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Bank Client Credit Rating by Multivariate Decision-Making Models, Fuzzy Artificial Intelligence, and Ant Colony

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ABSTRACT

The issue of perceiving behavior of bank clients and how to rate their credit is of the most critical issues which determines how to interact with the client. There are plenty of studies in this field. Numerous features are found in the literature and new studies can distinguish themselves from the rest by focusing on few of these features regardless of the results. Therefore, the most critical features were selected based on consultation with experts and TOPSIS method. Then, optimization of the features was done by ant colony method and based on detecting relationships between them using data mining algorithm and adaptive fuzzy neural network. A hybrid method was introduced to interoperate the concepts of client behavior. The results showed success of the proposed method to predict behavior of the client in the future regarding their credit

KEYWORDS: behavior of bank clients, data mining, adaptive fuzzy neural network system, ant colony, TOPSIS

INTRODUCTION

Taking into account the risks caused by wrong credit decisions, credit risk assessment decisions are critical for finance institutes. It is even a more serious issue as such institutes are experiencing intense competition in recent years. Credit rating is one of appealing fields of research as improvement of monetary flow, credit profiles, and cutting risks bring in more profit to finance institutes. Consequently, several techniques have been introduced to help banks and researchers in credit rating and solving the problem through the assessing process. The purpose of credit rating models is to grant credit or extent credit to trustworthy and credential clients, or to grant credit to clients with poor record. Therefore, credit rating, in general term, is a classification problem.

Since invention of money followed by emergence of banks and popularity of bank loan, the bankers have always tried to answer how to recognize good clients, good investors, and good loan takers. This question have triggered many studies around the world so that their roots can be traced back to humanities, psychology, and moral studies and extended to software engineering, artificial intelligence, and so forth.

Indeed, like any other decision-making problem, the main issue is to distinguish clients based on 0 & 1 logic. In other words, the loan taker is either good or bad. Serious questions can be raised here; what are evidences of goodness and badness? What are the measures of them? What is the effect of each index of the measure? Whether the result should be 0 or 1 or it can be something between them? and many others.

All these questions can inspire a research work and each induces different direction and methodology, which also leads to different results.

Therefore, in a general sense, the model of study is:

$$Y=F(X1, X2,\ldots, Xn)$$

Equation 1: A brief model of client's credit

Where Y is the variable answer that determines credit rating of the loan applicant and of discrete nature as bank customers are divided into two groups regarding credit rating. First group are good clients who are pay their debts on time and before due data.

The second group are the "customers with bad record" who fail to fulfill their obligations regarding the financial facilities they receive. Thus, Y is 0 for the first group and 1 for the second group of customers.

In addition, Xi is an independent variable and one of the factors in success of credit related decisions and choosing the effective indicators on credit risk for further assessment. Throughout two steps, the main indicators were selected by employing factor analysis and based on the experts' judgment. These indicators were then use for assessing performance of the business customers.

Default risk analysis: with the definition of the variable Y, Pi either represents the risk of failure to meet the obligation by the i^{th} customer (Yi=1), or the risk of fulfilling the obligation by the same customer (Yi=0). Thus, the mathematical hope is defined as follows:

$$E(Yi/Xi)=0*P(Yi=0/Xi)+1*P(Yi=1/Xi)=P(Yi=1/Xi)=Pi$$

Equation 2: default risk

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In other words, the expected value of Yi is equal with probability of default by i^{th} customer (Pi). Thus, by estimating default of customers, one can make decision regarding their immediate performance.

LITERATURE REVIEW

Nowadays, credit rating models that employ statistic techniques, operational researches, and AI are widely developed (Thomas, 2000). Credit rating model helps finance institutes to evaluate their credit performance based on characteristics of their customers such as age, income, and marital status (Chen and Hong, 2003). The purpose of credit rating models is to rank the application; those with better financial record as "good credit", and those with not much interesting financial record as "bad credit." Therefore, crediting is a rating problems in nature (India 1981; Sieh, 2004; Lee et al, 2006). When the rating is carried out properly, the applications with higher credit enjoy more profit and those with poor credit have less chance to obtain credit, which eventuate in less loss for the instituted (West, 2000).

Along with development of financial market, banks and credit institutes commission researches on evaluating credit applications using different methods such as linear division analysis (LDA), logic regression analysis (LRA), multivariate adoptive regression spline (MARS), classification and regression tree (CART), artificial neural network (ANN), support vector machine (SVM), and genetic algorithm (GA). LDA and LRA have been widely used in credit rating. Still, LDA is built on assumptions such as linear relationship between independent variables and normal distribution of the variables. It is also criticized for not being able to reach an alignment between the assumptions (Thomas, 2000; West, 2000). LRA is used on a set of data with two-part results. In spite of LDA, it does not rely on normal data distribution; although the both models assume that there is a linear relationship between the variables. That is, these models may fail to achieve required accuracy in rating (Luncher et al., 1995; Lee and Chen, 2005; Thomas 2000; West, 2000).

Recent two decades have been featured with great attention to neural networks in financial forecast studies. Many have worked on these networks due to their high accuracy. Artificial neural networks naturally are based on remanufacturing brain processes in computer environment. Artificial neural networks, in spite of statistical techniques, does not rely on any assumption and shows better performance comparing with LDA and LRA (Abdo, 2008; Chen and Hong, 2003; Desai et al., 1996; Lee and Chen, 2005; Lee et al., 2002; Malhorta and Malhorta, 2003; Sostersik, 2009; Tesai, 2009; and West, 2000). At any rate, artificial neural networks have been criticized in three cases: 1- the time consuming process of developing the architecture of an optimum network; 2- failure to recognize relative weight of potential input variables; 3- the model acts as a black box with no logic or rule regarding input-output estimates. This is to say that the model is not capable of explaining the ruling principles for rejecting decisions (Chen and Hong, 2003; Piramotal, 1999; Tripi and Turban, 1996; West, 2000). Dorand (1941) was first in credit rating using LDA through inquiring differences between bad and good credit groups. Since then, many have tried to use statistic techniques, LDA, and LRA in particular in financial forecast studies (Altman, 1968; Martin, 1977; Mir and Pifer, 1970; Sinki, 1975; West, 1985).

Artificial neural networks have been used for credit rating models since 1990. Desi et al. (1996) proposed a credit rating model using artificial neural networks using a set of data from 1962 customers of a charity institute. Among the available models, artificial neural networks outperform the others especially when it comes to forecast bad credits. Malhorta and Malhorta (2003) found similar results on a set of data from 1078 customers of 12 charity institutes. West (2000) compared performance of five credit rating model using LDA, LRA, *k* of the closest neighbor, default intensity estimate, and CART. He argued that artificial neural networks were successful in credit rating, while LRA can replace them.

Lee et al. (2002) introduced a hybrid credit rating model comprised of artificial neural network and LDA. The hybrid models easily outperformed LDA, LRA, and artificial neural network. Abdu (2008) used participants loan record data and concluded that artificially neural network demonstrate better performance comparing with LDA and LRA. Sinko (2006) showed success of CART on the data of credit cards. Using artificial networks, Negilna (2008) achieved an average 7% error on a data set including small and average sized Italian banks. It was argued by Sostersik et al. (2009) that credit rating models based on artificial neural networks were better than LRA on the customer's credit data when the independents variables are reduced by GA. Chen and Hong (2003) used GA in a the process of transferring three rated credit applications in conditional acceptance group. They concluded that the models that employ CART and MARS on credit data were more effective than LDA, LRA, artificial neural networks, MARS, and MARS-ANN on a set of data of mortgage loans granted by local Thai banks. The best performance was achieved by the artificial neural network, which use heavier variables weighted by MARS. Chong and Leen (2009) obtained performance of LDA, LRA, CART, artificial neural networks, MARS-ANN equal with 76%, 76.5%, 77.5%, 79.5%, and 82.5% respectively. They also used case based reasoning (CBR) and showed that accuracy reached 86%. Tesai et al. (2009) found that artificial neural network and data envelope analysis (DEA) were more successful than LDA, and LRA on the credit data of Taiwanese customers.

Recently a similar rating has been introduced to improve performance of credit rating models. The main idea of this rating is to combine several rating models in one model. West argued that artificial neural network classification model reduced error of a single rating mode to 5 or 3%. Yu (2008) found that artificial neural networks had higher performance than LRA so that artificial neural networks had the best performance among other. In a similar way, a study by Nani and Lumini showed that artificial neural network was the best option among the non-combined models; while the best performance among combined models was obtained by Levenberg-Marquardt's semi-spatial neural network. Tesi held that combined artificial neural network classification had better performance regarding the three sets of data. Sie and Hong (2010) introduced a multi-credit rating model after classifying credit data of German customers in good, bad, and margin groups. Fineli (2011) compared the performance of mutli-credit rating model and found that error-reduction and amplification method outperforms the other models.

Majority of the studies have focused on the theme of whether banks must grant loan to the customers under study or not? The models, which are used for making decision on how to assess the customer's application (e.g. raising credit ceiling) are known as behavioral rating models (Thomas, 2000). Sie (2004) introduced behavioral rating models on credit data using self-organizing graphs of artificial neural network. He classified the customers into three groups and the results were used in deciding about marketing strategy. In another study, Sie (2005) concluded that cluster analyses improve performance of credit rating models, which are based on artificial neural networks.

It is common to used more than one technology of artificial intelligence in combined models of credit rating. Advantage of such models is that strength of each AI technology is accumulated in one model. Fuzzy-neural systems are one of recently introduced artificial intelligence technologies. Few studies have worked on credit rating using these systems. Piramota (1999) found that artificial neural networks are more successful than fuzzy-neural networks; although he emphasized on using fuzzy-neural networks when the way decisions about granting credit are made are under concern. Fuzzy-neural credit rating models were found to be better than the models based on linear analysis in a study by Malhotra and Malhotra (2002). They also analyzed fuzzy-neural credit rating models. Ode et al. (2010) tested credit rating models including artificial neural network and adoptive fuzzy neural deductive system for a data set collected from American banks and acknowledged that bank internal ranking system is essential.

Taking into account the role of credit risk assessment, a surge of research works on the matter was started. First, several statistic analysis and optimization methods such as linear discrimination analysis (Fisher, 1936), logical analysis (Viginton, 1980), comparative analysis (Gerboloskai and Tali, 1981), linear programming (Glor, 1990), integer programming (Mangasarin, 1965), *k* - nearest neighbor (KNN) (Helny and Hend, 1996), cluster tree (Makoski, 1985) were widely used for assessing credit risk and tasks modeling. Although, these methods were mainly used for assessing credit risk, distinguishing good customer from bad customer remained unsolved and natural limitation of the current models can be a subject for future works. Recent studies have demonstrated that AI techniques such as ANN, evolutionary computations, GA, and SVM all have advantages in statistical analysis and the methods for optimizing credit risk in practical results.

Although, all rating methods are used for assessing credit risk, some combined rating techniques comprised of two or more methods have been proved to be a reliable strategy to achieve higher performance specially when it is not easy to develop a strong classification system. Combined modeling is a growing field of credit risk assessment. Recent models are neural discrimination model (Lee et al., 2002), fuzzy-neural model, SVM fuzzy models, and combined neural network model. A review of the credit rating modeling was carried out in recent studies. Many of recent works have approached ANN and fuzzy logic from financial management viewpoint. Gensen (1992) demonstrated using a backward feedback standard neural network for loan rating. He showed that the model was accurate on the test sample between 76 to 80%; although the study used a small sample group comprised of 125 participants. Tom and Kiang (1992) compared ANN with linear rating, language regression model, KNN, and ID3 for forecasting wrong decision in banking industry. They concluded that neural network are far more accurate, flexible, and resilient than other methods. Kot and Fent (1993) showed that, when it comes to determine financial development of companies, neural networks are more efficient than discriminatory analysis. Lacher et al. (1995) used neural networks to estimate future tax health of businesses. Neural networks were used to forecast financial soundness of a financial institute by Salchenberg (1992). He compared neural networks with traditional statistic models and concluded that the former does not need limiting assumptions, while it provides higher accuracy and resilience. Furthermore, Altman et al. (1995) compared performance of neural networks and multiple discriminatory analysis for forecasting soundness of a business. They showed that performance of the former is less than that of the latter. Desai et al. (1996) argued that language regression performance is comparable with that of back feedback networks for rating loan applicants. They stated that more customized architectures are needed to develop general models and rank applicants of credit. Jong et al. (1999) compared advantages of fuzzy-neural systems and neural systems for evaluating credit risk.

Glaserman and Roies-Mata (2006) compared efficiency of Monte-Carlo simulation with combined methods for simulating the factors using loss distribution techniques. Numeral conversion and inversion and estimating saddle point are cause of a portion of errors in calculating conditional default probability. Popularity of the technique explains why a great deal of studies has worked on it.

Glaserman (2008) introduced an algorithm to generate loss distribution, in which two types of parameters were dealt with (respondents to heavy and light default systems assuming independence of debtors in the system). The model uses a combination of the parameters. It can be used in credit assessment of portfolio with 20 to 100 credits for a specific period.

Credit portfolio can be divided into two clusters of credits, each in turn are divided into heavy and light defaults.

The causes of outstanding claims and undue debts of Bank Maskan was studied by Nodehi (1998) for period between 1986-1997. As the results revealed, factors such as market interest rate, difference between facilities interest rate and delay penalty, interest rate of open market, all were effective on the rate of outstanding claims. One thing in common in all the mentioned studies is that macro-economic variables are aligned with profit (loss) of banks.

Ebrahimlu (2005) conducted a practical experience and estimated probability of default by business customers who applied for loan to Bank Saman. The study took the experience as an internal rating process. The rating model was estimated using a sequential probit model and final estimated model classified qualitative and quantitative characteristics of 92 credit customers of the bank in three general groups (good record, undue payments, outstanding). The study represented some rules for credit rating the customers. These rules and the propose model assumed that Bank Saman is capable of pricing the loans and optimizing loan granting process.

Heidari et al. (2010) focused, in their work, on the effects of macro-economy shocks on delayed accounts of banks for time period 2000-2008. They started their work with ARDL model.

Taherizadeh (2010) used reduced models for risk analysis. These models are relatively new and show higher modeling capacity owing to more realistic assumptions comparing with structured models. He analyzed the effect of macro-economic and firm's specific factors in default risk of the customers of a bank. The results revealed that among the first group of the factors, inflation and stock yield and among the second group of the factors, firms debt rate, sale to total assets rate, and default record played a key role.

Since exogenous variables in the model are featured with endogenous effects, VAR model was used to show the dynamic relationships between the variables. In addition, future reaction function was used to survey the effect of reaction to outstanding account in return of economic crisis; while variance analysis was used to analyze stress test. Based on the models of which goodness of fit was ascertained, economic variables shocks caused by implementation of financial and monetary policies (including. inflation, GDP minus oil revenue, money supply volume, facilities interest rate in the term of importance) were effective on outstanding debts of the bank system.

Mohtashami and Salami (2011) used discriminate analysis (DA) to determine the factors, which distinguish low-risk and risky bank customer. They used data of 6000 loans granted to business customers between 1991 and 2004. The results supported the hypothesis which states among credit indicators, credit of the director of the firm, number of bank accounts, creditable guarantor, number of dishonored checks were the main factors in distinguishing good and bad applicants; and among indicators pertinent to facilities, the term, rest time, interest rate, exchangeable installments, number of installments; and among variables pertinent to nature of firms, rural cooperative businesses, limited business to few provinces, regional drought were found as the distinguishing factors.

Bahri (2002) employed statistical models in performance accounting field, which were based on theory of constrains, to measure outstanding account of banks. He identified the factors effective of outstanding costs and ranked them within the framework of system performance accounting.

In late 1970, linear probability and multiple probability situational models for forecasting bankruptcy. Mathematical programming models were also became popular in many research works between 1980 and 1990. Removing limiting assumptions of previous studies, improving reliability and accuracy of classification were the main purposes of these studies. In the early 1990, decision-making support system was used along multiple decision-making systems to solve financial classification problems. Among many, Royder used electre model, Demitras (1998) employed Rogest and Morgan's model for designing credit rating model, and Tracy (1998) used value under risk model to estimate undue payment probability density function.

Neural networks among many, nowadays, have become one of the most accurate analyzing tools. Desai et al. (1996) surveyed capabilities of neural networks and conventional statistical techniques such as linear discriminate analysis, linear regression analysis and WEST in developing credit rating models.

Among the studies in this regard, those by Briant (2001) on using expert systems for evaluating loans to agricultural sector and Lee et al. (2002) to combine neural network and analysis and Lee Venchen (2005) on designing combined two-stage credit discriminate analysis-ranking model (including artificial neural networks (ANN) adaptive-multivariable-Spilinse regression) are notable.

In addition, recent years experienced increase of attention drawn by utilization of genetic algorithms and support vector machines in credit rating fields. Hoan et al. (2006) studied designing two-stage genetic programming and Long Hoang et al. (2007) examined credit rating using support vector machines for credit rating with data mining approach. Although, neural networks and other traditional methods for credit rating need "predicted" information for predicting commercial bankruptcy, developing a credit rating model, in practice, based on financial information based on "actual data" is more fruitful. In the late of 1990, data envelop analysis (DEA) was introduced to "analyze group of peers" with specific financial characteristics that differentiate two or more groups. In spite of multiple discrimination analysis approach, neural networks and linear regression analysis, DEA only relies on actual information of observed set of input/output data – to calculate credit rating. Ye is one of the pioneers of combining DEA and financial ratios analysis. He used DEA for evaluating performance of banks and his experiences showed that DEA in associations with financial ratios analysis is capable of accounting complicated ratios of payments and classifying them in financial aspects of significance. These features enable the analyzer to obtain insight into operational strategies of the bank.

Amol et al. (2003) proposed a credit rating methodology based on DEA. They used current financial information of 82 producing/industrial companies that participated in credit portfolio of one of the biggest banks in Turkey. Based on the findings of literature review, 42 financial ratios were selected in this study and then 6 ratios out of them were selected. Amol et al. obtained from model credit rating with regression analyses that DEA is capable of estimating credit rank of companies and its performance regarding credit rating is satisfactory.

In their study titled "multiple approach to credit rating by using DEA: evaluating loan applicants based on private financial projects" Chan et al. (2007) proposed four multiple approaches. They compared variety of credit rating techniques such as discriminate analysis, data-decision envelope analysis, neural networks and so forth.

Literature of credit rating models showed great emphasis of researchers on accuracy. Credit rating models have been tested by credit institutes and researchers using variety of credit data such as credit cards, loan files, mortgages contracts, SME loans, and guild union loans. It is not easy to find the best model in every fields. Therefore, an advantage of credit rating model can be used in combination with that of other models.

However, there is paucity of studies in novel fields such as combination of multi-criteria decision-making and AI and ANN. Therefore, the present study is an attempt to survey different types of these methods and propose a way to combine them.

METHODOLOGY

This section deals with methodology and the executive steps of the study in details. Methodology refers to a set of rules, tools, and reliable/systematic ways to survey the facts, discover the unknowns, and achieve solutions to the problems (Musakhani et al., 2011).

Any research work is a systematic and methodological attempt to find answers or solutions to a problem. In this regard, research work can be categorized based on their objectives, which in the case of this work, it is an applied work.

As noted in the conclusion of the previous section, majority of the customer's behavior surveys use data mining methods or mathematical-based models. In other words, the researcher tries either to discover patterns used by the customer through data mining or to use mathematical models and assumptions to predict the future. The present study tries to combine these two approaches, which are rooted in different paradigm. The purpose of doing this is to use advantages of the both in detecting behavioral patterns of the customer and use them to determine behavioral features and make decision in this regard. What is highlighted by data mining centered methods is centered on ways to predict relationships, which are used to review the idea of common platform to predict the customer's behavior.

The science of designing was used in this work to reach the goals of the study. This method, by emphasizing on proposing approaches to the problem, tries to make alignment between scientific principles and the solution of the problem. As discussed below, no specific method is in the mind of the researchers, and depending on the nature of the study, the author chooses the best method. The steps of the study are as follows (Pertz 2011, Berfers et al., 2007).

- Determining the problem and trying to find the solution;
- Defining the purposes that the solution (outcome) is designed for it;
- Developing and designing the solution;
- Analyzing usages of the solution;
- Analyzing and evaluating the solution; and
- Sharing experiences of using the solution with managers of business and other researchers.

Given the fact that research method in this work is hybrid and each section needs variety of information, a brief introduction to each section comes next.

First phase deals with surveying and determining variety of the variables found in the literature; then some of these variables are selected for doing the study based on consultation with the experts and multi-criteria decision-making methods (e.g. TOPSIS). Then the study is followed using data mining method with emphasis on available data of the customers. Such data can be collected from customers' databases available in customer relation ward or E-business ward. The data must be up dated periodically and missed values must be at minimum. For this purpose, data mining prediction tool such as neural network can be used. However, since many variables under study are featured with ambiguity and in verbal expression form, using fuzzy variables is inevitable. In light of these two issues, adaptive fuzzy neural network system was used. The key point in this regard is number of layers, number of neurons of each layer, and weight of the arcs that constitute the whole architecture of the network. Although, the architecture can be used by the method itself, it is tried here to use AI (ant colony) to survey different aspects of the architecture and reach an optimized architecture.

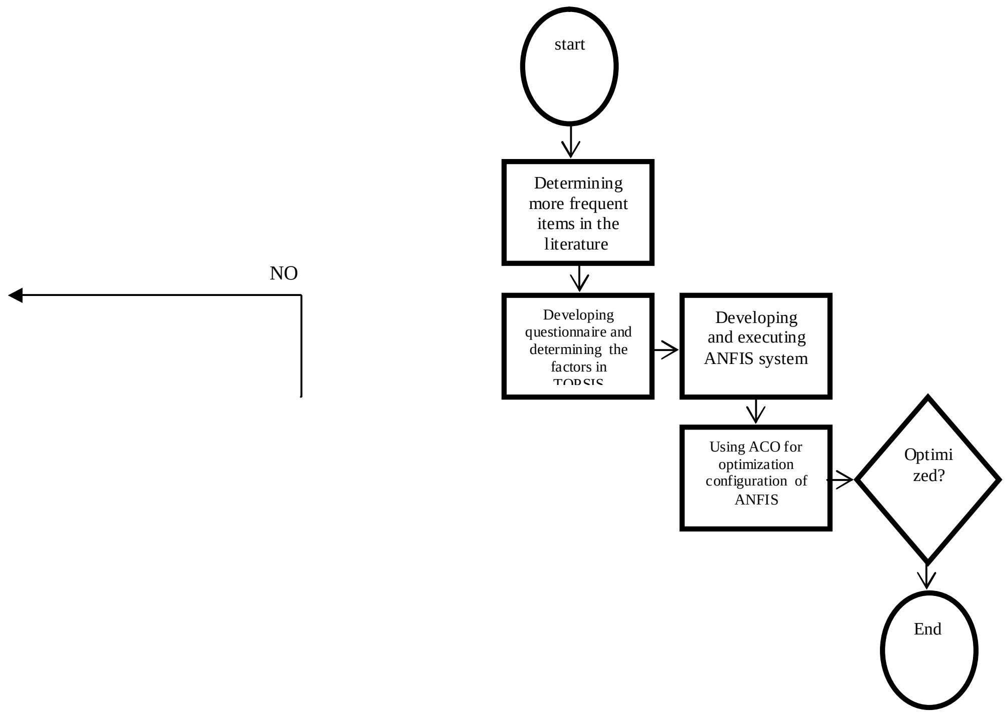

Figure 1- steps of the research

Neural network technique was used in data mining and estimating some the parameters of mathematical model. The technique is capable of learning some of the relationships between phenomena and developing habit of the such behavior. To this end, a structure similar to human neural network, which continuously learns form and interact with its environment, is developed. The following steps must be followed in using neural networks:

- Designing architecture of neural network: number of neurons, layers, hidden layers, and the rest of the features of the network and needed default values of communications (arcs) between the neurons must be determined at this step. This is done with the help of software and eventually ant colony.
- Training: first neurons are given time to use the environment of the problem. To this end, a solved problem is administered to the network so that the network can understand the situation and coordinate its structure with the situation. The point is that this practice must not be overused as it may lead to development of habits by the neurons.
- Final test: having the neurons prepared it is easier to administer larger problems and expect outputs from the network. Through this, number of activated neurons and weight of the arcs are estimated. In the problem under study, accuracy in determining behavior of the customer regarding online purchase can be a reliable performance index.

Implementation of the proposed method and analyzing the results

This section focuses on the results of running the adaptive fuzzy neural network and ant colony on the data collected through analyzing variety of the factors found in the literature.

Factors with higher frequency were first extracted from the literature and then the most important of them were determined by administering a questionnaire to about sixty experts. The obtained information helped us is surveying behavior of improved adaptive fuzzy network by ant colony.

Based on the results from the questionnaire, the most important factors (see the appendix) were age, gender, marital status, number of children, number of household, record of the client with the bank, default of record, using short-term services and band facilities, average number of account opening/average fiscal turnover annually, type of account and withdrawals, job title, type of job, debt to asset ratio, average income and interest of each year, and guarantee (mortgage).

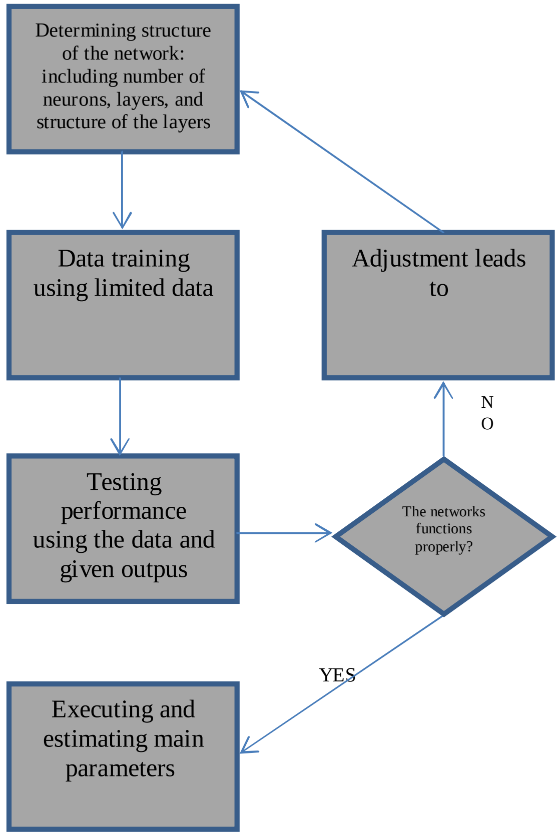

Figure 2- the algorithm

Inclusion of all behavioral items and prediction of future course

It is assumed that all behavioral items have actual programming values. By inserting information of all customers, one can predict future course for each customer. Afterward, given the actual results, performance of the algorithm can be evaluated.

Inclusion of the most effective behavior item and comparing their performance when other items are given

The aspects that are most effective in reducing error of the system are determined using the best architecture by ant colony and adaptive neural fuzzy system. In other words, minimum number of the behavioral items that bring error of the system to a minimum of 5% are determined first and then, it is determine adding what items lead to even more increase of accuracy of the model and decrease of the error.

The results were compared based on the obtained weights and testing few combinations (including the one based on Pareto rule). As explained in the previous section, 30% of the data was used for training, 40% for reviewing and adjustment, and 30% for measuring accuracy. The error level based on different combinations is illustrated by the Figure below.

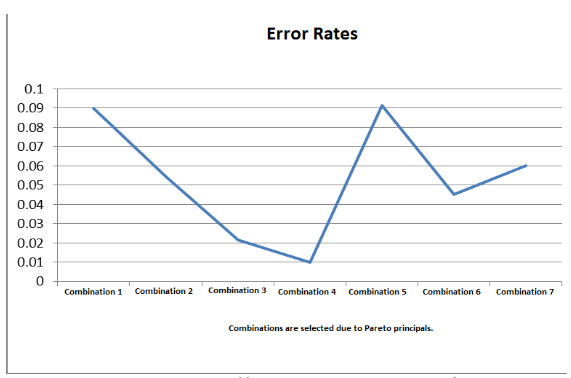

Figure 3- Error level based on different combinations found in the literature

Following Pareto rule (rule 80-20) the 20% that contributed in 80% of the weight were first determined among the combinations. Then, combinations No. 5, 6, and 7 were obtained by removing some of items randomly and combinations 1, 2, and 3 by adding some of items randomly. The Figure above is a clear demonstration of the fact that removing the items increases error and adding the items reduces error level.

There are variety of indices to measure reliability of the model; most important of them were introduced in literature review section. These indices were inserted in the code of the software to achieve an accurate measure to this end. The list of the measures is in Table (1). Following the training stage of each system, the measures were arranged in a table and the system that points to more number of these measures was selected as the optimized system.

Survey of the effect of combined ant colony optimization

Ant colony, as an AI method can be used as a toll for optimizing data mining methods. While the data mining tool strives to offer highest accuracy in discovering relationships and knowledge patterns, ant colony can be used as complementary method to improve performance of data mining technique.

Interaction between the AI algorithm and adaptive fuzzy neural network is similar with utilization of genetic algorithm in simple neural network that leads to an ANN combined method. In the case of ANN, weight of the arcs between the neurons, which is determined by a chromosome in the genetic algorithm, is given to the neural network and then the neuron network is asked to carry out training, evaluation, and modification based on the weights. Majority of the studies have recommended this method.

In this paper, each ant tries to find optimum path so that using different pheromones weights possible arcs between different layers and neurons. By creating an array, which is also implemented in MATLAB R2010a, we can expect the needed inputs for formation of the adaptive fuzzy neuron network.

Although this method is theoretically appealing, using 100 ants with 100 replications does not seem enough to cover the search area given the multiple layers and number of neurons. Therefore, we cannot expect to always reach a better answer than that by adaptive fuzzy neural network. This is illustrated in the Figure below. First, performance of adaptive fuzzy neural network is evaluated with 10 consecutive tests without using ant colony; and then the experiments are repeated with ant colony. The results indicate that the combined method yields better performance in 2 out of 10 (20%) cases.

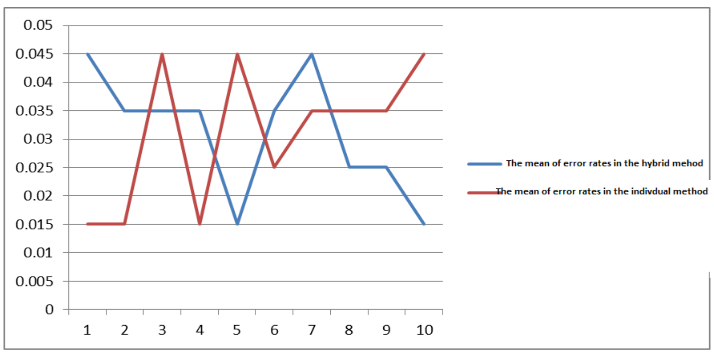

Figure 4- Comparison of performance of adaptive fuzzy neural network and with and without ant colony

Table 1 presents the method employed to measure reliability of adaptive neural fuzzy system

Table 1- comparing adaptive neural network and its combination with ant colony

Optimum value	Range	Reliability measure
The closer to 0, the better	0 - ∞	Sum of Squares due to Errors (SSE)
The closer to 0, the better (excellent <0.1)	0 - ∞	RMSE
0.8<good<0.6 1 < excellent < 0.8	0-1	R^2
0.8<good<0.6 1 < excellent < 0.8	0-1	Adjusted-R^2
The closer to 0, the better	0 - ∞	Mean Squared Error (MSE)
The closer to 0, the better	0 - ∞	Mean Absolute Error (MAE)

RMSE, MSE and MAE were used to measure accuracy of the system and the extent to which the estimates were close to actual values. Value of these indices are compared with each other and in the case of the system under study, the lower the value of each one of the indices in design and training stages, the closer the system to optimum conditions (estimates are closer to actual values). R^2 and adjusted R^2 were used to measure accuracy of the outputs. The latter is better measure than the former to measure accuracy of estimates.

Figure 4 and 5 show goodness of fit of the Figure on the outputs and Figure 6 indicates value of reliability on the training data. The same values are computed for the reliability test data.

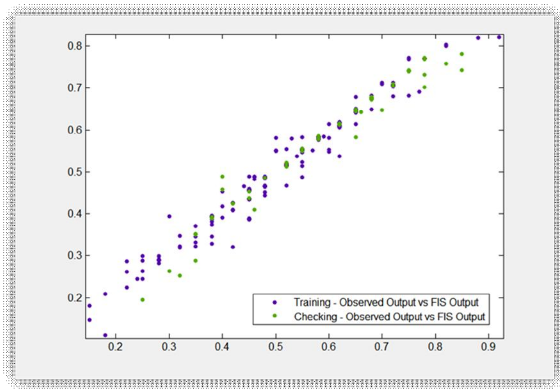

Figure 4- actual values and obtained results by the system based on training and reliability test data

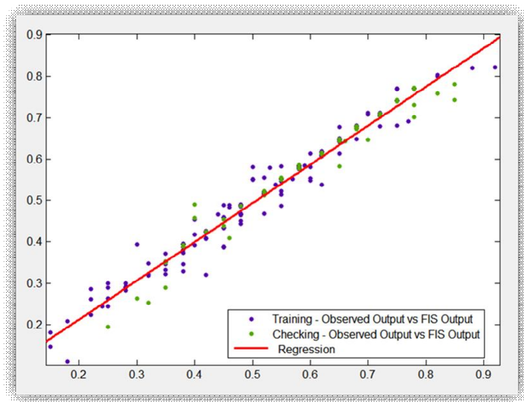

Figure 5- goodness of fit of regression Figure on the training and reliability test data

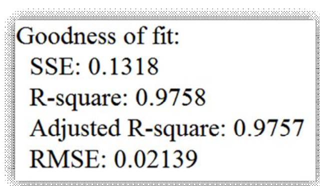
Goodness of fit:
SSE: 0.1318
R-square: 0.9758
Adjusted R-square: 0.9757
RMSE: 0.02139

Figure 6- Results of reliability test obtained by the tool box for the training data

Conclusion and recommendation for future works

Utilization of adaptive neural fuzzy technique to predict default in payment of loan installments in Iran banking system was discussed. Given that majority of conventional techniques, which are based on probability and random processes, do not produce satisfactory results with fuzzy and vague data, this study focused on a wide range of fuzzy methods in the literature. The proposed method was examined with adequate amount of data for training and reliability test with several replications in the software. What distinguishes the present study with other similar works is combination of three techniques. So that advantages of the different methods were employed to cover their shortcomings; although, different viewpoints such as multi-criteria decision making, data mining (for knowledge extraction), and combined optimization algorithm were used. The results indicated that the method can be used to reach a reliable prediction and also assess current situation.

First, the neural network was designed and then 30% of the data were used for training purpose and 60% as test data. Afterward, the configuration was revised and the same data was used to evaluate behavior of the system. The network was assumed ready to work when performance reached 95%. Eventually, remaining 10% of the data was used to evaluate performance of the system, which yielded 89%. That is in 89% of the cases the system can reach a reliable estimate of cost and income of the insured clients.

Therefore, the system can be used as a reliable tool for supporting decision-making process with confidence level of 90%. So that the system can effectively predict default in payment of loan installment using cost and income of the loan takers. To put in another way, the system can be used for the client with an account in the bank and those without any record in the bank.

To answer the questions of the study:

- The main variables can be categorized as individual, financial, and business variables. Therefore, given evident different between the insured clients, not all the variables can be surveyed with the same importance level. Still, the main indices were tested based on final weight of the neural network arc.
- Regarding the second question, efficiency of about 90% can assures reliability of the system. The data-oriented approach of the method, in contrast with mathematical and statistical modeling methods, makes sure that the assumption that lead to simplistic are neglected and only the essence and nature of the problem are dealt with.
- It is possible to convert efficiency of the method to a neural network through specific processes and by proving plenty of data, proper configuration of neural network, adoptive proper training methods and performance assessment. The developed neural network can be used as a reliable backup tool for decision-making.
- The proposed method is distinguishable from other similar methods (limited to data without distortion) introduced in the literature as it function with distorted data or missed values with good performance.

To highlight distinguishing features of the proposed method, Arab Mazad (2006) is notable; where the main detected factors were previous activities, cooperation record, delayed payments, amount of loan, average deposit, account turnover and assets, current ratio, cash ration, total debt to asset ratio, current capital, claim receive period ratio, current debt to specific value ratio. However, due to specific economic condition of the country, financial record of the client is no longer a reliable indicator. Therefore, instead of emphasis on financial leverage by Arab Mazad, we focused on economic and business stability.

Concerning Akhbari et al. (2010) who proposed a fuzzy neural network based method by focusing on financial variables such as current ration, immediate ratio, quick ratio, debt ratio, investment ratio, activity ratio, claims receive period ratio, return ratio of specific value, assets return ratio, profit margin, deposit turnover ratio, specific value to total assets ratio; one may say that retrospective financial indicators are no longer the most important indicators. In other words, several factors that have led to current economic instability are not negligible so that status quo of the industry that the business is active in, situation of similar businesses, and personal characteristics are among important factors to be concerned about.

Data mining technique employed in this study was actually a neural network. Given introduction of novel approaches in data mining literature especially multivariate analysis, new regression and clustering methods and so on, they can be used in combination with neural network or for comparison purposes.

REFERENCES

[1]. Abdou, H. and Pointon, J. (2008) ‘Neural nets versus conventional techniques in credit scoring in Egyptian banking’, Expert Systems with Applications, Vol. 35, pp.1275

[2]. Sustersic, M., Mramor, D. and Zupan, J. (2009) ‘Consumer credit scoring models with limited data’, Expert Systems with Applications, Vol. 36, pp.4736

[3]. Nanni, L. and Lumini, A. (2009) ‘An experimental comparison of ensemble of classifiers for

[4]. bankruptcy prediction and credit scoring’, Expert Systems with Applications, Vol. 36, pp.3028

[5]. Hsieh, N. C. and Hung, L. P. (2010) ‘A data driven ensemble classifier for credit scoring analysis’, Expert Systems with Applications, Vol. 37, pp.534

[6]. Chen, W., Ma, C., and Ma, L., 2009, "Mining the customer credit using hybrid support vector machine technique." Expert Systems with Applications 36(4), 7611-7616.

[7]. Malhotra, R., and Malhotra, D.K. ., 2002, "differentiating between good credits and bad credits using neuro-fuzzy systems." European Journal of Operational Research, 136(1), 190-211.

[8]. Lee, T. S., and Chen, I. F., 2005, "A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines." Expert Systems with Applications 28(4), 743–752

[9]. Hsieh, N. C., 2005, "Hybrid mining approach in the design of credit scoring models." Expert Systems with Applications 28(4), 655–665.

[10]. Chen, F. L., and Li, F. C., 2010, "Combination of feature selection approaches with SVM in credit scoring"Expert Systems with Applications.

[11]. Chen, M.-C. and S.-H. Huang. (2003). Credit scoring and rejected instances reassigning through evolutionary computation techniques. Expert Systems with Applications. 24(4), 433-441.

[12]. Lee, T.-S., et al. (2002). Credit scoring using the hybrid neural discriminant technique. Expert Systems with Applications. 23(3), 245-254.

[13]. Lee, T.S. and I.F. Chen. (2005). A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines. Expert Systems with Applications. 28(4), 743-752.

[14]. Yu, L., Wang, S., and Lai, K. K., 2008a, "Credit risk assessment with a multistage neural network ensemble learning approach." Expert Systems with Applications 34(2), 1434-1444

[15]. West, D., 2000, "Neural network credit scoring models." Computers & Operations Research 27(11-12), 1131-1152

[16]. Chen, M.-C. and S.-H. Huang. (2003). Credit scoring and rejected instances reassigning through evolutionary computation techniques. Expert Systems with Applications. 24(4), 433-441.

[17]. Tsai, M. C., Lin, S. P., Cheng, C. C., and Lin, Y. P., 2009, "The consumer loan default predicting model – An application of DEA–DA and neural network." Expert Systems with Applications, 36(9), 11682–11690

[18]. Altman, E. I., 1968, "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." Journal of Finance, 23(4), 589–609.

[19]. Durand, D., 1941, Risk elements in consumer instalments financing.

[20]. Fisher, R., 1936, "The use of multiple measurements in taxonomic problems." Annals of Eugenics, 7, 179–188.

[21]. Huang, C.L., M.C. Chen, and C.J. Wang. (2007). Credit scoring with a data mining approach based on support vector machines. Expert Systems with Applications. 33(4), 847-856

[22]. Lee, T. S., Chiu, C. C., Lu, C. J. and Chen, I. F. (2002) 'Credit scoring using the hybrid neural discriminant technique', Expert Systems with Applications, Vol. 23, pp.245

[23]. Hand, D.J. and W.E. Henley. (1997). Statistical classification methods in consumer credit scoring: a review. Journal of the Royal Statistical Society: Series A (Statistics in Society). 160(3), 523-541.

[24]. Tam K.Y., Kiang M.Y., (1992) Managerial applications of neural networks: the case of bank failure predictions, Management Science 38, 926-947.

[25]. Makowski P., (1985) Credit scoring branches out, The Credit world, 75, 30-37

[26]. Mangasarian O.L., (1965) Linear and nonlinear separation of patterns by linear programming,

[27]. Operations Research 13, 444-452.

[28]. Desai V.S., Crook J.N., Overstreet G.A., (1996) A comparison of neural networks and linear scoring models in the credit environment, European J. Operational Res.95, 24-37.

[29]. Grablowsky, B. J., & Talley, W. K. (1981). Probit and Jost, A. (1998). Data mining. In: Mays, E. (Ed.), Credit discriminant functions for classifying credit applicants; risk modeling, Glenlake Publishing, Chicago, pp. 129– a comparison. Journal of Economics and Business 33, 154. 254–261.

[30]. Wiginton, J. C. (1980). A note on the comparison of logit and discriminant models of consumer credit behaviour. Journal of Financial and Quantitative Analysis 15, 757–770.

[31]. Glover, F. (1990). Improved Linear programming models for discriminant analysis. Decision Science,21,771–785.

[32]. Dimitras,A.I.,Slowinski, R.,Sunsmaga,R., & Zopounidis, C.(1999).Business failure prediction using rough sets. European Journal of Operational Research, 114 , 263–280.

[33]. Piramuthu, S., "Feature Selection for Credit-Risk Evaluation Decisions," INFORMS Journal on Computing, 11(3), pp. 258-266, 1999.

[34]. Hashemi Nodehi, M.M. (1998). Causes of past due receivables and deferred claims of Maskan Bank.

[35]. Sinkey, Joseph. F. & M.B. Greenwalt, 1991, "Loan-Loss Experience and Risk-Taking Behvior at Large Commercial Banks." Journal of Financial Services Research, 5:43-59.

[36]. Sinkey, Jr., Joseph, F., 2002, "commercial bank financial management", Prentice Hall, New Jersey, USA. p.90

[37]. Mohtashami T, Salami HO.2006. Discriminative factors of civil customers with low risk from customers with high risk on the commercial banks, case study: Agree bank of Iran, college of economic and Agree development, Tehran University

[38]. Paul Glasserman. Measuring Marginal Risk Contributions in Credit Portfolios. Journal of Computational Finance, Vol. 9, No. 2, (Winter 2005/06), pp. 1-41. Winter 2005/06