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Research on the Application of Customer Value Clustering and Risk Control Technology in the Guarantee System

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Abstract

The paper researchs on the intelligent problem of guarantee system. For traditional guarantee system, because of low efficiency in risk control and mining customer value, increased risk of Guarantee Corporation oans and too long approval cycle results in serious loss of customers. To solve the above problem, put forward a new risk control method based on rough set neural network mode, and use Analytic Hierarchy Process and Activity Based Classification model to achieve customer segmentation. To do simulation with the sample data of 2005-2015 offered by Shenzhen Surety Association. The rough set and Back Propagation to be used in control risk, and the credit approval time is significantly reduce, and with the Analytic Hierarchy Process and Activity Based Classification model is to be achieved customer segmentation, that result in the company profit significantly increases. So the technique presented effectively in this paper.

Key words

Risk Control, Rough Set, Neural Network, Analytic Hierarchy Process.

1. Introductions

With the continuous development of social economy, guarantee corporation's lend business growing quickly but because of the manual loan approval or too long approval time, the customer satisfaction decreases gradually, and causes a serious loss, even causes company bankruptcy.Aim at the above problem, many scholars put forward a number of solutions at home, for example, Professor Lina Wu proposed “the design and implementation of credit guarantee integrated management system, which based on Java” [1-3], but the system didn’t use risk control technology; Professor Hong yuan Wang’s “Design and implementation of experimental system of logistics information management platform based on B/S structure” [4], but the system need too long approval time, that applied difficultly;

Professor Zhao Yang put forward “The Improvement of Customer Relationship Management in Social Networking”[5], whose system calculates customer value from the social network shows lower practicability. Professor Jing Yang put forward “the application research of business function technology in Customer Relationship Management” [6], but did not give a specific implementation process.

Based on the above present situation, the paper puts forward a new risk control method based on rough set neutral net model (Abbreviated RS-BP method), the method can solve the problems of too long approval time and serious loss of customer. The Rough sets back propagation method shakes down a large number of enterprises to find out key index of influencing enterprise credit, and then to use the Back-propagation method to train the index, at last, to establish an effective risk control model which is suiTable for the enterprise. According to the simulation experiment, the Rough sets back propagation method significantly shortens the approval time of Guarantee corporation which under the same accuracy of the approval guarantee.

The paper also puts forward a new customer segmentation method with Analytic Hierarchy Process and Activity Based Classification model (Abbreviated AHP-ABC method), that is, to make a model for all index which influence guarantee corporation profitability, to do quantitative calculation for all index, then to score the customer index weights, which can call the total score “customer value”, then to correct the customer value according to the company profit from each customer In order to get valid customer value, use AHP-ABC classification method shows it is effective.

2. The design of security system based on risk control and customer value segmentation

2.1 Objectives of system design

A business of intelligence security management system, in addition to the guarantee management system common functions, should possess the function of risk control and customer segmentation etc. This system can realize the automatic risk assessment on guarantee enterprise and risk approval and automatic calculation of effective customer index.

2.2 System principle

The guarantee system of business intelligence mainly reflected in two points: 1) realization of risk control, 2) achievement customer segmentation.

2.2.1 Customer segmentation principle

This system realizes the function based on ABC and AHP algorithm [7], which calculates the customer index weight, and obtains the customer value and then corrects the customer values according to the company profit from each customer, so that gets the valid customer value, such as formula (1). At last, classify customer by ABC classification, that finds out the important customers for the enterprise.

Effective value = customer value * the company profit from each customer/**100 (1)**

2.2.2 Risk control theory

The realization of this system function is based combination algorithm [8] of rough set neural network. Because the credit index of the secured enterprise is numerous, to check all index during credit approval will waste too much time. But by rough set theory will simplify the index which can influence credit and find out the key index. Then use the improved BP algorithm method for classification, which will realize automatic and intelligent risk control.

2.3 system architecture

The system is composed of the customer relationship subsystem and the risk control subsystem, the management subsystem for being secured customer and the management subsystem for customer at maturity. For customer at maturity. at first, customers fill out the application form through the website, and then the website system transfer the customer data to the risk control subsystem for loan approval, If the loan approval is passed, the loan will be in management subsystem for being secured customer, when become due, the loan will be in the management subsystem for customer at maturity. And the data of customer relationship subsystem is offered by the risk control subsystem and the management subsystem for customer at maturity.

3. Intelligent security system modeling

3.1 Customer segmentation model

The customer segmentation model is based on AHP and ABC model. The advantages of this model are better than other clustering model, not only because can calculate the value of each customer, but also can correct the customer value according to the company profit from each customer. So that can keep the real valid customer for the company.

3.1.1 Customer value calculation

The customer value calculation model is to evaluate the company's customer index system by analytic hierarchy process. At first, calculate the weight of each index, and score, then calculate the total customer value, namely customer value. Customer index should be evaluated from two aspects: financial and non-financial.

The paper divides all the customers index into two categories in which each category is divided into four degrees, and the index system of enterprise customer evaluation is shown in Table 4. Customer value calculation steps are as follows:

The first step: To classify customer index, is shown in Table 4.

Second step: Constructing judgment matrix. Prior to the construction of the judgment matrix, to understand the judgment matrix quantization table, such as Table 1, and the average random consistency index RI numerical table, as shown in Table 2. Table 3 lists the relationship between customer satisfaction, customer contribution, customer loyalty and customer retention index.

Table 1. Comparison scale a_{ijt} table

A_i than A_j	The Same	Slightly stronger	strong	Much stronger	Absolutely strong
a_{ij}	1	3	5	7	9

In Table 1, 2, 4, 6, 8, and their reciprocal values have similar meanings, get value in the middle above number.

Table 2. The average value of random consistency index *RI*

N	1	2	3	4	5	6	7	8
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41

Judgment matrix W_{21}-W_{21i} show the calculation of single layer weight。

Table 3. Matrix W_{21}-W_{21i}

W_{21}	W_{211}	W_{212}	W_{213}	W_{214}	W_{21}
W_{211}	1	8	5	3	0.560
W_{212}	1/8	5	2	1/4	0.090
W_{213}	1/5	1/2	1	1/5	0.070
W_{214}	1/3	4	5	1	0.280

Third step: Consistency check, to determine the largest eigenvalue of the matrix λ_{max} =4.192, calculate consistency index CI= (λ_{max} -n) / (n-1) =0.064, calculate random consistency index CR=CI/RI=0.071<0.1, we can discriminate the matrix meets the consistency requirements. According to the above method, all the weights and total weights are calculated as shown in table4.

Analytic Hierarchy Process model is often applied to multi-objective, multi criteria, multi factor and multi-level unstructured complex decision making problems, especially strategic decision problems, which has a wide range of practical applications. It is a important method of combining qualitative and quantitative methods which can put a non-structured management problem into semi-structured or structured management problems. At present the method has been applied in various industries and is very mature. This paper also uses the method to solve customer management problems.

Table 4. correspondence of each index

	First-order weight	Second level weight	Third level weight
Enterprise customer value W	Financial indicators W_1	Profit index W_{11}	Economic profit ratio W_{111}
			Profit growth rate W_{112}
			Other business profit margin W_{113}
		Risk index W_{12}	Bad debt ratio W_{121}
			Deposit and loan ratio W_{122}
			fixed assets W_{123}
	Non-financial indicators W_2	Service class index W_{21}	Satisfaction W_{211}
			Contribution degree W_{212}
			Loyalty W_{213}
			Retention W_{214}
		Process index W_{22}	Business effect W_{221}
			Innovation ability W_{222}
			Accident rate W_{223}

		Employee development indicators W_{23}	Management ability W_{231}
			Retention rate W_{232}
			Satisfaction W_{233}
			Training rate W_{234}
			Communication rate W_{235}

Table 5. The weight index table

	First-order weight	Second level weight	Third level weight	Total weight
W=1	W_1=0.38	W_{11}=0.333	W_{111}=0.137	0.018
			W_{112}=0.623	0.079
			W_{113}=0.239	0.030
		W_{12}=0.667	W_{121}=0.568	0.162
			W_{122}=0.334	0.096
			W_{123}=0.098	0.028
	W_2=0.62	$W_{21=}$0.462	W_{211}=0.067	0.016
			W_{212}=0.090	0.020
			W_{213}=0.564	0.126
			W_{214}=0.277	0.062
		$W_{22=}$0.177	W_{221}=0.292	0.032
			W_{222}=0.292	0.032
			W_{223}=0.417	0.046
		$W_{23=}$0.361	W_{231}=0.160	0.041
			W_{232}=0.043	0.011
			W_{233}=0.038	0.010
			W_{234}=0.420	0.106
			W_{235}=0.339	0.086

3.1.2 Customer segmentation

Customer segmentation process:at first, score the indexes of each enterprise, which combined with the weight score, such as Table 4, and got customer value, and then according to the formula (1), obtain effective customer value of each enterprise. Finally, use the ABC model to classify customer according to effective value of customers So as to realize the reservation of key customers and more important customers, which is called the customer segmentation technology for AHP-ABC Specific steps are as follows:

(1) The most important and most tedious step. Refer to the previous section, customer use AHP to calculate the weight of each index.

(2) The various indicators were scored with percentile system, and calculate the profit of each customer's company.

(3) The effective value of each company is calculated according to the formula (1)

(4) According to the effective value of the company, use ABC classification method to classify customer.

(5) According to the classification of customer, determine effective classification measures.

3.2 Risk control model

Risk control model is rough set neural network combination algorithm, referred to as RS-BP algorithm. Rough sets have important applications in the fields of economy, transportation, management, automatic control and so on. The reduction of data by rough set can reduce the input dimension of neural network, thus reducing the time and space complexity of the system. And the neural network has strong anti-interference ability. Therefore, compared with other models, this model has the advantages of fast processing speed, high efficiency and sTable system.

3.2.1 Rough set neural network mode

Rough set (Rough set, RS for short) is a new mathematical method to deal with the uncertainty, which is based on the belief network, genetics, chaos theory, probability theory and fuzzy set. It is a supplement to the method of Soft Computing [9].

Artificial neural network was proposed by Dr. PallWerbas in 1974, the paper uses error back-propagation learning algorithm- BP algorithm with variable learning step. The difference between it and ordinary BP neural network is that it can change the learning step $\eta(t)$, the advantage is to effectively prevent the shock, speed up convergence[10].

Make I_i as the input samples, O_j as output samples, T_i as expect output samples, η as learning rate∈(0, 1), f (x) as a sigmoid function selects the S curve, and ω_{ij} is the weights from the i node to the j node, f '(x) is derived function of f (x), the forward propagation is from the input layer to the output layer of the upper layer, every output layer also is the input of next layer. The relation between the input and output of the formula involved in the forward propagation is shown in the formula (2) and the sigmoid function, as shown in formula (3), Where θ is the offset value.

$$O_j = f(\sum_{i=1}^{n} \omega_{ij} * I_i + \theta_j) \tag{2}$$

$$O = \frac{1}{1 + e^{-I}} \tag{3}$$

Weight adjustment formula:

$$\omega_{ij} = \omega_{ij}(n) + \eta * \delta_j I_i \tag{4}$$

Output node error:

$$\delta_j = (T_i - O_i) * f'(\sum_{i=1}^{n} \omega_{ij} * I_i) \tag{5}$$

For non-output node error:

$$\delta j = f'(\sum_{i=1}^{n} \omega_{ij} * I_i *) * \sum_{i=1}^{n} \delta_k * \omega_{ij} \tag{6}$$

In the traditional BP algorithm, the learning step is a fixed value. in the variable step size algorithm with error rate of change, the learning step is a variable, which is shown by the correction formula (7)

$$\eta(t+1) = \eta(t) - \beta_1 \Delta E / E \tag{7}$$

Where $\eta(t+1)$ is the adjusted step size, $\eta(t)$ for the unadjusted step size, $\beta_1 < 1$ constant, which

$$E(t) = \frac{1}{2}(\sum_{k=1}^{m} T_k t - O_k t) \tag{8}$$

3.2.2 Financial index system and financial management of enterprises

Because of some uncertain factors in the financial indicators, there will be a variety of defects or errors in the process of data collection, these defects or errors are mainly manifested in the following aspects, the first aspect is the data definition which is not unified; the second aspect is the marking error; the third aspect is the record which is empty. So, the raw data must be pre-processed, namely, the data were standardized to fill the empty data and to discretize the continuous data.

Processing these data requires a lot of work. The purpose of discretization of continuous attributes is to simplify data structures, and data discretization techniques can be used to reduce the number of continuous attribute values given. Discretization methods are often used as data mining tools. The common normal assumption is continuous variable, and discretization reduces the dependence on the distribution hypothesis, so discrete data is sometimes more effective.

In this paper, using the financial data of small and medium-sized enterprises in Shenzhen, we select the data of the last ten years. After a simple analysis, found that for a lot of companies, some data is 0 or no record, and the author made a simple deletion of the data, and finally confirmed that the twenty-nine data, that shown in Table 5 are qualified.

Table 5. The index of a financial organization in Shenzhen

Y_1	Return on sales	Y_{11}	Ratio of assets to liabilities	Y_{21}	Long term debt and liquidity ratio
Y_2	Profit income ratio	Y_{12}	Equity ratio	Y_{22}	Non - raised cash to current

					liabilities ratio
Y_3	Net sales rate	Y_{13}	Tangible net debt ratio	Y_{23}	Operating cash and operating liabilities ratio
Y_4	Cost ratio	Y_{14}	Working capital ratio	Y_{24}	Gross profit and operating income ratio
Y_5	Total asset turnover	Y_{15}	Acid test ratio	Y_{25}	Return on equity
Y_6	Fixed asset turnover	Y_{16}	Cash withdrawal rate	Y_{26}	Main cash income ratio
Y_7	Collection ratio	Y_{17}	Ratio of all equity	Y_{27}	Cash flow from operating activities this month
Y_8	inventory turnover	Y_{18}	Sales growth rate	Y_{28}	This month's net cash
Y_9	Assets income rate	Y_{19}	Growth rate of net profit	Y_{29}	Revenue growth ratio
Y_{10}	Return on net assets	Y_{20}	Asset liability ratio	Y_{30}	

In order to reduce these data, we must first deal with these twenty-nine indicators with equal interval classification, namely to classify the data belonging to the same interval into one class of cause maybe in the classification process. There will be some sample data far away from the sample group, and these data should be placed in the final classification, According to the effect of the risk assessment, the effect of credit and credit divided into two categories of credit effect and no credit effect, which is treated by 1 or 0, The interval processing method can refer to the method proposed by Wang Yan[11].

3.2.3 Conditional attribute reduction

The knowledge system R={Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, Y_8, Y_9, Y_{10}, Y_{11}, Y_{12}, Y_{13}, Y_{14}, Y_{15}, Y_{16}, Y_{17}, Y_{18}, Y_{19}, Y_{20}, Y_{21}, Y_{22}, Y_{23}, Y_{24}, Y_{25}, Y_{26}, Y_{27}, Y_{28}, Y_{29}, D} and the value property of conditional attributes C={Y_1, • • •, Y_{29}}, are D.The field of U, and the use of the value of the attribute D on the domain U are divided into U/D. In this paper, the importance algorithm steps of Pawlak[12, 13] are as follows:

1)Calculating the relative D of the C kernel $CORE_D(C)$;

2) $B = CORE_D(C),\ pos_B(D) = pos_c(D),$ Go to 5);

3) $\forall c_i \in C \setminus B,$ calculate attribute importance $sig(c_i, B) = |pos_{B\cup\{c_i\}}(D)| - |pos_B(D)|$, and Obtained $c_m = \arg\max_{c_i \in C\setminus B} sig(c_i, B)$, $B = B \cup \{C_m\}$;

4) IF $pos_{B\cup\{c_i\}}(D) \neq pos_B(D)$, Go to 3);

5) output $B \in RED_C(D)$, implementation end.

3.2.4 Rough set threshold optimization problem

For rough set decision process, rough set theory is through 2 sets and 3 sets of state action to start, the Ω ={X, -X} as the set of States, said an element either belongs to X, or to -X. Conditional probability $P(w_i|x)$, represents the probability that the object x is in the w_i state, The conditional probability $\lambda(a_j|w_i)$ represents the decision loss caused by the occurrence of the behavior a_j in the w_i state; For an object x, the expected loss resulting from the act of a_j is:

$$R(a_j|x) = \sum_{i=1}^{m} \lambda(a_j|w_i)P(w_i|x) \tag{9}$$

Therefore, hypothesis is P(X|[x])=p, Then (9) become (10)

$$R_P = R(a_P\,|\,[x]) = \lambda_{PP}\,p + \lambda_{PN}(1-p)$$
$$R_B = R(a_B\,|\,[x]) = \lambda_{BP}\,p + \lambda_{BN}(1-p)$$
$$R_N = R(a_N\,|\,[x]) = \lambda_{NP}\,p + \lambda_{NN}(1-p) \quad (10)$$

For a given object x, make $\tau(x)$ a regular function for object space to Q, among $\tau(x) \in Q$, suppose f is the total expected loss of decision under the given decision rule τ, its formula can be expressed as:

$$f = \sum_{x \in U} R(\tau(x) \mid x) P(x) \tag{11}$$

Among them, P (x) is the prior probability of x, $R(\tau(x) \mid x)$ is the loss when the state of the object x is $\tau(x)$, U is the domain, according to Bias decision rule, To find the most ideal decision, f must make a minimum.

Let A={a_P, a_N, a_B }, among them, a_P, a_N, a_B were said that the state of a set of elements were into the positive domain, negative region, boundary region respectively, the different operation may cause different losses, therefore, when x belongs to the X collection, when performing a_P, a_N and, a_B operations, the loss respectively is said to λ_{PP}, λ_{NP}, λ_{BP}; When x belongs to the -X collection, when performing a_P, a_N, and, a_B operations, the loss respectively is said to λ_{PN}, λ_{NN}, λ_{BN}.

In the rough set model, the threshold α, β and γ are calculated by 6 loss functions, such as λ_{PP}, λ_{BP}, λ_{NP}, λ_{NN}, λ_{BN} and λ_{PN} etc. In these six functions, one of the most common situation is λ_{PP}=λ_{NN}=0, that is to say the decision risk loss caused by the correct classification decision is 0, which can be concluded: α、β、γ threshold, and only 4, loss function. Then according to the formula (10) can be 4 loss function in order to express:

$$\begin{aligned}
&\lambda_{NN} = \lambda_{PP} = 0 \\
&\lambda_{NP} = \frac{1-\gamma}{\gamma} \lambda_{PN} \\
&\lambda_{BN} = \frac{\beta(\alpha-\gamma)}{\gamma(\alpha-\beta)} \lambda_{PN} \\
&\lambda_{BP} = \frac{(1-\alpha) \bullet (\gamma-\beta)}{\gamma(\alpha-\beta)} \lambda_{PN}
\end{aligned} \tag{12}$$

As can be seen from the equation (10), the loss function can be represented by a threshold such as (α, β, γ) because $\lambda_{PP} = \lambda_{NN} = 0$ and let $\lambda_{PN} = 1$ the total decision risk loss of the formula (11) is:

$$f=\sum_{x\in U}R(\tau(x)\mid x)P(x)$$

$$f=\sum_{p\geq\alpha_i}(1-p_i)+\sum_{p_j\leq\beta}\frac{1-\gamma}{\gamma}\bullet p_j+\varepsilon\bullet\sum_{\beta<p_k<\alpha}[\frac{(1-\alpha)\bullet(\gamma-\beta)}{\gamma\bullet(\alpha-\beta)}\bullet p_k+\frac{\beta\bullet(\alpha-\gamma)}{\gamma\bullet(\alpha-\beta)}\bullet(1-p_k)]$$

$$s.t.\quad 0\leq\beta<\gamma<\alpha\leq 1,\quad \varepsilon\geq 1 \tag{13}$$

where εpunish coefficient in order to prevent the excessive sample into the border area. According to the formula (13) can be seen, this paper will calculate the threshold problem was transformed to the decision risk total loss, as long as can obtain the minimum total loss risk decision problem solution can solve this problem, is the value of the optimal threshold. For the three problem, set the decision threshold into formula (13) optimization problem, the minimum value of the total time in the decision-making risk loss, that is when the optimal threshold, therefore, the central idea of this paper, is the minimum value function for the first, and then take the minimum function value of the solution is. (α, β, γ) is the most appropriate, when the optimal threshold value. In this paper, the optimal threshold generation algorithm based on grid search, is just a method to find the optimal solution. After all the above indicators, we can get

$B=\{Y_3, Y_5, Y_7, Y_8, Y_{10}, Y_{12}, Y_{14}, Y_{16}\}$,

Where Y_3 is net sales rate. Y_5 is total asset turnover Y_7 is collection ratio. Y_8 is inventory turnover. Y_{10} is return on net assets Y_{12} is equity ratio. Y_{14} is working capital ratio、 Y_{16} is cash withdrawal rate etc. 8 indicators.

In order to improve the accuracy and speed of the BP operation, all the data of the enterprise are pre processed, and all the data of the eight indexes are mapped in the [0, 1] interval.

The sample data are more than 50 small and medium-sized enterprises in the trade association database were collected as training data. Using three layers of BP network for training. Because the input data is the numerical type, the neurons in the input layer should be 8, the output is a two dimensional classification problem, the output of neurons is the 1 dimension, the initial learning rate η(t)= 0.9, and the total error of E (K) ≤ 0.001.

The training steps are as follows:

1) BP initialization, the weighted value, the bias value is randomly set of a small number,

you can use a random numbers of uniform distribution, but must ensure that the BP network is not a weighted value of saturation.

2) Choose a data set

$\left\{Y_3{}^k,\ Y_5{}^k,\ Y_7{}^k,\ Y_8{}^k,\ Y_{10}{}^k,\ Y_{12}{}^k,\ Y_{14}{}^k,\ Y_{16}{}^k,\ T^k,\ D\right\}$

Where K is the k^{st} sample, D is decision attribute expectation.

From more than 50 given training data all input will be added to the input layer.

3) The data is transmitted forward through the BP network, and the nodes of the first layer are calculated by formula (2), until all the calculations are finished

4) Calculate the error value of each node in the output layer by formula (5), calculate the error value of each node in each layer by formula (6), until all the calculations are finished.

5) Calculate every sample error and total error if E (W) is less than 0.001, stop, otherwise the go to next step.

6) According to the formula (7) to adjust the learning step.

7) Use weighted correction $\Delta\omega_{ij}^{m} = \eta * \delta_j^m * O_i^{m-1}$ (m for the network level) and the formula (4) to amend all connections.

8) Return to second 2) step.

4. Simulation Results Analysis

4.1 Customer segmentation simulation

In order to examine the difference between the AHP-ABC grouping technology and the traditional method of grouping customers according to the customer profit, it is different from the development of the company. According to customer profit, from the Shenzhen Guarantee Association, selected 10 companies with the same size to count their average profit growth rate of 2000-2015, the data can be found. Before 5 years, using the AHP-ABC clustering technique and traditional customer segmentation technology, the average rate of profit growth is not obvious. With the longer time of implementation and the average growth rate of corporate profits with the AHP-ABC clustering technique will become more apparent.So the AHP-ABC clustering technique is effective as showed in figure 1.

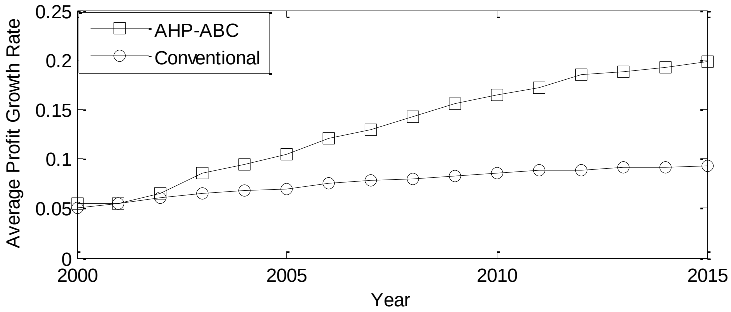

Figure 1. Comparison of AHP-ABC and the traditional customer segmentation technology in The contribution to enterprise profits.

4.2 Risk control simulation

In order to verify the effectiveness of the risk control technology, the RS-BP Model-algorithm is compared with the traditional BP algorithm, select 2000 customer samples from the Shenzhen Institute of guarantee. Figure 2 shows that, with the increase in the number of sample data, the time spent by the RS-BP algorithm is much less than that of the traditional BP classification algorithm.

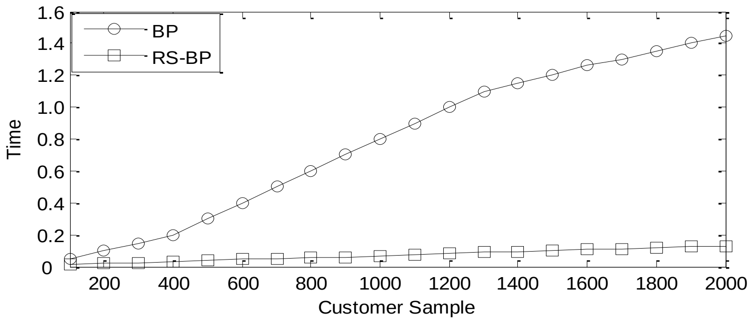

Figure 2. Comparison of RS-BP and BP classification accuracy in spending time

At the same time, we will select 2000 data samples from the Shenzhen security association to test the accuracy of the RS-BP algorithm and the traditional BP algorithm. You can see from Figure 3, in limited data samples, the accuracy of RS-BP algorithm is slightly less than traditional BP algorithm accuracy rate, but when the number of samples increases gradually, especially when the number of test samples is more than 1000, the accuracy rate is basically the same. Therefore, From the risk control simulation, RS-BP risk control technology spent significantly less training time but with the same accuracy, we can say RS-BP risk control technique is effective and has a good practical value for application to credit risk control department of the Credit Guarantee Corporation.

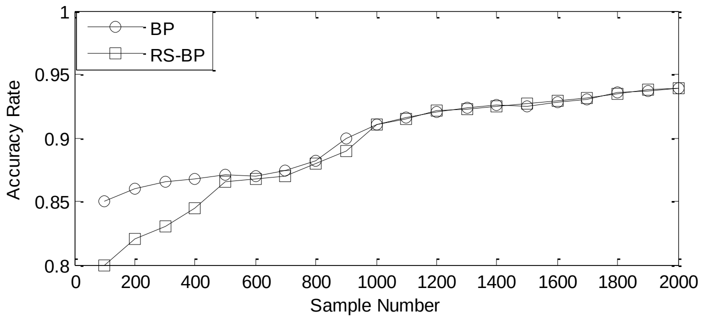

Figure 3. Comparison of RS-BP and BP classification in accuracy

5. Conclusion

As the traditional security management system in the risk control of the processing time is too long, customer segmentation and is not reasonable. This paper proposes a risk control model based on rough set and neural network. The risk control technology is used to reduce the rough set, in the case of keeping the classification attributes unchanged. The index of the enterprise is reduced from 29 to 8, and then these 8 indexes is trained with the BP. The risk control simulation shows, RS-BP risk control technology spent significantly less training time but with the same accuracy, so we can say RS-BP risk control technique is effective in simulation. At the same time, to observe the difference between the AHP-ABC clustering technique and the traditional clustering technology. According to customer profit from the Shenzhen Guarantee Association selected 10 companies with the same size to count their average profit growth rate of 2000-2015, with the longer time of implementation, and the average growth rate of corporate profits with the AHP-ABC clustering technique will become more apparent. So the AHP-ABC Model clustering technique is effective. Therefore, the RS-BP technology and AHP-ABC technology proposed in this paper are better than the traditional BP technology and ABC Technology.

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