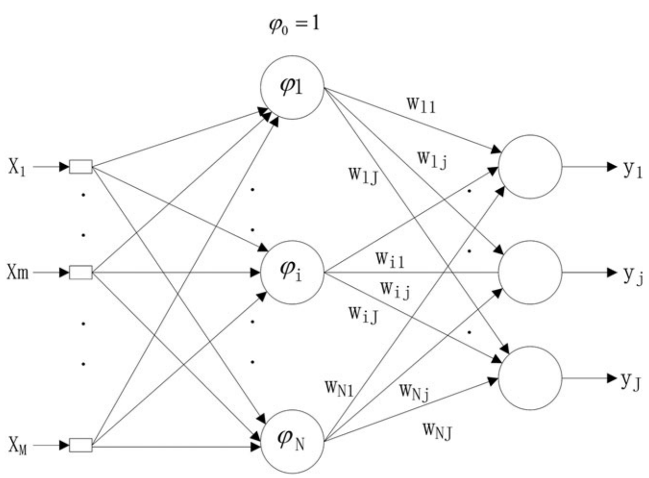

FIGURE 1 The structure of RBF neural network

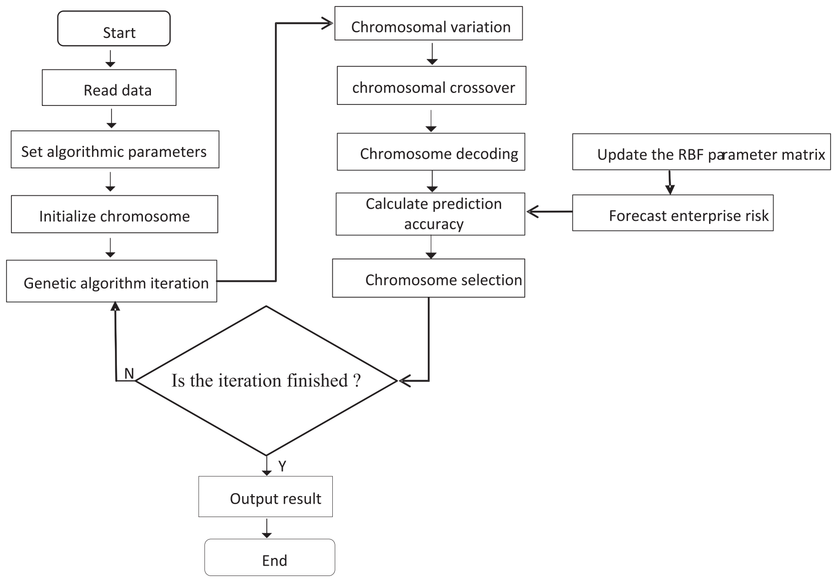

FIGURE 2 The flow chart of genetic algorithm

The algorithm design of the genetic algorithm is as follows:

1. Chromosome coding. The mapping between variables and individuals is implemented by coding. The operation objects of GA are individuals, and each individual is a string. In this paper, the floating point coding method is adopted. The coding method is *n* points; the coding length is *n*. The gene has *n* real numbers arranged in sequence, and the range meets the intervals specified by lb and ub. For example, if $n = 5$, then a legal chromosome can be expressed as [2.1,3.5,1.6,10,15.4].
2. Population initialization. An initial population consisting of several initial solutions is provided for genetic operation to meet the needs of population operation for genetic algorithms. Therefore, the final initial population size is determined to be 200.
3. Fitness function. The fitness function value can be used to evaluate the quality of an individual. In the design of fitness function, it needs to be determined according to the requirements of the problem itself. The higher the value of the fitness function, the better the quality of the solution. In this paper, the fitness function is the reciprocal of the objective function.
4. Selection operation. In this paper, the roulette selection method is used; that is, the selection is carried out according to the proportion of individual fitness degree in the sum of all the individual fitness degrees. The probability that an individual is selected is positively related to the fitness function value. The population size is set to *n*, and the fitness degree of individual *i* is set to be F_i, then the probability that an individual *i* is selected to inherit to the next generation is

$$P_i = \frac{F_i}{\sum_{i=1}^{n} F_i} \quad j = (1,\ 2, \ldots, N) \tag{7}$$

1. Cross operation. The cross operation is the most important operation in the genetic algorithm. First, two chromosomes are randomly selected from the population as the male parent, and two random numbers r1 and r2 are generated. The gene fragments between the two parental chromosomes r1 and r2 are exchanged by the cross of two points, and two offspring chromosomes are obtained.
2. Mutation operation. Mutation adopts single point of mutation, and the mutation process is random. In general, the probability of mutation P_m is very small. The mutation operation needs to cooperate with the cross operation to tap the diversity of individuals in the population.

3 | THE ESTABLISHMENT OF EVALUATION INDICATOR SYSTEM

When considering the risk early warning indicators, the qualitative indicators and quantitative indicators should be combined. In this paper, the US IRIS and FAST system, the insurance regulatory indicator system issued by the China Insurance Regulatory Commission, and the relevant literature, combined with the non–life insurance company's balance sheet, profit statement, profit and loss statement, and business statement, are used for references. There are 13 indicators that are selected from the aspects of solvency, profitability, and growth ability. These indicators include financial leverage ratio, asset liability ratio, liquidity ratio, receivable premium rate, the reserve change rate, the rate of return on investment, rate of return on net assets, net profit margin of assets, reinsurance ratio, change rate of premium income, change rate of compensation expenses, and change rate of owner's equity. The financial risk early warning indicator system of non–life insurance companies is shown in Table 1.

In this paper, the selected financial indicators are described as follows:

1. Capital adequacy ratio, that is, solvency adequacy rate. This indicator represents the capital adequacy of non–life insurance companies. Non–life insurance companies should retain corresponding capital based on their own risk and size. By comparing the owner's equity and premium income, the company's status of capital to the premium income can be reflected.
2. Financial leverage ratio. This indicator reflects the ratio of debt financing. If a company overuses the financial leverage, it may lose the solvency, which results in bankruptcy.
3. The asset liability ratio reflects the share of funds raised by liabilities in the total assets. It is also an important indicator to measure the ability of non–life insurance companies to use the funds provided by creditors for production and operation activities.
4. The liquidity ratio refers to the ability of converting current assets into cash for repayment of current liabilities. A company's ability to realize liquidity is directly proportional to its solvency.
5. The level of receivable premium rate can measure the quality of a company's underwriting business. The normal range of this indicator should not be less than 8%.
6. The change rate of reserve. This indicator measures the change of liability reserve and the operation robustness of non–life insurance companies. If this indicator is large and positive, it indicates that the company extracts abundant liability reserve and the operation of this company is good.
7. The return rate of investment. The non–life insurance companies may encounter investment risks in the operation process. It is an important indicator to reflect the investment profitability of insurance companies. It can be seen the obtained net profit income of each year in the investment process for an insurance company.
8. The rate of return on net assets. This indicator measures the profitability of an insurance company's net assets, and it is also an indicator to measure the cost of debt capital.
9. The net interest rate of total assets. This indicator measures the profitability of an insurance company using all its assets. It can be used to determine whether the company's financial risk increases or decreases.

TABLE 1 Financial early warning index system of non–life insurance companies

Index	Index Description	Index Calculation Formula	Index Property
Solvency (A)	Capital adequacy ratio (A1)	$\frac{\text{Owners equity}}{\text{Retention premium}}$	Inverse
	Financial leverage ratio (A2)	$\frac{\text{Liability}}{\text{Owner's equity}}$	Positive
	The asset liability ratio (A3)	$\frac{\text{Total liability}}{\text{Total asset}}$	Positive
	The liquidity ratio (A4)	$\frac{\text{Liquid asset}}{\text{Liquid liability}}$	Optimized
	The level of receivable premium rate (A5)	$\frac{\text{Premiums receivable}}{\text{Premium income}}$	Positive
	The change rate of reserve (A6)	$\frac{(\text{This year's reserve} - \text{Last year's reserve})}{\text{Last year's reserve}}$	Optimized
Profitability (B)	The return rate of investment (B1)	$\frac{\text{Investment income}}{\text{Average investment}}$	Inverse
	The rate of return on net assets (B2)	$\frac{\text{Net profit}}{\text{Average net assets}}$	Inverse
	The net interest rate of total assets (B3)	$\frac{\text{Net profit}}{\text{Average total assets}}$	Inverse
Growth ability (C)	The reinsurance rate (C1)	$\frac{\text{The ceded-out premium}}{\text{Premium income} + \text{Reinsurance premium income}}$	Inverse
	The change rate of premium income (C2)	$\frac{\text{This year's premium income} - \text{Last year's premium income}}{\text{Last year's premium income}}$	Optimized
	The change rate of compensation payments (C3)	$\frac{\text{The compensation of this year} - \text{The compensation amount of last year}}{\text{The compensation amount of last year}}$	Positive
	The change rate of owner's equity (C4)	$\frac{\text{Owner's equity of this year} - \text{Owner's equity of last year}}{\text{Owner's equity of last year}}$	Optimized

10. The reinsurance rate. In China, all kinds of insurance institutions need to take out parts of their premium to control the risk. The reinsurance ratio is generally greater than 20% and less than 70%.
11. The change rate of premium income. This indicator measures the change of premium income for non–life insurance companies. The moderate increase of premium income change rate indicates that the premium income will increase compared with last year, and the operation of the company is good.
12. The change rate of compensation payments reflects the changes of economic compensation of the insurer to the beneficiaries each year when the insurance accidents happen.
13. The change rate of owner's equity. If the company's business is loss, the owner's equity will decrease. If the company's business is profitable, the owner's equity will increase accordingly. This indicator can measure the stability degree of non–life insurance companies.

4 | EMPIRICAL ANALYSIS

4.1 | Data dimensionless processing

This paper selects the data of 50 non–life insurance companies between 2013 and 2015 as the research objects. After excluding outliers and samples that do not have data for two consecutive years, the 520 data from 40 non–life insurance companies are finally selected as the modeling samples. All the data come from China insurance yearbook from 2014 to 2016.

Due to the objective evaluation characteristic of entropy method, the data need to be dimensionless before evaluation, and then the indicators are weighted. Since different evaluation indicators usually have different dimensions and units, this situation has an impact on the data analysis results. In general, we eliminate the dimensional effects between indicators by data standardize processing, so that the comparability between data indicators can be solved. We normalized the data to the range of [−1,1]. The MATLAB software is used to normalize the data, and the normalized data are shown in Table 2.

The entropy and weight of each indicator can be obtained using the MATLAB software to process the normalized data. The results are shown in Tables 3 and 4.

4.2 | The training of RBF neural network

This paper creates an accurate training function of RBF network using the MATLAB software. net = newrbe (*P*, *T*, goal, spread, MN, DF). This function uses iterative calculation method, and each iteration will bring one more neuron. The iteration is terminated when the number of neurons reached the maximum value or the sum of squared errors is smaller than the target error.

P	input sample vector
T	output target vector
Goal	the target value of mean square deviation
Spread	radial basis functions of propagation
MN	maximum number of neurons
DF	the displayed frequency of the iteration process

The training process is shown in Figure 3, where the horizontal axis represents training times and the vertical axis represents training errors. The 27 samples of non–life insurance companies from 2013 to 2014 were used as training set. And 13 companies were used as test set. Too large or too small Spreads are most likely fail to achieve the desired results in the data fitting process. Therefore, the most important thing in the training process is to select appropriate spread value. When Spread = 5, i.e., the training accuracy is achieved by 5 steps of training iteration, the approximation performance of network is the best. This model has a good fitting performance for training samples.

Figure 4 shows the effect of RBF center nodes number on the training error. With the gradual increase of center width, the training error of sample gets smaller and smaller. The error is close to zero when the center width is 2, which shows that the RBF itself has some optimization effect on the center width.

The sample data of non–life insurance companies between 2013 and 2014 are used for training. It can be seen from Figure 5 that the curve trends of training data and predicted training data have no obvious difference. The network training has high precision, and the obtained network after training can well approximate the real value of a given sample. The predicted values of test data in Figure 6 and the actual test data have differences in two test samples, and the rest samples are consistent. This shows that the cognitive ability of RBF neural network is strong, and the prediction results by RBF network are reliable and feasible.

4.3 | The financial risk prediction based on GA-RBF model

The optimization of RBF neural network using genetic algorithm is mainly on three parameters. The three parameters are the central width of radial basis function, the variance of radial basis function, and the weight between hidden layer and output layer. In the design of network structure, in

TABLE 2 Normalized sample data

Year	Company	A1	A2	A3	A4	A5	A6	B1	B2	B3	C1	C2	C3	C4	
2013	Taibao	0.2745	0.3139	0.7062	0.0823	0.1635	0.9440	0.1877	0.2966	0.2764	0.1634	0.7725	0.0414	0.1197	0.018
	Taiping	0.2810	0.3610	0.7424	0.0989	0.1350	0.9553	0.2141	0.2919	0.2426	0.1475	0.99	0.2800	0.99	0.0295
	Huatai	0.3753	0.4448	0.7930	0.1788	0.3322	0.9398	0.2173	0.3232	0.2522	0.1901	0.7501	0.2204	0.1894	0.0304
	Lianhe	0.2252	0.4027	0.7694	0.1445	0.0597	0.9421	0.2874	0.3885	0.2986	0.1069	0.8087	0.1274	0.2153	0.0185
	Tian'an	0.2928	0.3257	0.7158	0.0720	0.2596	0.9418	0.3222	0.3022	0.2754	0.0906	0.8224	0.0728	0.1752	0.0199
	Yongcheng	0.3753	0.01	0.01	0.1787	0.3322	0.9398	0.2173	0.3232	0.2522	0.1901	0.7501	0.2204	0.5625	0.0309
	Yangguang	0.2199	0.4490	0.7953	0.0615	0.2082	0.9437	0.2257	0.2083	0.2012	0.0419	0.8497	0.1336	0.1189	0.0170
	Pingan	0.01	0.4552	0.7984	0.1082	0.01	0.9497	0.3662	0.4924	0.3364	0.01	0.7649	0.1474	0.2153	0.0138
	Dadi	0.2702	0.2847	0.6798	0.5602	0.1318	0.9484	0.2574	0.1254	0.3107	0.0983	0.7233	0.1097	0.0848	0.0213
	Anbang	0.1283	0.99	0.9436	0.99	0.0285	0.9637	0.0368	0.8775	0.2971	0.0205	0.7013	0.99	0.3422	0.0472
	Dubang	0.3018	0.2313	0.6264	0.2348	0.0187	0.01	0.3522	0.3776	0.4343	0.0337	0.6861	0.0208	0.2258	0.0133
	Yongan	0.2843	0.2839	0.6790	0.2803	0.0974	0.9394	0.3254	0.2135	0.2249	0.0406	0.6607	0.0929	0.0980	0.0156
	Huaan	0.4890	0.1578	0.5108	0.4445	0.0564	0.9466	0.1040	0.1772	0.3622	0.0209	0.7464	0.1122	0.1558	0.0163
2014	Taibao	0.2594	0.3221	0.7129	0.4699	0.1678	0.9476	0.2738	0.1589	0.2587	0.1289	0.7325	0.1101	0.2049	0.0233
	Taiping	0.2545	0.3203	0.7114	0.6092	0.1356	0.9519	0.3462	0.2888	0.2587	0.1069	0.8271	0.2048	0.2434	0.0265
	Huatai	0.2498	0.3180	0.7095	0.5382	0.1045	0.9440	0.7317	0.5188	0.3864	0.0993	0.7693	0.1044	0.3744	0.0262
	Lianhe	0.3792	0.3097	0.7024	0.1139	0.2967	0.9375	0.2313	0.1139	0.1598	0.1591	0.6608	0.0193	0.1778	0.0213
	Tianan	0.4952	0.6481	0.6941	0.1937	0.2317	0.9365	0.01	0.2375	0.2032	0.1131	0.7119	0.1293	0.8619	0.0276
	Yongcheng	0.0102	0.3589	0.7409	0.1055	0.0116	0.9531	0.3682	0.5584	0.3879	0.01	0.8362	0.1068	0.4901	0.0148
	Yangguang	0.2884	0.3456	0.7312	0.1378	0.1072	0.9510	0.2690	0.4939	0.3511	0.1212	0.7232	0.0828	0.5221	0.0216
	Pingan	0.2653	0.4274	0.7836	0.3996	0.6644	0.9523	0.2313	0.5012	0.3440	0.99	0.8740	0.0884	0.4454	0.0690
	Dadi	0.0160	0.2329	0.6238	0.8461	0.0351	0.9508	0.99	0.99	0.6322	0.0186	0.6801	0.1630	0.3422	0.0280
	Anbang	0.2976	0.2313	0.6219	0.0690	0.0258	0.9388	0.3490	0.1693	0.2032	0.0302	0.6562	0.0573	0.2261	0.0112
	Dubang	0.3541	0.2032	0.5847	0.0789	0.1465	0.9424	0.6044	0.2935	0.2941	0.0870	0.7233	0.1248	0.4947	0.0217
	Yongan	0.3918	0.1909	0.5663	0.3794	0.1318	0.9267	0.6116	0.4872	0.4404	0.0408	0.5298	0.0634	0.3587	0.0215
	Huaan	0.4669	0.1655	0.5251	0.5924	0.0750	0.9421	0.2365	0.2227	0.2658	0.0177	0.7574	0.1027	0.1987	0.0185
	Yingda	0.3853	0.2293	0.6194	0.3602	0.1509	0.99	0.1901	0.1796	0.2486	0.1367	0.5701	0.1220	0.2130	0.0223
2015	Taibao	0.3022	0.2775	0.6728	0.5287	0.1798	0.9391	0.4091	0.4307	0.3607	0.1233	0.6147	0.0580	0.2718	0.0251
	Taiping	0.9812	0.3031	0.6967	0.3759	0.3148	0.9486	0.3246	0.3627	0.3127	0.3163	0.01	0.1420	0.3772	0.0391
	Huatai	0.2702	0.3145	0.7067	0.01	0.1203	0.9413	0.5432	0.4935	0.3935	0.0793	0.7259	0.3094	0.2852	0.0240
	Lianhe	0.3531	0.2723	0.6675	0.6288	0.2574	0.9363	0.8170	0.2213	0.2285	0.1459	0.7436	0.1207	0.1687	0.0304
	Tian'an	0.99	0.0994	0.99	0.1263	0.0580	0.9419	0.2726	0.1569	0.1538	0.2562	0.7526	0.0824	0.9067	0.0289
	Yongcheng	0.3002	0.3499	0.7343	0.0952	0.9025	0.9499	0.2986	0.5807	0.4222	0.1145	0.7425	0.1150	0.3769	0.0395
	Yangguang	0.0763	0.2812	0.6764	0.5055	0.99	0.9480	0.4475	0.5980	0.4409	0.1197	0.8170	0.1552	0.5951	0.0476
	Pingan	0.3198	0.2985	0.6926	0.3816	0.1367	0.9415	0.3530	0.5269	0.4096	0.1042	0.7104	0.0986	0.3291	0.0238
	Dadi	0.4194	0.1603	0.5156	0.0560	0.1345	0.9380	0.3718	0.5	0.5025	0.0381	0.7597	0.01	0.3145	0.0159
	Anbang	0.2472	0.3103	0.7031	0.0571	0.0181	0.9478	0.3018	0.01	0.01	0.0334	0.7118	0.0524	0.0189	0.008
	Dubang	0.3268	0.2599	0.6546	0.1140	0.1787	0.9522	0.4759	0.3457	0.3339	0.0804	0.7866	0.0921	0.1848	0.0195
	Yongan	0.4125	0.1723	0.5367	0.7885	0.1165	0.9414	0.6004	0.3930	0.4132	0.0861	0.7258	0.1123	0.01	0.0254
	Yingda	0.4367	0.2134	0.5988	0.3556	0.1389	0.9441	0.1581	0.2655	0.99	0.1235	0.7241	0.1043	0.3568	0.0247

TABLE 3 Entropy determination

Index	Entropy Value *e*	Index	Entropy Value *e*
A1	0.954945	B2	0.961249
A2	0.969477	B3	0.973736
A3	0.990918	C1	0.877424
A4	0.916196	C2	0.992022
A5	0.881828	C3	0.909752
A6	0.993530	C4	0.941491
B1	0.958451		

TABLE 4 Weight

	Index	Weight	Index	Weight
Financial early warning index system of non–life insurance companies	Solvency (A)	0.431689	Capital adequacy ratio (A1)	0.066356
			Financial leverage ratio (A2)	0.044954
			The asset liability ratio (A3)	0.013375
			The liquidity ratio (A4)	0.123428
			The level of receivable premium rate (A5)	0.174045
			The change rate of reserve (A6)	0.009528
	Profitability (B)	0.156947	The return rate of investment (B1)	0.061193
			The rate of return on net assets (B2)	0.057073
			The net interest rate of total assets (B3)	0.038681
	Growth ability (C)	0.411362	The reinsurance rate (C1)	0.180532
			The change rate of premium income (C2)	0.011739
			The change rate of compensation payments (C3)	0.132918
			The change rate of owner's equity (C4)	0.086173

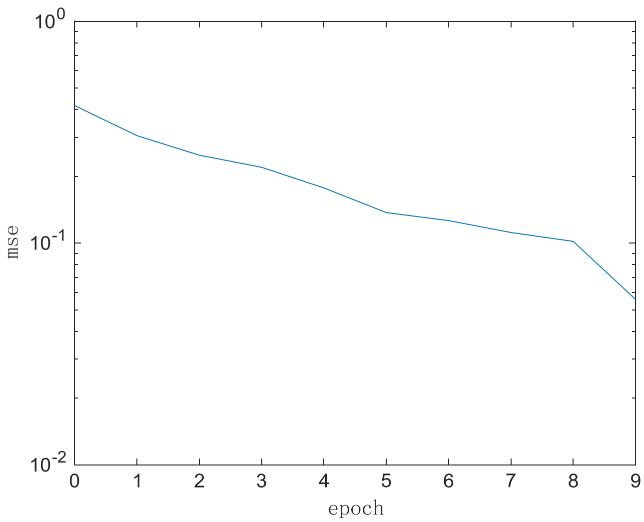

FIGURE 3 The diagram of network training process based on RBF algorithm

order to facilitate the comparison of two algorithms, the GA-RBP neural network still uses the network structure of three layers. The node number of input layer is 13, the node number of hidden layer is 27, and the node number of output layer is 3. The target error is set to 0.001. The maximum number of training is set to 1000; however, the training will automatically terminate when the error change is small.

There are a lot of genetic algorithm toolbox in Matlab. This paper optimizes the RBF with the genetic algorithm toolbox developed by the Sheffield University in the UK. The initial population number of genetic algorithm is set to 200, and the maximum evolution number is 200. In this experiment, the crossover probability Pc = 0.8 and the mutation probability Pm = 0.05.

As can be seen from Figure 7, the sum of squared errors tends to be stable after about 140 times iterations. That is, the fitness function value reaches the maximum, and the iteration achieves the optimal solution.

Figure 8 is the training error diagram of GA-RBF neural network. It shows the changing trend of the network training error with the increase of genetic generation number. It can be seen that the error continue decreases with the increase of evolutionary generation number. This shows that the GA-RBF algorithm is effective, and the optimization performance is obvious. It can be seen from Figure 9 that the prediction results of GA-RBF algorithm are improved compared with Figure 7, and the error is further decreased.

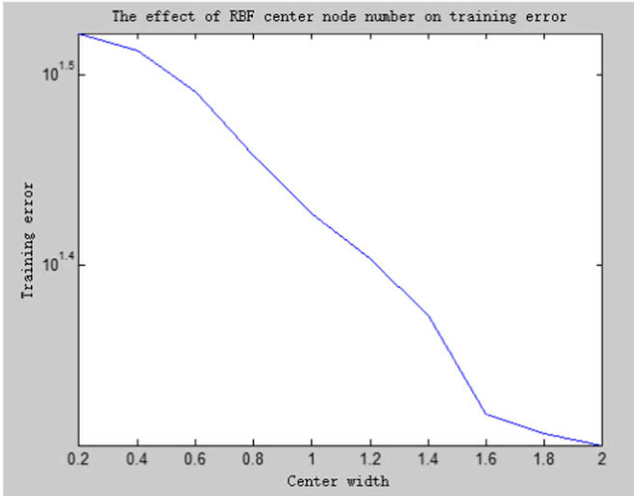

FIGURE 4 The effect of RBF center node on training error (vertical axis: training error; horizontal axis: central width)

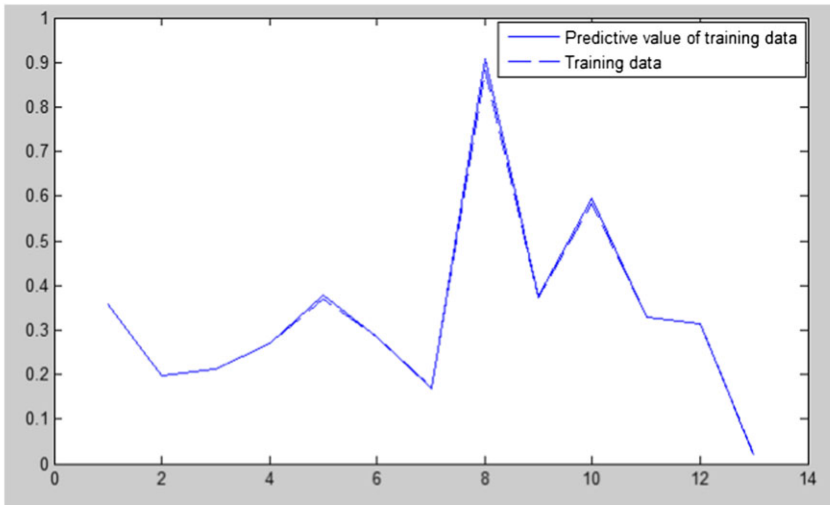

FIGURE 5 The sample prediction diagram of non–life insurance companies based on RBF (legends: the predicted value of training data, training data)

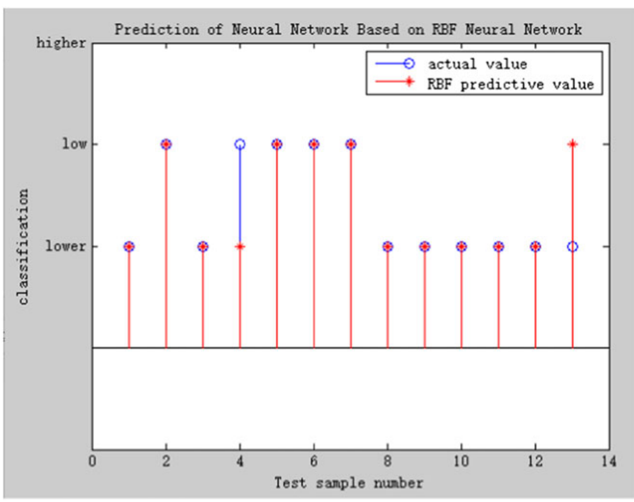

FIGURE 6 The prediction results diagram of RBF neural network

In summary, the prediction accurate rate of the algorithm that is trained with the sample data using the RBF neural network is 84%, and the error rate is 16%. The prediction accurate rate of the proposed GA-RBF algorithm is 93%, which has a 9% improvement compared with the prediction accurate rate of the traditional RBF network. The RBF neural network optimized by the genetic algorithm has a strong adaptability to

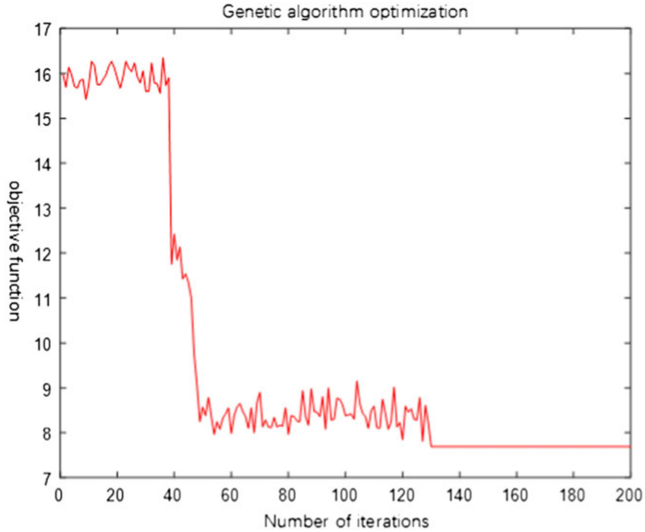

FIGURE 7 The diagram of network training process based on GA-RBF

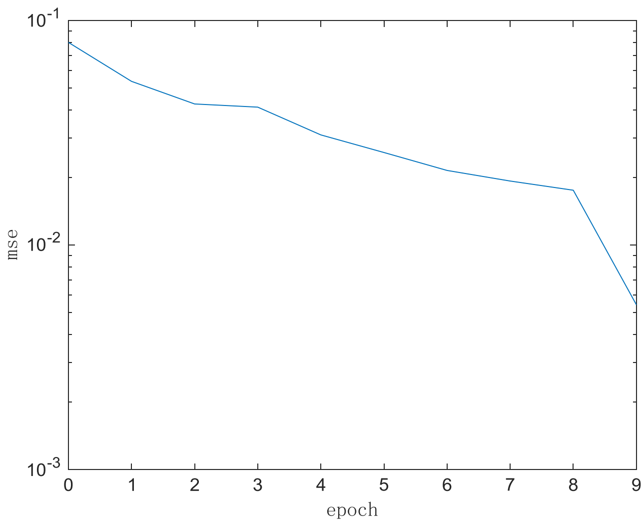

FIGURE 8 The training error diagram of GA-RBF neural network

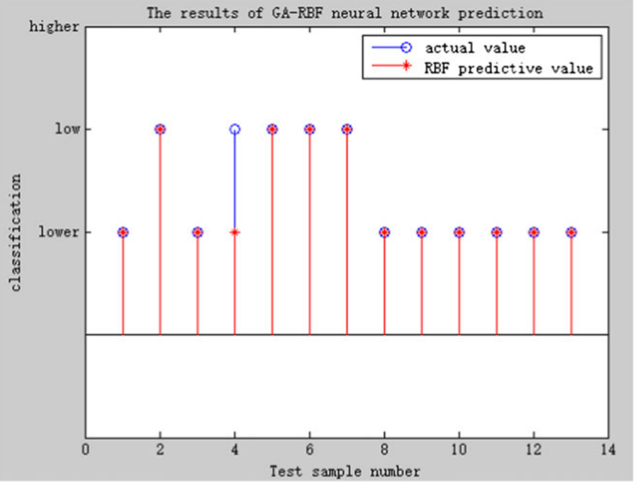

FIGURE 9 The prediction results diagram of neural network based on GA-RBF

the data of non–life insurance companies. The training convergence and error of network have obvious improvements, and the prediction accurate rate of the GA-RBF neural network model is higher.

5 | CONCLUSIONS

In the context of the new normal economy, the non–life insurance companies have both opportunities and challenges. Therefore, it is urgent to prevent and predict the financial risks of non–life insurance companies.

In this paper, the comprehensive financial risk evaluation system of companies is established from the aspects of solvency, profitability, and growth ability. Based on objective weighting of the evaluation indicators using the entropy method, the genetic algorithm is used to improve the RBF neural network for the construction of the financial risk early warning mechanism. The empirical analysis shows that the GA-RBF neural network model has the characteristics of learning self-evolution, self-adapting, and self-organization. It can deal with complex nonlinear problems quickly and effectively and can predict the financial risk accurately for non–life insurance companies. On the one hand, it overcomes the problem of subjective evaluation caused by human factors and ensures the objectivity and accuracy of the evaluation results. On the other hand, the early warning model has strong dynamic, and the early warning performance can be used in practice.

In summary, the financial early warning of non–life insurance companies based on genetic algorithm and radial basis neural network is helpful for the companies' managers to find the financial crisis and reduce the financial risks timely. Finally, in order to enhance the ability to resist risks, non–life insurance companies should adapt to the new economic normal, accelerate the transformation and upgrading of non–life insurance industry, and promote the normalization of financial risk warning.

ACKNOWLEDGMENTS

This work was financially supported by National Natural Science Foundation of China (no. 61502280 and no. 61472228).

ORCID

Wei Liu http://orcid.org/0000-0001-6468-3232

REFERENCES

1. Yan C, Sun H, Liu W. Study of fuzzy association rules and cross-selling toward property insurance customers based on FARMA. *J Intell Fuzzy Syst*. 2016;31(6):2789–2794. https://doi.org/10.3233/JIFS-169160.
2. Li Y, Yan C, Liu W, Li MZ. A principle component analysis-based random forest with the potential nearest neighbor method for automobile insurance fraud identification. *Appl Soft Comput*. 2017. https://doi.org/10.1016/j.asoc.2017.07.027.
3. Gulsun I, Umit G. Early warning model with statistical analysis procedures in Turkish insurance companies. *Afr J Bus Manag*. 2010;4(5):623–630. https://doi.org/10.1109/CCDC.2010.5498491.
4. Dickson DCM, Li SM. The distributions of the time to reach a given level and the duration of negative surplus in the Erlang (2) risk model. *Insur Math Econ*. 2013;52(3):490–497. https://doi.org/10.1016/j.insmatheco.2013.02.013.
5. Xie C, Zhao YJ, Zhang LW. Research on financial distress prediction based on CFaR model and logistic regression. *Theory Pract Finance Econ*. 2014;35(187):57–62. http://en.cnki.com.cn/Article_en/CJFDTotal-CLSJ201401010.htm
6. Bai Z, Li MG. Insurance companies' financial early warning and capital allocation based on conditional ruin probability. *Chin J Manag Sci*. 2016;24(7):36–42. https://doi.org/10.16381/j.cnki.issn1003-207x.2016.07.005.
7. Tseng FM, Hu YC. Comparing four bankruptcy prediction models: logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Syst Appl*. 2010;37:1846–1853. https://doi.org/10.1016/j.eswa.2009.07.081.
8. Deng QB, Wen H. Financial early warning research of non-life insurance company based on RBF neural network. *Theory Pract Finance Econ*. 2011;32(9):27–29. http://www.cnki.com.cn/Article/CJFDTOTAL-CLSJ201101005.htm
9. Luo X, Niu XC. Financial crisis warning research based on neural network model. *Technol Ind*. 2014;14(11):95–144. http://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFQ&dbname=CJFD2014&filename=CYYK201411019&v=MTQzMzBab0Z5amxVYi9CSmpUU1piRzRIOVhOcm85RWJZUjhlWDFMdXhZUzdEaDFUM3FUcldNMUZyQ1VSTDJmYis=
10. Xu ZP. Modeling and simulation of financial crisis warning system based on RBF neural network. Robots & Intelligent System (ICRIS), 2016 International Conference on. IEEE, 2016: 264-267. DOI: 10.1109/ICRIS.2016.53
11. Du PY, Luo XP, *et al*. The application of genetic algorithm-radial basis function (GA-RBF) neural network in stock forecasting. *Control Decis Conf*. 2010;1745–1748. https://doi.org/10.1109/CCDC.2010.5498491.
12. Wang MZ *et al*. GA-RBF prediction model of stock. *J Liaoning Eng Univ*. 2014;33(7):971–973. http://www.cnki.com.cn/Article/CJFDTOTAL-FXKY201407022.htm

How to cite this article: Yan C, Wang L, Liu W, Qi M. Financial early warning of non–life insurance company based on RBF neural network optimized by genetic algorithm. *Concurrency Computat: Pract Exper*. 2017:e4343. https://doi.org/10.1002/cpe.4343