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A Decision Management Model for Small and Medium-sized Enterprises Based on Artificial Neural Network

James Yong Liao*

Philippine Christian University, Philippine

James.liaoyong@pcu.edu.ph

**corresponding author*

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Abstract: The development of small and medium-sized enterprises (SaMSE) is related to the country's economic and social development. Most of our enterprises are SaMSE, which play an important role in the employment of urban population, foreign trade and technological innovation. Now, the main source of financing is commercial banks, but commercial banks are also worried about the financing of SMEs. The reason is that, on the one hand, the financial data and other information of SaMSE are not made public; Therefore, it is particularly important to improve the credit rating system for SMEs. The main purpose of this paper is to study the decision-making management model of SaMSE based on ANN. According to the characteristics of artificial neural network (ANN), this paper discusses the applicability and superiority of the ANN model in the credit risk assessment of commercial banks, and proposes a new idea for the development of the credit risk assessment system. The enterprise credit risk assessment model is implemented with matlab tools. Through the example of matlab network training, it is analyzed that the combination of rough set attribute reduction theory and NN method can improve the performance of NN credit evaluation model.

1. Introduction

Due to the short operating period of many SaMSE, frequent changes in main business, and market changes in marketing and other business conditions, the growth capacity of the enterprise should be fully considered when setting this table, not only the current financial indicators to the existing scale , capital structure, etc. We should pay attention to the long-term nature of the enterprise, and examine the innovation ability, profit growth ability, and development potential of the enterprise. Therefore, the setting of qualitative indicators needs to be based on the basic situation of the enterprise, the basic situation of the actual controller, the competitive strength, and the external environment. Inspect and decompose each index, and comprehensively evaluate the credit risk of the enterprise [1-2].

In a related study, Abbasi et al. identified the determinants of social media marketing adoption in SMEs by considering competitive industries as moderators. proposed a two-stage analysis involving partial least squares techniques and artificial intelligence, called deep ANNs [3]. The application of deep ANN architecture was used to predict 91% accuracy of the proposed model. Kachalov et al. provide new ideas for the risk assessment of implementing innovative projects. Based on the ideas of George Kleiner and ANN tools, the possibility of successful completion of innovative projects is explained from the perspective of risk management [4]. The influence of anti-risk management is excluded, and the weights of various risk factors in the problem formalization are not considered. A practical application of the findings is for decision makers seeking a visual interpretation of the final data, which contains a small number of possible scenarios that differ significantly from each other.

Based on ANN, this paper studies the decision-making management model of SaMSE. According to the characteristics of ANN, this paper discusses the applicability and superiority of ANN model in commercial bank credit risk assessment, and proposes a new idea for the development of credit risk assessment system [5-6]. On the basis of establishing the index system of the credit risk assessment model for SaMSE, the network model is tested according to the limited data, and the basic idea and calculation method of the method are preliminarily verified to be clear and fully applicable to practice.

2. Design Research

2.1. Main Credit Risk Characteristics

The credit risk of SaMSE in my country has obvious characteristics, including:

(1) my country's SaMSE are in fierce competition in the industry, with low access and low negotiating position. They are squeezed by large upstream enterprises, and their survival is generally difficult and their lifespan is short. Some SaMSE, especially those in my country at the current stage, have a certain degree of lag in capital accumulation and often have a strong desire to expand. Without sufficient market research and strategic analysis, it is easy to blindly expand across industries and at the expense of high debt. Extremely lead to the breakage of the capital chain, and even affect the previous policy operation [7-8].

(2) The financial operation of SaMSE is not standardized, the financial data is not transparent, the report preparation is flawed, the report quality is uneven, the subject adjustment is arbitrary, and it is not audited.

(3) The boundaries between SME shareholders' assets and company assets are blurred, the corporate governance structure is not straightened out, and the management lacks scientificity.

(4) SaMSE have small capital, low ability to resist market risks, weak competitiveness, and are easy to be acquired by large capital.

(5) The information asymmetry of SaMSE and financial institutions, their corporate credit information and the personal credit information data of business owners are not optimistic, and the acquisition of their credit information data is difficult to reflect through the current official query system [9-10].

(6) SaMSE generally have insufficient research and development capabilities. As technology is increasingly updated, it is easy to be eliminated due to backward technology.

2.2. Credit Information

The development of credit reporting in my country in recent years can be summarized as follows: actively promote the continuous improvement of credit reporting laws and regulations, take national laws and regulations as the leading role in the formulation and establishment, and continuously improve the system construction of some and local documents. With the simultaneous development of private credit reporting agencies, the demand for credit reporting continues to increase, and the demand field continues to expand. The credit reporting industry is booming in my country.

The role of credit reporting is mainly reflected in:

First, provide risk warnings for financial institutions. Commercial banks or other financial institutions provide personal credit inquiries and corporate credit inquiries, and participate in risk assessment in the process of financial institutions' experience in credit [11-12].

Second, provide basic credit services for the credit market. The methods of providing services include credit reports, credit scores, etc.

Third, provide valuable material for financial supervision. Since the data collected by credit reporting companies and official credit reporting records are complementary, they can provide a data basis for government supervision.

Fourth, it serves macroeconomic research and analysis. Through the collection of credit market data, it is convenient for the research department to conduct macroeconomic analysis, make statistics on the credit market in various regions, and analyze different groups of people in different industries.

Fifth, effectively reveal market risks. Using the customer data collected by credit investigation, processing and sorting, and through comprehensive scoring, it can effectively reveal the risks of individuals and enterprises, and effectively prevent risks.

Sixth, it is conducive to the establishment of a social integrity mechanism and the formation of positive incentives.

Due to the important role of credit reporting on economic development and the development of the financial industry, it is necessary to use credit reporting data as a non-financial indicator of credit rating. It is of great significance for SaMSE to incorporate the credit information of enterprises and the personal information of business owners into the index system [13-14].

First of all, the characteristics of SaMSE are that the information is not transparent, so they do not attract the attention of the media like large enterprises, their past history is often unknown, and it is difficult to obtain the integrity information of business owners (the credit information system of the People's Bank of China can only query personal financial Information such as system loans and mortgages, economic information from other and non-financial institutions is difficult to query). Secondly, the inclusion of credit information into the rating indicators is conducive to the construction of social integrity. It is an incentive for integrity and law-abiding, and the interception of fraud and illegal activities, so as to avoid the occurrence of "adverse selection". Third, for certain industries such as medical care, food, health, etc., the credit data of enterprises and business owners is more important, and incorporating this into the index system of the rating is conducive to ensuring the healthy development of the industry. In the rating system, the credit data is quantified, such as score calculation, to form a positive guide for the supervision of food and other industries, which is a beneficial supplement to the regulatory authorities.

2.3. NN Model

The NN model generally includes the two processes of training and prediction [15-16]. The multi-layer perceptual (MLP) NN is a model that is widely used in the field of credit risk management. The model generally consists of an IL and an OL. It is composed of the HL, and different simulated neurons connect the IL and the OL to form the HL, and then according to the variance and minimization principle of the output value and the expected value, the connection weight (CW) between the neurons is continuously adjusted in reverse, so that It is more suitable for dealing with complex nonlinear relationships [17-18].

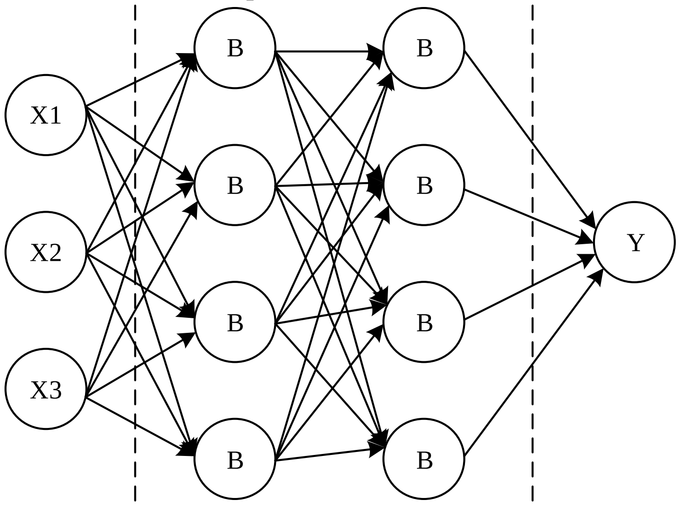

Figure 1. Topological diagram of NN structure

According to the above topology diagram of the NN structure, it can be found that the IL and OL of the NN are separate layers, and the number of nodes is determined according to the specific problem to be solved, but the number of HLs is generally determined by trial and error and method of confirmation. According to Kolmogorov's principle, when the number of HLs in the network is N ⩾ 1, any nonlinear function can be approximated to a certain extent in a closed system by adjusting the number of nodes. When the original data set is $X = [(x^{(1)})^T, (x^{(2)})^T, \Lambda, (x^{(m)})^T]^T$, it means that there are m sample enterprises in the data set, and each sample has n risk characteristic values $x_i = [(x_1^i, x_2^i, \Lambda, x_n^i)]^T$, so there are n neurons in the IL of the corresponding NN model. In this network, the actual parameter θ=(W, b).

When building a NN model, it is generally necessary to set the number of training times, learning efficiency and accuracy, and initialize the number of nodes, CWs bi(l) and thresholds at each level. The calculation process of the model is as follows:

IL:

$$H_j = \int (\sum_{i=1}^{k} w_{ij} X_i - a_j) \qquad i = 1,2,\Lambda, n; j = 1,2,\Lambda, k \tag{1}$$

OL:

$$Y_j = \sum_{j=1}^{k} H_j w_{ij} - b_j, i = 1,2,\Lambda, m \tag{2}$$

Excitation function:

$$\varphi(v) = \frac{1}{1 + \exp(-av)} \tag{3}$$

The parameter α>0 controls its slope. Sigmoid compresses a real-valued input to the range of [0, 1] and can also be used in the OL of binary classification.

Error calculation:

$$E = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \tag{4}$$

When the output error calculated during the training process is greater than the set minimum precision, the model will conduct the error in reverse, and adjust the CW wij between the layers to continue to reduce the error value until the error is less than the minimum precision. Expected training results. The NN model has good nonlinear mapping ability, so it can get rid of the limitation that most traditional statistical prediction models are mostly linear functions. In addition, the model can learn from the sample data in the training set, extract the intrinsic relationship between the data and achieve optimization by continuously adjusting the link weight and threshold, and has high self-learning ability and adaptability. The model can get rid of the drawbacks of over-reliance on empirical knowledge and rules in risk assessment, and alleviate the human factors in the process of determining the weight of indicators. The disadvantage is that it cannot provide a good economic explanation for the output results, which is not conducive to analyzing the substantial relationship between variables.

3. Experimental Study

3.1. Risk Prediction Model Based on NN

The NN can process the information in the nervous system by simulating the form of neurons. The model can reduce the error through continuous training and back propagation to achieve the best classification effect. A general NN consists of an IL, a HL and an OL. There are weight ratios and mapping equations between different layers. The optimal result is obtained by continuously adjusting the threshold and weight during the training process. In the process of model building, the network structure and network parameter setting are mainly considered.

(1) Determine the network structure

Some scholars have proved that under given conditions, a NN with a three-layer structure can approximate any mapping relationship with arbitrary precision. Excessive number of layers and nodes does not necessarily guarantee the reduction of errors, but will affect the length of learning time and the fault tolerance of the model, resulting in a decrease in generalization performance. Therefore, the number of layers of the NN structure constructed in this paper is three layers.

IL: The number of nodes in the IL depends on the number of independent variables. The original data of the indicators in the credit risk evaluation system constructed in this paper are dimensionally reduced and 11 comprehensive influencing factors are selected. Therefore, the number of nodes in the IL is set is 11.

Output layer (OL): The number of nodes in the OL depends on the classification of the dependent variable. The output value defined in this paper is whether the SaMSE in the SC have credit risk. The risky enterprise is assigned a value of 0, and a risk-free enterprise is assigned a value of 1. Therefore, this article Set the number of output nodes to 2.

Hidden layer (HL): At present, there is no uniform standard for the number of nodes in the HL. Scholars have determined the following empirical formula through experience summary:

$$H = \sqrt{I + O} + C \tag{5}$$

Among them, I is the number of nodes in the input layer (IL), O is the number of nodes in the OL, and C is a random number in the range of [0, 10]. After calculation, the ideal number of nodes in this paper is between 4 and 14, and then the optimal number of HL nodes is determined by trial and error method to be 8.

(2) Network parameter settings

①The initial synaptic CW is generally generated by a random number program, and a random number of [-1, 1] is selected as the initial weight value of the synaptic connection.

②The learning rate is generally determined based on experience. Too high a learning rate may lead to an increase in the instability of the network. The learning rate in this paper is set to 0.02.

③Division of training samples and prediction samples, this paper divides the total number of enterprise samples into training set and test set according to the empirical principle of 7:3 in small samples. There is no intersection between the two sets to prevent overfitting in the test set happening.

3.2. The Steps of SME Credit Risk Assessment Based on NN

(1) Collect data extensively, collect initial credit rating indicators, and establish an initial indicator set.

(2) Collect and screen data samples

(3) The initial index set is reduced by the rough set attribute reduction algorithm, and the redundant index is eliminated while ensuring the accuracy, and the final credit index set and the SME credit evaluation index system are established.

(4) Design the network model with the reduced final index set as the pre-system of the BP NN credit risk assessment model. Including: determining the network model structure, initializing the NN structure parameters.

(5) Select an appropriate number of training samples, preprocess the index descriptions that do not meet the conditions, convert them into standard data, and input the sample data into the model to complete network training.

(6) Input a new test evaluation index vector into the trained NN to obtain the NN output vector. According to the output vector, compare with Table 1, determine the evaluation result of enterprise credit risk.

Table 1. Credit ratings and their corresponding risk ratings and their output vectors

Credit rating corresponding risk	Output vector
High (low) A	1000
Medium (medium) B	0100
Low (higher) C	0010
Very low (very high) D	0001

4. Experiment Analysis

4.1. NN Test

Input test samples to train the network, and the detection results are shown in Table 2 below.

Table 2. NN test results

Test sample serial number	Target output (desired output)	Actual output				Credit rating and risk
1	0010	0.39	0.02	0.91	0.13	Low credit rating high risk
2	0001	0.09	0.01	0.23	0.87	Very low credit rating High risk
3	0100	0.02	0.98	0.25	0.05	Medium credit rating medium risk
4	1000	0.98	0.17	0.36	0.09	High credit rating, low risk

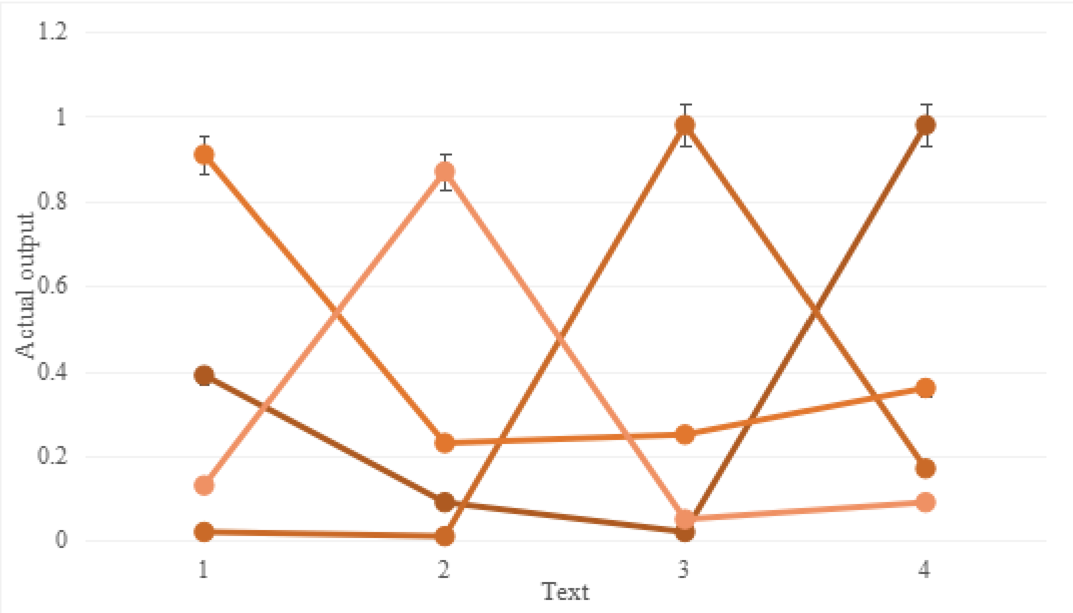

Figure 2. Analysis of NN test results

The test results show that the actual output is basically the same as the target output, and the constructed NN model has good performance and can be used in the real commercial banks to evaluate the credit risk of SMEs.

4.2. NN Model Fitting

(1) NN model fitting results

The initial NN prediction model will have a certain degree of randomness, and the accuracy of a single prediction in predicting the credit risk of SaMSE in the SC lacks reliability. In order to overcome the above problems, this paper conducts multiple cyclic tests on the NN during the training process, and uses a combination of the scaled gradient conjugate method and the gradient descent method in the optimization algorithm to adjust the learning rate and learning boundary multiple times to improve the training efficiency and prevent falling into the local optimal solution. Finally, the NN model is obtained as shown in the following diagram:

Table 3. NN model parameters

Model parameters	Numerical value
IL nodes	11
HL nodes	8
OL nodes	2
Activation function	Sigmoid function
Optimizer	SGD/SCGA
Maximum number of studies	5000
Learning rate	0.02

(2) Comparative analysis of prediction results

The logistic regression model predicts the classification: According to the model classification table 4.8, it can be concluded that the sensitivity of the model is 96.9%, the specificity is 62.1%, and the overall prediction rate of the model is 89.0%. It can be seen from the classification table that the model has relatively low classification accuracy when judging risky enterprises.

Table 4. Logistic model prediction classification table

Measured	Predict			
	Classification of venture companies			Correct
Classification of venture companies		0	1	Percentage
	0	41	25	62.1
	1	7	218	96.9
Overall percentage				89.0

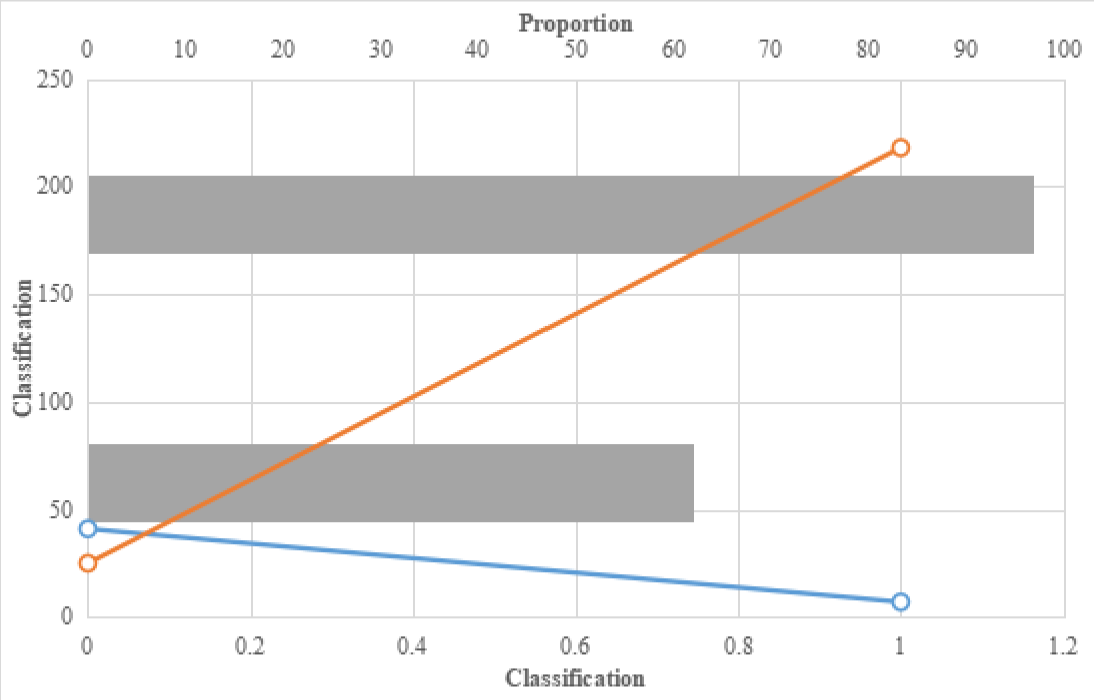

Figure 3. Logistic model prediction classification analysis diagram

The NN model predicts the classification: According to the model classification in Figure 3, it can be concluded that the model has a sensitivity of 93.8% and a specificity of 75.0% in predicting unknown samples, and the overall prediction rate of the model is 89.3%. By comparison, it can be seen that the overall prediction rates of the two models are basically the same. Compared with the Logistic model, the NN model is more accurate in discriminating risk companies.

Table 5. NN model prediction classification table

			Predicted	
Sample	Observed	.00	1.00	Correct percentage
Train	.00	31	16	66%
	1.00	1	159	99%
	Total percentage	16%	85%	92%
Test	.00	15	5	75%
	1.00	4	60	94%
	Total percentage	23%	77%	89%

By comparing the prediction effects of the two models, it can be found that the Logistic regression model is prone to the second type of errors in prediction. The relevant data in the first time will lead to the failure to detect the credit risk of the enterprise in time; secondly, the core enterprises with good strength and high credit rating in the supply chain (SC) have played a role in enhancing the credit of SaMSE, but due to the SC synergy mechanism is still If it is not perfect, it is more prone to credit risk. The NN model has certain advantages in identifying risky enterprises with a small number of samples. The reason may be that the NN model enhances the ability of network nodes to identify their risk characteristics by cyclically testing and training samples.

5. Conclusion

SaMSE play an important role in the economic structure of our country. As the most economically dynamic enterprise group in the market economy, the financing needs of SaMSE are relatively strong. Bad debt losses often set more financing restrictions, resulting in many difficulties for SaMSE to conduct external financing. SC finance can be used as a new financing method to effectively solve the current financing problems of SaMSE. Through the information sharing between enterprises in the SC, core enterprises are introduced to provide credit guarantees for their upstream and downstream cooperative enterprises, which effectively avoids the problem of information inconsistency. Credit risk arising from symmetric and adverse selection. In addition, this new financing model can enhance the control over the use of credit funds, thereby effectively reducing the bad debt risk of financial institutions.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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