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Research article

Model and application of farmers' credit risk early warning system based on T-S fuzzy neural network application

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Abstract: In China, farmers' loan difficulties have become a major problem restricting increases in farmers' incomes and the economic development of rural areas. The existing studies of the management and control of farmers' credit risk have mostly been pre-management, which cannot efficiently prevent and reduce the occurrence of farmers' credit risk in time. This paper uses the T-S neural network model to build a farmers' credit risk early warning system so that formal financial institutions can predict the occurrence of and changes in the farmers' credit risks in a timely manner and quickly undertake countermeasures to reduce losses. After training and testing, a model with a higher degree of fit is used to analyze the credit level of farmers in Shaanxi Province from 2016 to 2018. The results demonstrate that the credit level of farmers in this area is continuously improving, in agreement with the actual situation. The results also show that the prediction accuracy of the T-S fuzzy neural network is high, verifying the rationality of the selection of test samples.

Keywords: farmers' credit risk; early warning system; T-S fuzzy neural network

1. Introduction

The problem of financing restricting the economic development of rural areas in China and the problem of farmers' loan difficulties are particularly prominent. China's agricultural population accounts for 64.71% [1] of the total population. This enormous population has determined that the problem of farmers' loan difficulties has become a major problem restricting increases in farmers' incomes and economic development in rural areas. These problems should be urgently solved among China's "agriculture, rural areas and farmers" issues. Due to the heterogeneity of agricultural risks, the lack of mortgages, dispersion of farmers' residences, imperfect financial information, supervision costs, and transaction costs and the credit risks of formal financial loans to farmers being so high, formal financial institutions are unwilling to lend to farmers. Therefore, it is necessary to develop a timely, efficient and dynamic farmers' credit risk evaluation and early warning system to predict and supervise the changes in farmers' credit risk. Doing so could also prevent losses to formal financial institutions due to farmers' breach of contract and reduce the cost of supervision. It could also efficiently resolve the loan financing difficulties of farmers and provide a reliable basis for the determination of subsequent loan interest rates for farmers.

The willingness of farmers to honor contracts is constantly changing due to the influence of the surrounding environment and other farmers. Due to the heterogeneity of agricultural risks and the long cycle of agricultural production, the agricultural income of farmers is uncertain. These factors have further caused continuous changes in the credit ratings of farmers. Therefore, premanagement of credit risk cannot efficiently reduce farmers' credit risk. A mechanism is required to allow formal financial institutions to predict the occurrence of and changes in farmers' credit risk in a timely manner to quickly respond to measures and reduce losses.

The current studies of credit risk management of farmer loans have mainly focused on the willingness and ability of farmers to repay loans, the credit risk ratings of farmers, and the establishment of a credit indicator system. Consequently, formal financial institutions decide whether to extend a loan and the amount of the loan. For instance, N. A. Jatto et al. studied the reasons for delays in the repayment of agricultural loans by farmers in Kwara State [2]. Li Li and Zhang Zongyi conducted an empirical analysis of the impact of farmers' quality on farmers' credit based on the loan data of 16,101 farmers [3]. Zhang Yanping studied the financial needs of farmers against the background of land ownership confirmation [4], etc., based on time differences, influencing factors and default risks.

The more commonly used methods for farmers' credit risk evaluation include the fuzzy comprehensive evaluation method, regression analysis method and neural network method. For instance, Ma Yongjie et al. used a multivariate statistical model to study the credit risk of farmers. They believed that their model had a higher discrimination rate for the classification of farmers' risks [5]. Wang Ying et al. used the fuzzy comprehensive evaluation method to rate the credit of farmers. They believed that their model was applicable and scientific in studying the credit risk of farmers [6–8]. Liu Chang et al. used the neural network model combined with the traditional expert scoring method to evaluate the credit risk of farmers. They deduced that the application of this method could efficiently improve the ability of credit institutions to prevent the credit risk of farmers [9]. Consequently, this paper uses the neural network model to construct a credit risk early warning system for farmers.

The backpropagation neural network model is the most common form of neural network. However, its convergence rate is slow, and it can easily fall into the local minimum network form [10]. Several researchers have proposed improved methods, such as the genetic algorithm, particle swarm algorithm and fuzzy algorithm. However, when the number of samples is small and the distribution is uneven, the genetic algorithm cannot cause the optimized neural network to achieve the effect of accurate prediction [11]. Particle swarm optimization might not reach the global optimum due to a lack of momentum [12]. The Takagi-Sugeno (T-S) fuzzy neural network retains the advantages of fuzzy logic and neural networks. It is a fuzzy system with strong adaptive ability [13]. The results of the existing studies have shown that the model has a fast convergence speed and high prediction accuracy [14]. Currently, it is widely used in mechanical engineering evaluation, water quality evaluation, transportation and medicine, and it is less used in the evaluation of farmers' credit risk. For instance, Pei Qiaoling et. al. determined the risk early warning value according to the T-S fuzzy neural network fusion model. They also performed three-dimensional control of subway construction safety risks [15]. Yang Cheng et al. used the T-S fuzzy neural network model to evaluate the water quality of Mingcui Lake. The evaluation results were consistent with the actual local conditions [16].

This paper uses the T-S fuzzy neural network to construct a farmers' credit risk early warning system from the perspective of formal financial institutions. Compared with the existing models [3,5,7,9], the proposed model can select farmers with higher credit ratings beforehand and avoid the risk of default. Afterward, it monitors the credit risk dynamics of farmers at any time to prevent and control the effects of changes in farmers' credit risks. In other words, it performs preloan assessment and postloan monitoring of farmers' credit risk. This model allows formal financial institutions to stop losing in a timely manner in the face of default risks and simultaneously facilitates long-term and stable loan cooperation between formal financial institutions and farmers, thereby alleviating farmers' loan problems.

In the following research, this paper first expounds the T-S neural network model and its structure and constructs the farmers' credit risk early warning model based on the T-S neural network. Then, referring to the literature and authoritative rating agencies, farmers' credit risk evaluation index system and farmers' credit risk evaluation standards are established, training samples are constructed and network training is conducted. Finally, this paper uses the farmers' data of three cities and one district in Shaanxi Province to apply the model and analyzes the research results.

2. Developing an early warning system for farmers' credit risk

2.1. Constructing the T-S fuzzy neural network

The T-S fuzzy neural network uses "if-then" rules for reasoning. More precisely, if R^i is a fuzzy rule, then the fuzzy reasoning can be expressed as:

$$R^i\text{: if } x_1 \text{ is } A^i_1,\ x_2 \text{ is } A^i_2,\ \ldots,\ x_k \text{ is } A^i_k\ ,$$

$$\text{Then, } y_i=p^i_0+p^i_1x_1+\ldots+p^i_kx_k,\ i=1,2,\ \ldots,\ n \tag{1}$$

where R^i (i = 1, 2, …, n) is the ith fuzzy rule, n is the number of fuzzy rules, x_j (j=1, 2, …, k) is the input variable, A^i_j is the jth fuzzy subset of the fuzzy system, p_{ij} (j=1, 2, …, k) is the parameter of the fuzzy system, and y_i is the network output.

Figure 1 shows that the T-S fuzzy neural network structure is divided into an antecedent network and a subsequent network. The antecedent network is divided into four layers, as shown in Figure 1.

(1) The first layer is the input layer. It can be seen from Equation (1) that the input value is fuzzy, while the output value is definite and linearly related to the input value. The function of the input layer is to connect with the input vector x_j. The input nodes have the same dimension as the input vector. Considering $x = [x_1, x_2, \ldots, x_k]$ as an example, the number of nodes in the input layer is k.

(2) The second layer is the fuzzification layer. This layer calculates the membership function $\mu_{A^i_j}$ of each input value belonging to the fuzzy set of each linguistic variable value. In this paper, the Gaussian function is considered the membership function. The membership function of the input

variable x_j is expressed as:

$$\mu_{A_j^i} = \exp\left[-\frac{\left(x_j - c_j^i\right)^2}{b_j^i}\right],\ j = 1,2,\cdots,k;\ i = 1,2,\cdots,n \tag{2}$$

where c^i_j is the center of the membership function, b^i_j is the width of the membership function, and k is the number of input variables.

In general, the values of c^i_j and b^i_j are set according to the input samples. By adjusting c^i_j and b^i_j, the membership functions of different shapes and positions can be obtained. Simultaneously, c^i_j and b^i_j can be adjusted to the most adaptive trend along with the network training process.

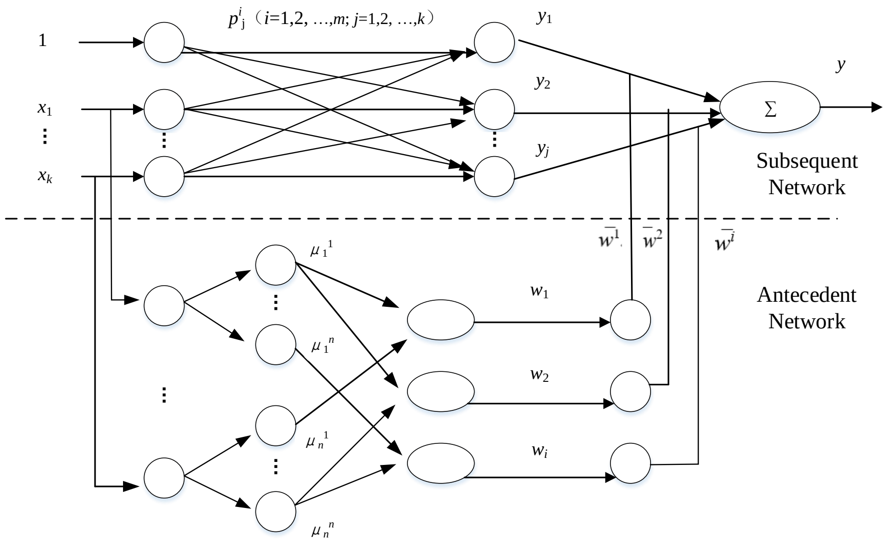

Figure 1. T-S fuzzy neural network structure.

(3) The third layer is the rule layer, which calculates the membership degree of fuzzy rules. Each node of this layer is a fuzzy rule. Using the continuous multiplication operator as the fuzzy operator, the output w_i of each node in the rule layer is computed as:

$$w_i = \prod_{A_j^i=1}^{k} \mu_{A_j^1} = \mu_{A_j^1}\left(x_1\right)\mu_{A_j^2}\left(x_2\right)\cdots\mu_{A_j^k}\left(x_k\right),\ i = 1,2,\cdots,n \tag{3}$$

Due to the different distances, an input point only has a greater degree of membership with the nearby language variables and a smaller degree of membership with the farther language variables. Therefore, only a few nodes in w_i have larger output values, while the other nodes have smaller output values.

(4) The fourth layer is the defuzzification layer, which normalizes the data. In this paper, the weighted average discrimination method is used for normalization calculation. The defuzzification process is expressed as:

$$\overline{w^i} = w^i \Big/ \sum_{i=1}^{n} w_i \tag{4}$$

The subsequent network can be divided into *r* sub-networks, while each output has a specific value. The structures of the sub-networks are similar. They consist of three layers.

(1) The first layer is the input layer, which serves the function of information transmission, passing variables and constant items to the second layer. The input value of the 0th node x_0 is set as a constant of 1, and constant items are provided for the fuzzy rule subsequent network

(2) The second layer is also referred to as the middle layer. Each node represents a rule, and the middle layer node output y_j is calculated according to the fuzzy rules:

$$y_j = p_0^j + p_1^i x_1 + \cdots + p_k^i x_k \tag{5}$$

(3) The third layer is the output layer. More precisely, the output of the antecedent network is used as the connection weight between the intermediate layer and the output layer of the subsequent network, and the output y_i of the entire system is computed as:

$$y_i = \sum_{i=1}^{n} y_j \overline{w^i} \tag{6}$$

To ensure the accuracy of the model, the error value *e* is computed as:

$$e = (y_d - y_c)^2/2 \tag{7}$$

where y_d is the expected output value of the T-S fuzzy neural network, and y_c is its actual output value.

It is then determined whether the error *e* meets the requirements by setting the error accuracy or the maximum number of training times, and the calculation stops if it meets the requirements.

3. Sample construction and network training

3.1. Index selection

The key to the evaluation of farmer credit risk lies in the choice of the evaluation index system, which should be selected based on the objective facts and the characteristics of the evaluation subject, while the same index system cannot be uniformly selected. This paper is based on the credit indicators of authoritative institutions, such as Standard & Poor's [17]. It comprehensively refers to the farmer microcredit rating indicator system of Agricultural Bank of China [18], Commercial Bank of China [19] and Industrial and the China Postal Savings Bank [20]. In addition, based on the existing studies [21–23], a credit risk evaluation index system for farmers is developed.

More precisely, it is divided into four parts: family structure characteristics, solvency, operating ability and credit status. A total of ten indicators exist. The specific indicator system is shown in Table 1.

In the family structure characteristics, the farmers' characteristics include the health status, age and gender of the farmer. The credit risk of a young, strong and healthy laborer is lower. The larger that the number of family laborers is, the greater that the total family income is, which is conducive to the repayment of the loan by the farmer. In addition, the education level has an inverse relationship with the credit risk of farmers. The education level is related to the application of modern agricultural science and technology, the ability of agricultural production and operation, and management ability, and it is inversely related to the credit risk of farmers.

In solvency, income and expenditures determine the ability of farmers to repay loans in the future. The higher that the income is, the lower that the expenditure are, and the greater that the probability is that the farmers will repay the loans. The more existing assets that there are, the lower that the family debt is, indicating that the past operating status was good, and the greater that the probability is of repaying the loan.

The setting of the operational capacity is mainly used to measure the ability of the farmers to repay in the future. According to the different types of operations, the stronger that the planting ability is, the better that the regional economy is, the higher that the income of farmers is in the future, and the lower that the credit risk is.

Credit status is mainly used to measure the past credit status of farmers. The better that the historical credit is, the greater that the probability is of repaying the loan.

Table 1. Farmer credit risk evaluation index system.

No.	First-level index	Second-level index
1	Family structure characteristics	Farmers' characteristics
2		The number of laborers in the family
3		Education level
4	Solvency	Income and expenditure status (expenditure/income %)
5		Family debt (yuan)
6		Existing property (yuan)
7	Operating ability	Management and planting capacity
8		Management type
9		Regional economic conditions
10	Credit status	Credit history

3.2. Constructing the training samples

Before performing the risk assessment of farmers, reasonable samples that consider commonalities and individualities should be selected to train and test the learning ability and generalization ability of the T-S fuzzy neural network model so that the model can accurately analyze the actual farmer data. However, it is very difficult to collect a large and reasonable sample of farmers receiving loans. Therefore, to ensure the accuracy and speed of the T-S fuzzy neural network model in providing an early warning of farmer credit risk, this paper refers to the relationship between different indicators in the literature and the credit risk of farmers. Simultaneously, it combines the opinions of farmers' credit risk research and scholars to formulate the criteria for the evaluation of farmers' credit risk. As shown in Table 2, the farmers' credit risk occurrence probability is sorted from A to E, that is, [A, B, C, D, E] = [good, better, general, poor, bad].

To ensure the learning ability and generalization ability of the T-S fuzzy neural network model, this paper considers standard samples and actual samples as the training samples for the TS fuzzy neural network model. The standard samples are type of samples selected according to the standards set in Table 2. The actual samples are the data on actual farmers' loans. In the training process, training samples are also involved. They are used to train the T-S fuzzy neural network model, while the test samples are used to test the cognitive ability and generalization ability of the T-S fuzzy neural network model after training.

Table 2. Farmer credit risk evaluation criteria.

No.	Index	A	B	C	D	E
1	Farmers' characteristics	≥ 0.90	≥ 0.70	≥ 0.50	≥ 0.30	≥ 0.10
2	The number of laborers in the family	≥ 5	≥ 4	≥ 2	≥ 1	＜ 1
3	Education level	Undergra duate and above	college	high school (higher vocational)	junior high school	below elementary school
4	Income and expenditure status (expenditure/income %)	≤ 30%	≥ 40%	≥ 50%	≥ 70%	≥ 80%
5	Family debt (ten thousand yuan)	≤ 1	≥ 2	≥ 4	≥ 6	≥ 8
6	Existing property (ten thousand yuan)	≥ 10	≥ 7	≥ 5	≥ 3	≤ 1
7	Management and planting capacity	≥ 0.90	≥ 0.80	≥ 0.60	≥ 0.40	≥ 0.20
8	Management type Agricultural income as a percentage of total income	≥ 80%	≥ 60%	≥ 40%	≥ 20%	＜ 20%
9	Regional economic conditions	≥ 0.90	≥ 0.85	≥ 0.65	≥ 0.45	≥ 0.25
10	Credit history	≥ 0.90	≥ 0.85	≥ 0.60	≥ 0.40	≥ 0.20

3.3. Network training

Due to the large differences in the risk evaluation index units of farmers, training directly using a network training sample leads to a flat area in the network function work. Therefore, the sample data should be standardized:

$$x = \frac{v - \min v}{\max v - \min v} \tag{8}$$

$$x = \frac{\max v - v}{\max v - \min v} \tag{9}$$

where *x* is the standardized value of the index, and *v* is the original data of the farmer.

To avoid problems such as poor model fitting ability, unreliable prediction results, low recognition accuracy and poor robustness caused by a sample size that is too small, the standard samples shown in Table 2 should be expanded. According to the farmers' credit risk evaluation criteria in Table 2, the method of linear function interpolation is used to expand the sample data. In addition, the RAND function is used to generate 500 samples with random uniform interpolation values. Simultaneously, 95 actual samples are randomly selected and combined with the standard samples to form a mixed sample. The number of mixed samples is 595. One hundred samples are randomly selected as test samples, and the remaining 495 samples are used as training samples. This paper uses MATLAB software to develop the farmers' credit risk early warning system based on the T-S fuzzy neural network model. The generated mixed samples and test samples are input into the network for network training and testing. Since the actual samples require more training times, the network training times are set at 5000 times. In addition, the error accuracy is set at 0.01. When the training result is less than this value, the network training effect is better and meets the requirements. The training results and error trend graphs are presented in Figure 2. The network detection results are shown in Figure 3, where [A,B,C,D,E] = [good, better, general, poor, bad] = [1,2,3,4,5].

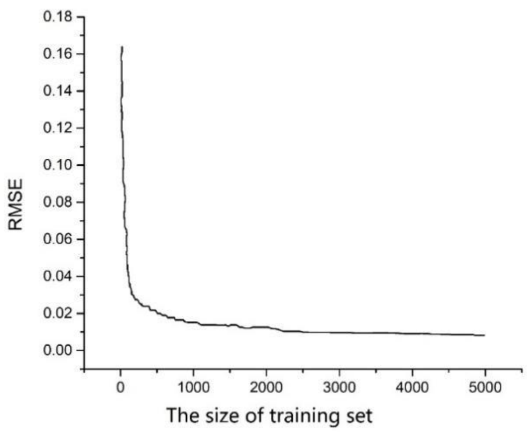

Figure 2. T-S fuzzy neural network training results.

Figure 2 shows that, after 5000 training iterations for the mixed samples, the prediction error gradually decreases, in line with the error accuracy set above. At the same time, Figure 3 shows that the error between the actual value and the predicted value is small, and it can predict the test samples more accurately and has good cognitive and generalization ability.

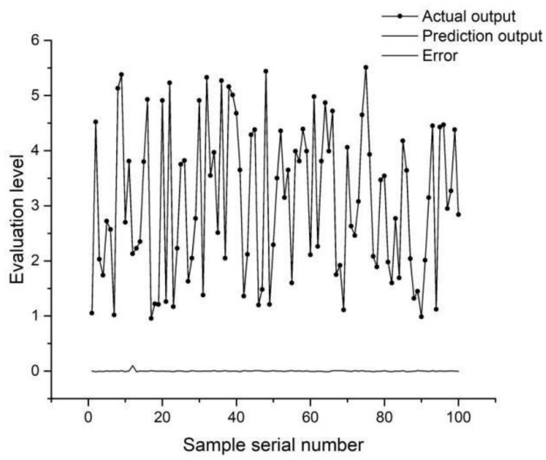

Figure 3. T-S fuzzy neural network test results.

4. Application of the farmers' credit risk early warning system

Based on the previous analysis, the proposed farmers' credit risk early warning system based on the T-S fuzzy neural network model is tested. It can be deduced that it has good stability and high prediction accuracy, and the network prediction error value meets the requirements. Using real-time data to evaluate the credit risk of farmers can better illustrate and present the advantages of the proposed model. However, it is difficult to collect real-time data about the credit risk evaluation indicators of farmers through investigation and visits. Therefore, this paper chooses this model for 2016–2018, and the credit risk of loan farmers in three cities, while one district and their surrounding areas in Shaanxi Province are analyzed. A total of 150 samples of credit risk evaluation index values of loan farmers in 2016, 2017 and 2018, with a total of 450 samples, are considered. After evaluating the T-S fuzzy neural network model, the analysis results of the credit risk of farmers from 2016 to 2018 are summarized in Figures 4–6.

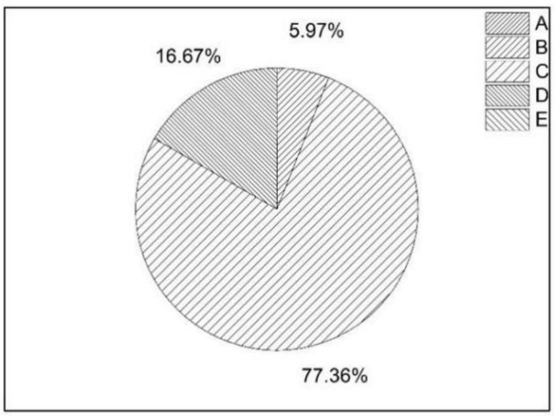

Figure 4. Analysis results of the farmers' credit risk in 2016.

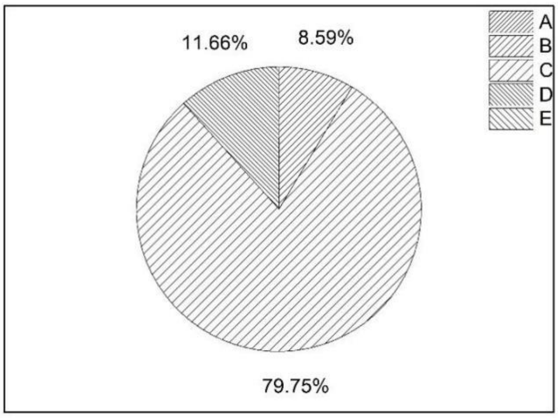

Figure 5. Analysis results of the farmers' credit risk in 2017.

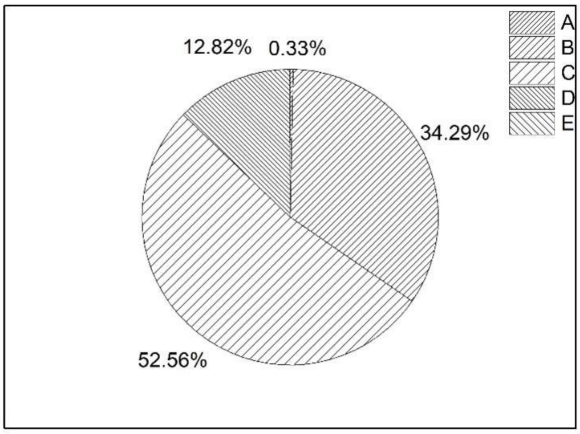

Figure 6. Analysis results of the farmers' credit risk in 2018.

As shown in Figures 4–6, the analysis of the credit risk of farmers in this region in 2016 is that 5.97% of farmers have a credit rating of B, 77.36% of farmers have a credit rating of C, and 16.67% of farmers have a credit rating of D. In 2017, 8.59% of farmers had a credit rating of B, 79.75% of farmers had a credit rating of C, and 11.66% of farmers had a credit rating of D. Compared with 2016, the numbers with B and C ratings increased, and the number of D ratings decreased; that is, the overall credit rating of farmers in 2017 increased compared to 2016. In 2018, 0.33% of farmers had a credit rating of A, 34.29% of farmers had a credit rating of B, 52.56% of farmers had a credit rating of C, and 12.86% of farmers had a credit rating of D. Compared with 2016, the numbers of A and B ratings increased, the number of C decreased faster, and the number of D increased slightly. The number of farmers above grade D was basically the same as in 2017, but the number of farmers in grades A and B increased. On the whole, the credit level of farmers in 2018 increased compared with that in 2017.

The credit level of farmers in this region has been on the rise for three years, and the credit risk is relatively low. The default risk of formal financial institutions is relatively small due to the issuance of loans, which are conducive to the financing of farmers. In recent years, the number of professional farmer cooperatives in this area has been increasing. Farmers have joined cooperatives and used the cooperatives as third-party guarantees to obtain loans from formal financial institutions. The cooperative promises that, when a farmer defaults, the cooperative will repay the loan on the farmer’s behalf, effectively reducing the credit risk of the farmer. Cooperatives and formal financial institutions jointly supervise loan farmers and formulate rewards and punishments. The overall credit level of farmers in the region has been continuously improved, and the scale of loans has continued to expand. The ratio of nonperforming loans in formal financial institutions has been declining annually. The evaluation result shows the accuracy of T-S fuzzy neural network prediction and verifies the rationality of the selection of test samples in this paper.

To ensure that farmers can obtain long-term financing through formal financial channels and reduce the occurrence of credit risks, it is necessary to actively develop individual credit accounts for farmers to achieve real-time updates of credit risk indicators and farmers' personal information data. On a monthly or quarterly basis, the personal credit level of farmers is measured, the credit sub-insurance of farmers is assessed in advance, and the farmers with higher credit ratings are screened. The credit risk dynamics of farmers are monitored at any time after the loans. The occurrence of the credit risk of farmers is prevented and controlled. Therefore, the loss to formal financial institutions caused by farmers' defaults is reduced. Finally, formal financial institutions can formulate corresponding reward and punishment policies by adjusting loan interest rates, facilitating long-term and stable loan cooperation between formal financial institutions and farmers, thereby resolving the financing difficulties of farmers.

5. Conclusion

This paper uses the T-S fuzzy neural network to develop an early warning system for rural households' credit risk. Based on the existing studies and the evaluation indicators of domestic and foreign authoritative institutions, a farmers’ credit risk indicator system and evaluation criteria are proposed. A mixed sample composed of actual samples and standard samples is considered to train the model. The number of training and error accuracies is controlled. The optimal model is selected, and the credit risk of loan farmers in three cities and one district in Shaanxi Province from 2016 to 2018 is analyzed. The obtained results demonstrate that the credit level of farmers in this area showed an overall upward trend over the past three years, in agreement with the actual local conditions. This outcome further verifies the rationality and practicability of the proposed model and shows that the T-S fuzzy neural network used in the evaluation of farmers’ credit risk has high prediction accuracy.

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Conflict of interest

The authors declare there is no conflicts of interest.

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