Designing Credit Analysis Model of Bank Customers Using Adaptive Neural Fuzzy Reasoning System

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***Abstract*—** The main objective of the research is to reduce banking credit risk and therefore the optimal use of resources and banking facilities which has been possible by model designing in order to rate customers using adaptive neural-fuzzy systems. By study the review of literature, 8 effective variables have been considered for rating customers. The population in this research consists of 450 customers of loaning facilities of Shiraz Saderat Bank in Shiraz in the last five years. A model has been designed by using adaptive neural-fuzzy systems which has been identified by testing data relevant to the customers in 2012, the efficiency of the designed model has been identified in a table including degree of detection, business risk, degree of sensitivity, credit risk and total accuracy. Such values have been obtained and compared for both types of hybrids and back-propagation. Moreover, after the aforesaid test, the model's efficiency is improved by the change of the model's parameters using graphical tools. Degree of detection, sensitivity and total accuracy of the model is 82%, 74% and 80% respectively.

***Keywords*—** Credit risk, adaptive neural fuzzy network, bank.

I. Introduction

In order to distinguish their own customers' needs, banks must identify their characteristics upon granting credit facilities. It leads to reduce banking risks including credit risk by the use of validation (Thomas, 2006). Credit institutions and banks are in need of credit rating system for customers due to two reasons. The credit rating system for customers provide the possibility of reducing credit portfolio risk as much as possible by focusing on such system and based on the available rates along with selecting the most reliable and low-risk customers among the applicants who have demanded facilities. In credit institutions where determination of facility rate is conducted based on risk and credit degree of the customers, credit rating system could assist such organizations in designing their own credit portfolio based on the principle of diversity (Mehrara et al., 2011). Of the solution to solve the problem of failure to repay loans, credit rating of the customers could be mentioned which means the bank grants scores to its customers based on the credit indexes and finally the customers' rate for facility grant is identified considering such scores. In the recent decade, researchers have applied Expert systems, Fuzzy and especially Neural Networks (NN) in order to advance such solution.

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II. Literature Review

Desaei eta al (1997) compared the neural networks, linear discriminate analysis and logistic regression. They concluded they perform better in categorizing loan applicants into good credit and bad credit customers of the neural networks compared to the linear discriminate analysis and they have similar performance comparing to the logistic regression. Some studies have used the theory of fuzzy collections in business and issues related to risk; for example Syau et al. (2001) mentioned they had utilized the theory of fuzzy collections in credit-rating of financial institutes in Taiwan. West in his researches made through studies over five neural network's model (LVQ, RBF, MOE, and MP) and a fuzzy adaptive reasoning in credit scoring procedure. The results of such studies along with traditional statistical methods such as Linera Logistic Regression, K- nearest Neighbor, linear discriminate analysis and decision tree in credit scoring turned to benchmark. In order to evaluate and compare, they collected their data from nine credit institutions, and they took advantages of seven pairs of various training and testing samples collected from these institutions. They applied 500 observations for training and 290 observations for testing two models. The results showed the performance of their fuzzy-neural network model was better than another model. Huffman et al. (2002) used neural-fuzzy and genetic-fuzzy classifiers for credit scoring and they gained positive results from their research. Lee et al. (2002) designed a hybrid system containing neural network and different technics for credit scoring. Discriminate analysis is firstly used in this model to build the credit scoring model, and then their outputs are used as the inputs of the artificial neural networks. The results showed this model had higher accuracy comparing to other traditional models along with having lower type 2 errors. Castillo & Melin (2002) utilized a proficient system by combination with artificial neural network and fuzzy logic in order to predict prices. They made comparison between Mamadani and Sugno's models and reported better efficiency out of Sugno reasoning systems. Additionally, they formed a Sugno model by the use of an adaptive fuzzy-neural reasoning system and used it in forecasting exchange rate (dollar / peso) and they indicated ANN is superior to the common regression methods along with suggesting it in prediction procedure. In addition, they showed ANN holds higher efficiency in certain predictions with short-term horizon (less than one week) comparing to the fuzzy reasoning systems, but the fuzzy reasoning systems perform better in long-term horizons (more than one week). Malhotra & Malhotra (2002) compared efficiency of the adaptive fuzzy-neural reasoning systems with Multiple Discriminate Analysis. They used a pack of 500 data sets (250 good customers and 250 bad customers) in which learning data (model) and testing (control) were selected randomly out of these observations. Their results show the superiority of ANFIS method to MDA. Huang et al. (2004) used algorithm genetic technics and neural networks to solve problems of the credit analysis.

III. Research Questions

- How much is the degree of sensitivity, credit risk, degree of detection and business risk of the designed model?
- How much is the total accuracy of adaptive neural-fuzzy reasoning system?
- How could we identify percentage of the loan paying to the applicants given the conducted analysis on the information of the loan applicants?

IV. Method

The population of this research includes all real customers applying for credit facility from Saderat Bank of Shiraz in the last 5 years. Given the use of fuzzy-neural networks and the statistical models, a number of the bank customers who have the given characteristics should be selected as sample. Facilities which include more partnership, civil partnerships, installment sales and promise of reward are divided into 4 clusters and they are selected simply by random and are used as input of the neural-fuzzy network model. Therefore, data of 200 facility applicants are first of all given to the training system and then data of 100 other applicants are evaluated and tested. The research methodology is developmental-applied due to submission of concepts of the expert system and the neural networks as well as possibility of performing it in the banking system in terms of target and it is analytical-descriptive in terms of performance.

V.Findings

To test the designed ANFIS model, we follow the procedure below: in the relevant M-File, we offer the sub-file which has been saved as “NEWS 3” by the following order to M-File, and then this file will be available as ANFISI afterwards:

```
ANFIS1= readfis ('New3');
```

The below orders lead to train information related to 200 first applicants by the file adjustments of ANFISI to designed ANFIS model and the output of the designed model in located in TrainOutput:

```
Train Outputs = evalfis (Train Inputs, ANFIS1);
```

Moreover, the below orders lead to test information related to 100 other applicants in the designed model and to place results in Test Outputs:

```
Test Outputs = evalfis (Test Inputs, ANFIS1);
```

Based on the fact that outputs must have one of the two values of one or zero, the below orders are used so that threshold has been considered 0/32 here:

```
Test Outputs (Test Outputs<0.32) = 0;
Test Outputs (Test Outputs>=0.32) = 1;
```

Finally, the following orders have been used to calculate and demonstrate the model’s efficiency including degree of detection, sensitivity and total accuracy from which business risk and credit risk are also calculable:

```
RIGHT=0;
For i=1:100
If (Test Outputs (i) ==Test Targets (i))
RIGHT=RIGHT+1;
End
End
Total Accuracy=RIGHT*100/100;
disp (Total Accuracy);
BAD_ACCOUNT=0;
For i=1:100
If (Test Targets (i) ==1)
BAD_ACCOUNT=BAD_ACCOUNT+1;
End
End
RIGHT=0;
For i=1:100
If (Test Outputs (i) ==Test Targets (i) &&Test Targets (i) ==1)
RIGHT=RIGHT+1;
End
End
Sensitivity Degree=RIGHT*100/BAD_ACCOUNT;
disp(RIGHT*100/BAD_ACCOUNT);
GOOD_ACCOUNT=100-BAD_ACCOUNT;
RIGHT=0;
For i=1:100
If (Test Outputs (i) ==Test Targets (i) &&Test Targets (i) ==0)
RIGHT=RIGHT+1;
End
End
Recognition Degree=RIGHT*100/GOOD_ACCOUNT;
disp (Recognition Degree);
```

Table I shows the efficiency of the designed model with regard to the above parameters.

It should be noted that according to the degree of detection, sensitivity or total accuracy with change in the threshold value, the percentages above are subject to change.

Figures 1 and 2 show target output values (collected from the bank) comparing to the output values obtained from the designed model in this research in certain diagrams for trading data to the model and tested data, respectively.

Figure 3 also shows the normalized graph of the Figure 1 given threshold value, all output values have turned to 0 and 1.

The thing to differentiate this research from the similar studies is to prioritize the applicants' facility receipt as well as percentage of the loans to the applicants which is offered to the bank. Therefore, the amount of the risk is lower even than what's mentioned in table 1. This research has tried to take advantages of the fuzzy capability of the designed model because the fuzzy system is able to calculate the series among bad and good. Therefore, the following orders causes to take necessary use of such property:

TABLE I
EFFICIENCY OF DESIGNED ANFIS MODEL

Total accuracy	Credit risk	Sensitivity degree	Business risk	Degree of Detection	Criteria Training Mode
%80	%26	%74	%18	%82	Hybrid (threshold: 32/0)
%54	%48	%52	%45	%55	Back propagation (threshold: 15/0)

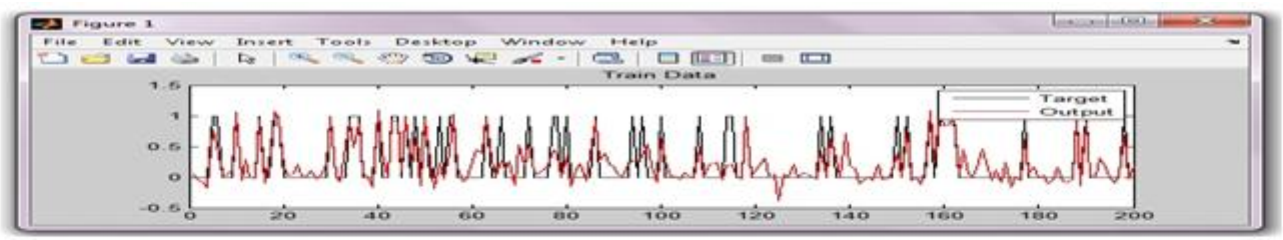

Fig. 1 Diagram of designed ANFIS model training

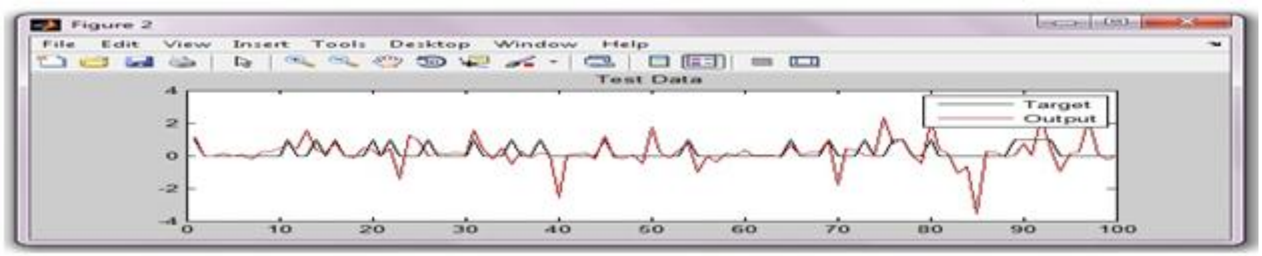

Fig. 2 Diagram of designed ANFIS model testing

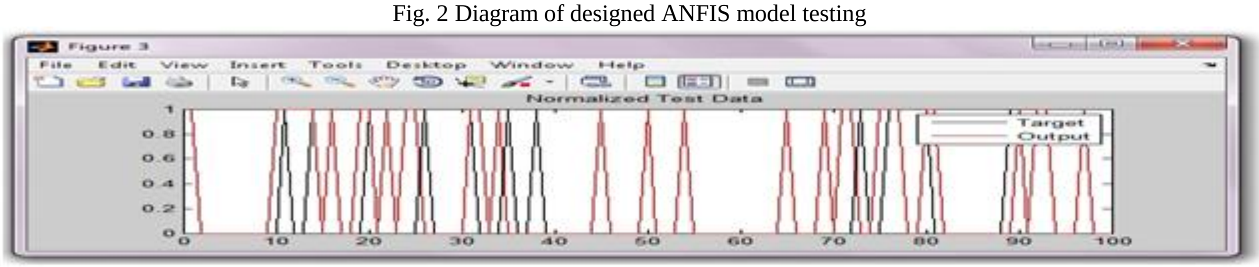

Fig. 3 normalized diagram of Figure 1 by applying a threshold value

```
TestOutputs1=Test Outputs;
TestOutputs2=Test Outputs;
TestOutputs1 (TestOutputs1<0) =0;
TestOutputs1 (TestOutputs1>1) =1;
TestOutputs1=100-floor (TestOutputs1*100);
TestOutputs2 (TestOutputs2>=0.66) =4;
TestOutputs2 (TestOutputs2<0.16) =1;
TestOutputs2 (TestOutputs2<0.32) =2;
TestOutputs2 (TestOutputs2<0.66) =3;
```

As it's shown, the TestOutputs1 array indicates the proposed percentage to the bank for facility granting to the applicant and TestOutputs2 array shows priority of the applicant to receive facilities that one of 1 to 4 facilities is allocated to him/her. Conceptual model of ANFIS system designed can be viewed in Figure 4.

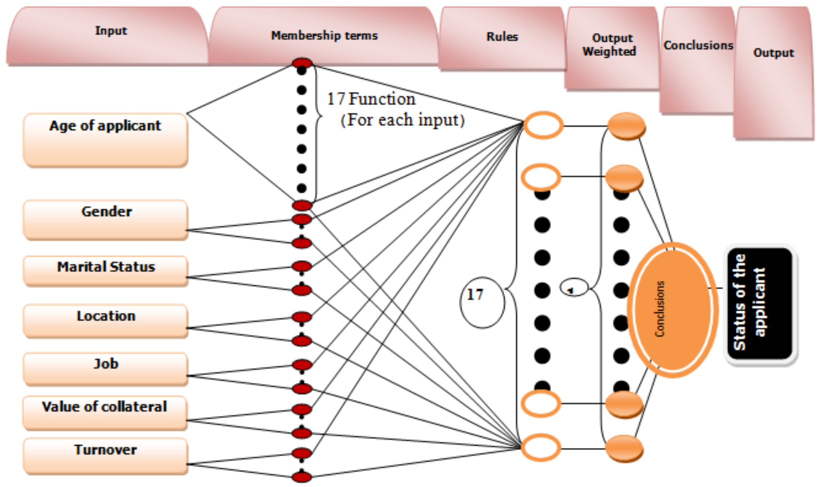

Fig. 4 Conceptual model of designed ANFIS system

VI. Conclusion

The thing to differentiate this research from the similar studies is to prioritize the applicants' facility receipt as well as percentage of the loans to the applicants which is offered to the bank. This research has attempted to take advantages of the fuzzy capability of the designed model as a fuzzy system is capable of calculating certain series between the good and bad. Therefore, the following orders cause to apply such property necessarily. First research question: How much is degree of sensitivity, credit risk, and degree of detection and business risk of the designed model? Degree of sensitivity, credit risk, and degree of detection and business risk of the designed model are 0.82, 0.18, 0.74 and 0.26 respectively. The second research question: How is the accuracy of the adaptive neural fuzzy reasoning system? The total accuracy of the adaptive neural-fuzzy reasoning system is calculated as 0.80 which is considered a high percentage comparing to the previous studies. The third research question: How can we determine the percentage of loan to be pay to applicants given the analysis performed on the loan applicant's data? In the end and before non-fuzzification stage, the figure obtained represents a fraction of the applicant's facility recommended to be paid by the bank. In this research, it's found although similar models may be used in most researches, adjustment of the applied model is highly significant. Examples of certain researches achieved some results relatively lower than this research by the use of ANFIS system in order to validation of loan applicants. Detection of suitable threshold is merely one of these parameters that a proper value could be chosen based on the said materials. Another important result of this research is the fact that in spite of the apparent

Importance, certain inputs may have negative impact on the model's output. However, it seems credit record of the customers is an essential parameter in right identification of the credit applicant's status, it has been shown such value has had no noteworthy importance in this identification. Additionally, it's necessary to point to the importance of graphical tool combination of MATLAB software and coding in M-File in which the benefits of each could complement another's properties. Graphical tools help observing the diagrams easily and adjusting their parameters. On the other hand, coding in M-File enables us to observe diagram of various models altogether as well as compare and analyze them or to repeat the given number of the coded piece and to manage it based on the research objectives.

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