Advances in Systems Science and Applications (2012) Vol.12 No.1 18-26

Empirical Analysis of Credit Risk Measure Using Fuzzy Adaptive Neural-Networks:For Small and Medium-Sized Enterprises

Zhichun Xu and Zongjun Wang
School of management, Huazhong University of Science Technology,Wuhan 430074 P.R.China

Abstract
Measuring credit risks of small and medium-sized enterprises should take a series of unique characteristics into consideration. Firstly, non-financial conditions should be combined to produce more accurate evaluation results. Secondly, to overcome the vague of non-financial and sharp boundaries of financial conditions, fuzzy approaches and a nonlinear classifier based on fuzzy adaptive neural-network(hereinafter referred to as "FAN") were introduced. A sample family of 65 firms was collected to test the performance of the above classifier, among which 29 firms were default and 36 firms were good. The result was shown as ROC curves. To compare the performance of the model, the empirical results of another 4 classifiers were shown at the same figures and tables. The results showed that FAN has the best performance and can effectively distinguish the good and default firms.
Keywords Fuzzy Adaptive Neural-Network, Small and Medium-Sized Enterprises, Credit Risk, Non-Financial conditions

1 Introduction

It is well known that small and medium-sized enterprises (SMEs) have a series of unique characteristics differing from large enterprises. For instance, many small and medium-sized and businesses are lack of audited financial statements, and the reliability of their financial statements is doubtful to lenders. Also, non-financial factors of the borrowers have deep impacts on the probability to meet their future obligations. These non-financial factors include the owners' personal finances, as well as other attributes like their morality and beliefs. At last, macroeconomic environments and industry policies have important influence to operating of the firms. Based on the above reasons, when we construct model to measure credit risk of SMEs, the unique characters should been taken serious consideration. In this paper, we will concentrate on these characters and put forward to a nonlinear classifier based on fuzzy adaptive neural-network to solve these problems.(Einstein, 1954).

The paper is structured as follows. The next section provides a survey of the technologies about credit risk modeling for SMEs and related work. Section 3 describes our data set used in the paper. Section 4 presents the feature extraction and the procedure of factors formation. Section 5 discusses the empirical results and analyzes the results together with a comparison between the two methods. We conclude the paper in Section 6.

2 Technologies about Credit Risk Measure for SMEs

Unlike many literatures emphasizing financial conditions, Edmister (1988) claimed that numerical financial ratios and human credit analysis could be combined to produce more accurate evaluation results for credit risk measure. Neglecting the information provided by these qualitative factors might result in undesirable consequences[1]. Based on the judgments, many non-financial conditions were introduced to model the credit risk of SMEs. But the non-financial conditions always were linguistic and vague, they could not be easily treated like financial ratios in linear discriminant models such as MDA and logistic regression model. Even for financial information, the sharp boundaries also need seriously treated[2].To overcome this problem, fuzzy approaches were introduced. Rommelfanger (1999) proposed the use of fuzzy logic to check the credit solvency of small business firms [3]. Weber (1999) used fuzzy logic for credit worthiness evaluation[4]. Syau et al. (2001) used fuzzy membership function to model the credit worthiness of an enterprise[5].

Chen (1999) presented a fuzzy credit-rating approach to deal with the problem arisen from the credit rating table used in Taiwan. The evaluation criteria were modeled as a hierarchical decision structure, and fuzzy integral was employed for aggregating credit information[6]. Resent research has been done by Jiao et al (2007). In their paper, fuzzy adaptive network was used to model the credit rating of small financial enterprises. The data of the credit rating problem was first represented by the use of fuzzy numbers. The network based on inference rules was constructed and was trained or learned by using the fuzzy number training data. Because of the learning and the linguistic representation ability of the fuzzy adaptive network, they showed that it was ideally suited for the modeling of credit rating[2].

Compared to Jian's work (2007), we consider the non-financial information when we classify SMEs by using fuzzy approaches together with neural-network. Furthermore, we conduct factor analysis as a pretreatment process to reduce the complexity and detect structure in the relationships between variables.In addition, we apply analytic Hierarchy Process to get the weights of non-financial conditions. The input vectors have 5 dimensions, the output has only one dimension. The result will show on ROC curves.

3 Data Acquisition

Statistics on SMEs are problematic almost by nature: the majority of them aren't public companies and the financial information together with non-financial information can't be obtained publicly. In contrast to most other Western countries, there is no long official default history that can be used. Only by combining different sources, and expensive and labor-intensive process, can a usable database of default be constructed.

As far as default companies are concerned, we adopt the definition in the Basel Accord II. The Basel II (2004) suggest a conservative definition of default for a bank, that a default is considered to have occurred with regard to a particular obligor when the obligor is past due more than 90 days on any material credit obligation to the banking group, or the bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security.

The accounting data used in this study are collected by a State-Owned bank's Credit Management System. Because the systems have been run since 2002, we get the data in the period between 2002 and 2008. When a firm is granted a credit rating by the bank, the bank's loan managers are obliged to register their customers' fixed information at first time together with accounting report each quarter of every year. During the period of 2002 to 2008, a total of 65 loans are selected. The data set comprises of 36 good loans (GL) and 29 bad (or default) loans (BL). All loans are under the normal loan scheme. All of the 65 loans correspond to 65 firms. The financial conditions are collected from the Credit Management System. The ratios are calculated based on the data in the balance sheets and income statements. The ratios of the default firms are calculated by the data of the years before default. The ratios of the good firms are computed by the newest data we can get. To obtain the objective evidence according to a company's non-financial conditions, a reliable way is to collect the views of experienced bank loan officers who are asked to assess the degree of each information source using five linguistic terms, namely"very good","good","fair","bar", and"very bad". We collect the 65 firms' basic information, and select 12 factors representing 4 kinds of abilities. The 12 non-financial factors are selected referring to the practices of loan risk classification of Chinese commercial banks. We produce consulting tables and distribute them to 30 bank's account managers and loan officers, and receive 24 answers. The answers are expressed by the above five linguistic. All the financial conditions and non-financial conditions are listed in Table 1.

4 Feature Selection and Factor Formation

Described as above section, the financial conditions listed as Table 1 have 10 items and non-financial conditions have 12 items. If all of them are used as inputs when we train fuzzy adaptive neural network, the nodes in hidden layer will become too large to properly work. In order to reduce the number of variables and to detect structure in the relationships between variables, an effective method to deal with financial conditions is the application of factor analytic techniques. We can combine the variables into several factors and reduce the complexity.

Table 1 Variables used in the model

Financial conditions(F)	**Non-financial conditions**
−−Debt payment ability Debt-to-asset ratio(F1) Quick ratio(F2) Current ratio(F3)	−−debt payment ability(NF1) Period matching of liabilities and assets(NF11) Ability of financing from outside in time(NF12) Collateral(NF3)
−− Earning ability Return on assets(F4) Return on net sales(F5)	−− Earning ability(NF2) Sustained profitability(NF21) Core Business(NF22) Quality of profit(NF23)
−− Management ability Total assets turnover(F6) Inventory turnover(F7)	−− Management ability(NF3) Innovation ability(NF31) Customer degree of satisfaction(NF32) Equipment and technologies(NF33)
−− Growth ability Sale growth ratio(F8) Net asset growth ratio(F9) Net profit growth ratio(F10)	−−Characteristics of company and owner(NF4) Education degree of the owner(NF41) Moral behavior of the owner(NF42) Specifications of management(NF43)

Differ from those financial conditions can be expressed by numerical ratios, Non-financial conditions are the problem we must seriously consider. As a result, we firstly put our focuses on the fuzzy processing of non-financial information. Similar to the work of Jiao(2007), Our purpose is to get an aggregative score to express the information. In order to get the total score, we should calculate the objective evidence of each information source. To obtain the objective evidence according to a company's non-financial conditions, we get five linguistic expressions by the above section's methods. For the subsequent fuzzy operations, these linguistic terms should be translated into fuzzy numbers. We use five triangular fuzzy numbers to describe these linguistic terms according to a kind of conversion scale. The definitions of these fuzzy numbers are (80, 90, 90), (70, 80, 90), (60, 70, 80), (50, 60, 70), and (50, 50, 70), respectively, as shown in Fig.1. By the fuzzy numbers, we can compute the average numbers of the non-financial conditions of each firm.

It should be noted that another problem is to decide the weighting of each non-financial criterion. Since this weighting depends on the particular problem at a particular time, the decision-maker usually determines it. An effective method to

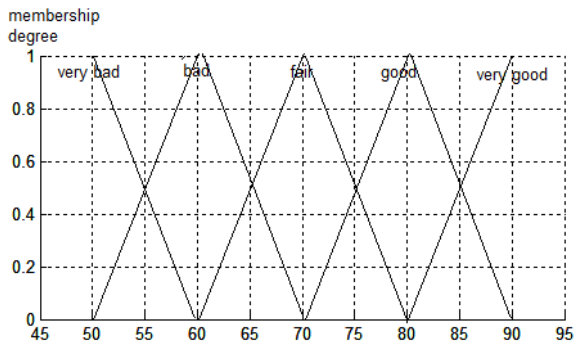

Fig.1 Membership functions of the five rating levels for Non-financial conditions

build up the weighting structure is analytic Hierarchy Process. Since the focus of this paper is to illustrate the application of fuzzy logic and neural network, the process of analytic hierarchy won't be described in detail. We simply give the result in Table 2.

Table 2 Normalized weights for the non-financial conditions category

Variables	NF11	NF12	NF13	NF21	NF2	NF23
Weights	0.23	0.45	0.32	0.25	0.35	0.30
Variables	NF31	NF32	NF33	NF41	NF42	NF43
Weights	0.19	0.23	0.42	0.31	0.53	0.16

Based on fuzzy arithmetic the aggregation of n fuzzy triangular numbers $x_i = \left(x_i{}^L, x_i{}^C, x_i{}^R\right)$,, i=1, 2, 3, .n, with normalized weights $W = (W_1, W_2, \ldots, W_n)$ can be carried out using the following equations:

$$a^C = \sum_{i=1}^{n} w_i x_i{}^c \quad a^L = \sum_{i=1}^{n} w_i x_i{}^L \quad a^R = \sum_{i=1}^{n} w_i x_i{}^R \tag{1}$$

The final aggregated triangular fuzzy number is assumed as $A = \left(a^L, a^C, a^R\right)$.

Using the normalized weights listed in Table 2, the triangular fuzzy numbers for non-financial conditions and E_q. (1), the aggregated triangular fuzzy numbers for the four non-financial conditions categories of each sample can be obtained, respectively.

In order to compare or rank the credit ratings of the fuzzy numbers obtained above, the overall existence ranking index (OERI) will be used. For triangular fuzzy numbers, the overall existence measure OM for fuzzy set A can be written as:

$$OM(A) = \frac{4a^L - a^C + a^R}{4} \tag{2}$$

Using E_q.(2), we can obtain the OERI ratings of each sample company.

We describe the process of feature selection as follows.

Step1. Use factor analytic approach to treat the financial conditions. As a result, we obtain four main components.

Step2. Build up the membership functions of the five rating levels for each non-financial criterion and the result criterion.

Step3. Decide the weights of each criterion using analytic Hierarchy Process.

Step4. Calculate the objective evidence of the four non-financial conditions categories by aggregating the triangular fuzzy numbers and rank the fuzzy numbers using the overall existence ranking index approach. Finally, a ranking numerical value for each sample can be obtained.

Using factor analysis technique, we can combine 10 variables into several main components. By analyzing the data described above, we get four main components representing the four categories respectively. Together with the aggregative score representing the non-financial conditions, we get five factors which represent the characters of a company and construct input vectors with five dimensions.

5 Classification Procedure and Results

Based on the above discussions, every sample company is represented by a five feature vector. The classifier will be constructed by fuzzy adaptive neural network. In order to check the performance of the classifier, a generalized dynamic fuzzy neural network (hereinafter referred to as "GDFNN") introduce by Wu et al.(2007), a common BP neural network and logistical regression classifiers are used to process the data respectively. A method name Round-Robin will be used to extract training samples and checking samples. During every round, N-1 samples are used as training samples and the remaining one is used as checking sample. The process will be repeated until all samples are checked once. The performance of classification will be evaluated by ROC methodology. The experiments were run on Matlab7.0. The results are shown as Fig.2,Fig.3 and Table 3.

By using FAN classifier, the ROC curve line area(AZ) reached 0.959, and corresponding true default rate and false default rate were 89.6% and 11.2%,respectively, and the overall rate of accuracy was 89.2%.

Another classifier is constructed by GDFNN, a General Dynamic Fuzzy Neural Network. The network is constructed based on RBF network and had four layers. The first layer is input layer. The second layer is membership function layer. The third layer is If-then rule layer and the last layer is normalizing layer. The GDFNN is equivalent to TSK fuzzy logic system. The classifier is trained like the above FAN classifier. And the result is shown as Fig.2 either. The ROC curve line area(AZ) reach 0.893, and the overall rate of accuracy is 81.5%.

The classifier BP haven't carried out fuzzy computation, and AZ=0.714, the rate of accuracy is 64.5%. The result of logistic regression classifier is listed as

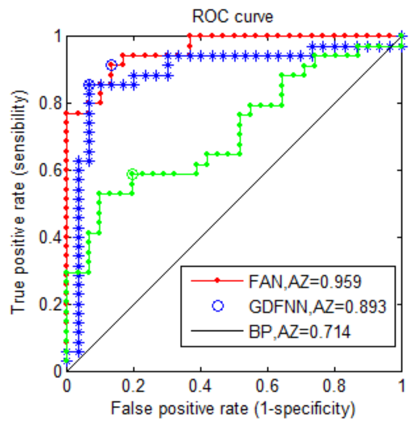

Fig.2 ROC curve created by FAN,GDFNN and BP classifier

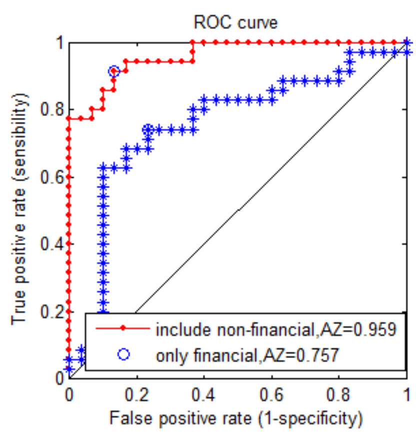

Fig.3 ROC curve created by FAN

Table 3. One can find that the rate of accuracy was lower than FAN and GDFN-N, but higher than BP.

The above four classifiers are tested by financial information and non-financial information. In order to test the effect of non-financial information, we build up a contrast experiment. The classifier is FAN, and the input vectors are conditions including non-financial and not including non-financial condition. The result is shown as ROC curves. The higher curve is for the input with non-financial conditions just as Fig.1, and the lower curve line is for the input without non-financial conditions. The Az is equal to 0.959 and 0.757 respectively. The results show that non-financial conditions can raise the rate of accuracy of default.

Table 3 Classification table

classifier	Observed	Predicted		
		Group	Percentage Correct	
		.00	1.00	
Logistic Regression	Group 0	28	8	77.7
	Group 1	4	25	86.2
	Overall Percentage			81.5
FAN	Group 0	32	4	88.8
	Group 1	3	26	89.2
	Overall Percentage			89.2
GDFF	Group 0	30	6	83.3
	Group 1	6	23	79.3
	Overall Percentage			81.5
BP	Group 0	25	11	69.4
	Group 1	12	17	58.6
	Overall Percentage			64.5

6 Conclusion

Small and medium-sized enterprises have uniquely financial features, models and methods to measure their credit risk need special treatments. In this paper, we have presented that non-financial conditions are helpful to produce more accurate evaluation results. In order to overcome the vague of non-financial and sharp boundaries of financial conditions, fuzzy approaches and a nonlinear classifier fuzzy adaptive neural network are conducted. Our numerical results demonstrated that fuzzy adaptive neural network is ideally suited for the modeling of problems such as credit rating or other financial systems when the variables or even the problem are vaguely defined. In addition, we showed the learning ability can improve the initially represented approximate model as more data become available.

References

[1] R.O. Edmister. (1988), "Combining human credit analysis and numerical credit scoring for business failure prediction", *Akron Business Economic Re-*

view, Vol.19, No.3, pp.6-14.

[2] Y. Jiao, Y.R. Syau, and S.E Lee. (2007), "Modeling credit rating by fuzzy adaptive network", *Mathematical and Computer Modeling*, Vol.45, pp.717-731.

[3] H.J.Rommelfanger. (1999), "Fuzzy logic based systems fro checking credit solvency of small business firms", *Soft Computing in Financial Engineering,* pp.371-387.

[4] R.Weber. (1999), "Applications of fuzzy logic for credit worthiness evaluation", *Soft Computing in Financial Engineering*, pp.388-401.

[5] Y.R. Syau, H.T. Hsieh, E.S. Lee. (2001), "Fuzzy numbers in the credit rating of enterprise financial conditions", *Review of Quatitative Finance and Accounting*, Vol.45, pp.351-360.

[6] L.H. Chen, T.W.Chiou. (1999), "A fuzzy credit rating approach for commercial loans, A Taiwan case, OMEGA international", *Journal of Management Science*, Vol.27, pp.407-419.

Corresponding author
Zhichun Xu can be contacted at: spring0267@yeah.net