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NEURO-FUZZY TYPE 2 CLIENT ASSESSMENT SYSTEM

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ABSTRACT

The client assessment is a difficult task for financial establishments. On one hand there is a vast amount of funds that needs to be put into circulation in the retail credit market in order to make profit, and on the other hand a serious effort has to be made towards the client evaluation to secure the return of the capital as well as the interest receivable. The client evaluation methodology vary from one establishment to another and because of the differing assessment criteria and technologies, there is no standard approach towards the problem. There are many different approaches that have been used over the years including statistical techniques and soft computing methods that offer the use of neural network, genetic algorithm and fuzzy logic. The client criteria used in all approaches classify the clients into various groups that reflect their common behavior. Such classification techniques produces distinct boundaries where expert systems experience difficulties in making critical decisions because of the uncertainty caused by client inputs and the resultant scores close to class boundaries. Some expert would call a certain data 'low' while another calls it 'medium'. Because of such paradox, fuzzy logic is inevitably the technology to consider. Fuzzy type 2 logic system is used due to the fact that the fuzzy inputs have uncertain boundaries in defining linguistic quantities. In this thesis a new Neure-Fuzzy-Type 2 (NFT2) client assessment system is introduced and tested where subtractive clustering technique is used for classification of client data for rule extraction. The rules are refined and used in training using feed forward neuro-fuzzy type 2 inference method.

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1. INTRODUCTION

The credit scoring is a complex decision process and due to this complexity, the process of credit scoring is not standardized [5]. There are various conventional loan assessment approaches where the criteria used vary from one financial establishment to another. The structure of the evaluating algorithms used in conventional loan assessment systems provide a result that relays on statistical data. That is, if a client scores a similar assessment results to the one that was previously proven sound then the loan is granted, if not the loan is refused. The rigidness of the evaluation algorithms can very easily ignore the fact that no two clients can be financially and morally the same or reflect similar personal behavior and characteristics. Such algorithms suggest that if a client obtains a high score then he or she qualifies as a sound candidate. A low score will be regarded as not sound and the candidate is rejected. Two of the most commonly used statistical techniques are Linear Discriminant Analysis and Logistic Regression. These are very often employed to benchmark the performance of the others [6]. These techniques leads to an uncertainty described as the classification problem which should be improved [4]. Since the outcome from such techniques is a binary logic then the only improvement can be made is to better decide where to draw the line to distinguish between the good and the bad client. The result can be quite disappointing as the shifting of the distinction line towards 0 (high score) or towards 1 (low score) is only the matter of optimism/pessimism at managerial level. Instead of drawing a solid line between the two classes (good/bad score) the emerging technologies such as fuzzy logic and neural networks methods can be employed to better describe the default risk with a degree.

Hybrid rule base generation methods using soft computing techniques have been widely used for client assessment. These techniques include fuzzy logic (Type 1), Neural Networks, Genetic Algorithm and support vector machines. In recent years data mining techniques were also used for client classification. Clustering techniques (mostly Fuzzy C-Means and Subtractive Clustering) were successfully implemented for data classification and rule extraction purposes.

Due to the fact that the rule bases are constructed using mostly linguistic variables and because different people interpret these variables to different quantitative information, the variables themselves contain uncertainty.

Fuzzy Type 2 sets can be used to handle such uncertainty and help generating a better rule-base to evaluate the client in an efficient way. The notion and properties of Type-2 Fuzzy sets was introduced by Lotfi Zadeh [23] and was further developed in [19], [22]. Fuzzy Type 2 Logic system is particularly useful in survey based data processing where words are interpreted differently by different people.

So far there has not been any work carried out on client assessment using Fuzzy Type-2 Logic. The thesis is aimed at creating a human cognitive rule base using a hybrid system that includes data clustering and neuro-fuzzy-type-2 reasoning.

This thesis is organized as follows. Chapter Two presents the evolution and importance of credit and finance and how risk is handled with most popular convessional client assessment techniques, Linear Discriminant Analysis and Logistic Regression. The chapter also introduces recent work on credit risk assessment using ordinary Type 1 Fuzzy Logic and neuro-fuzzy logic. Chapter Three shows the rule extraction using subtractive clustering. Chapter Four introduces the Fuzzy Type 2 logic principles and its advantages over the ordinary Fuzzy Logic reasoning. Chapter also presents the simulation experiments of the Neuro-Fuzzy Type 2 (NFT2) approach to client assessment problem where comparative results are provided.

2. CREDIT RISC ASSESSMENT

2.1. History and Importance of Consumer Credit

As Lewis (Lewis 1992) records consumer credit has been around for 3000 years since the time of the Babylonians. For the last 750 years of that time there has been an industry in lending to consumers, beginning with the pawn brokers and the usurers of the Middle Ages, but the lending to the mass market of consumers world is a phenomenon of the last fifty years [8]. In the 1920s, Henry Ford and A. P. Sloan had recognized that it was not enough to produce products, like cars, for the mass market but one also had to develop ways of financing their purchase. This led to the development of finance houses, e.g. GE Capital, GM Finance.

The advent of credit cards in the 1960s meant that consumers could finance all their purchases from hair clips to computer chips to holiday trips by credit. Subsequently the growth in credit card purchases was matched by the growth in credit extended by other products such as personal loans, car loans, bank overdrafts, store cards, payment of utilities in arrears, and dwarfed by the growth in consumer credit via mortgage lending. Each of these products has its own unique features, so that financial markets include a mix of credit and interest rate risk in a complex economic and financial environment. Consumer credit is large not only in monetary terms but also in the huge numbers of consumers involved and also the impact on those who are denied consumer credit. Because credit and debit cards are often used in lieu of checks and cash payments there has been an enormous influence on money payment mechanisms. Most of the adult population have some financial product from a bank or other financial institution, and most have more than one.

Major banks typically have millions of customers and carry out billions of transactions per year. The enormity of the role of consumer retail debt is suggested by the fact that the average debt of an individual over all sectors is about one dollar per dollar of disposable income. The growth in consumer credit outstanding over the last fifty years is truly spectacular [8]. The marketplace in the U.S. and Canada for total retail banking and consumer lending is enormous; it exceeds corporate debt by about 75% with household debt in the United States exceeding $8.4 trillion in the year 2002, more than double the amount owed in 1992. This number compares with corporate bond debt in the same period of about $2.5 trillion. Home mortgages and equity loans in the United States account for about 70% of this total (by contrast with 80% in the U.K.) with the next largest categories being credit card and then non-revolving credit, Figure 2.1. In 2002 there were over 500 million credit cards in Europe and the number of transaction was approaching 2,000,000,000. Not all of this growth is because of the borrowing on credit lines. Credit cards (and debit cards) have become increasingly important as a method of money transmission.

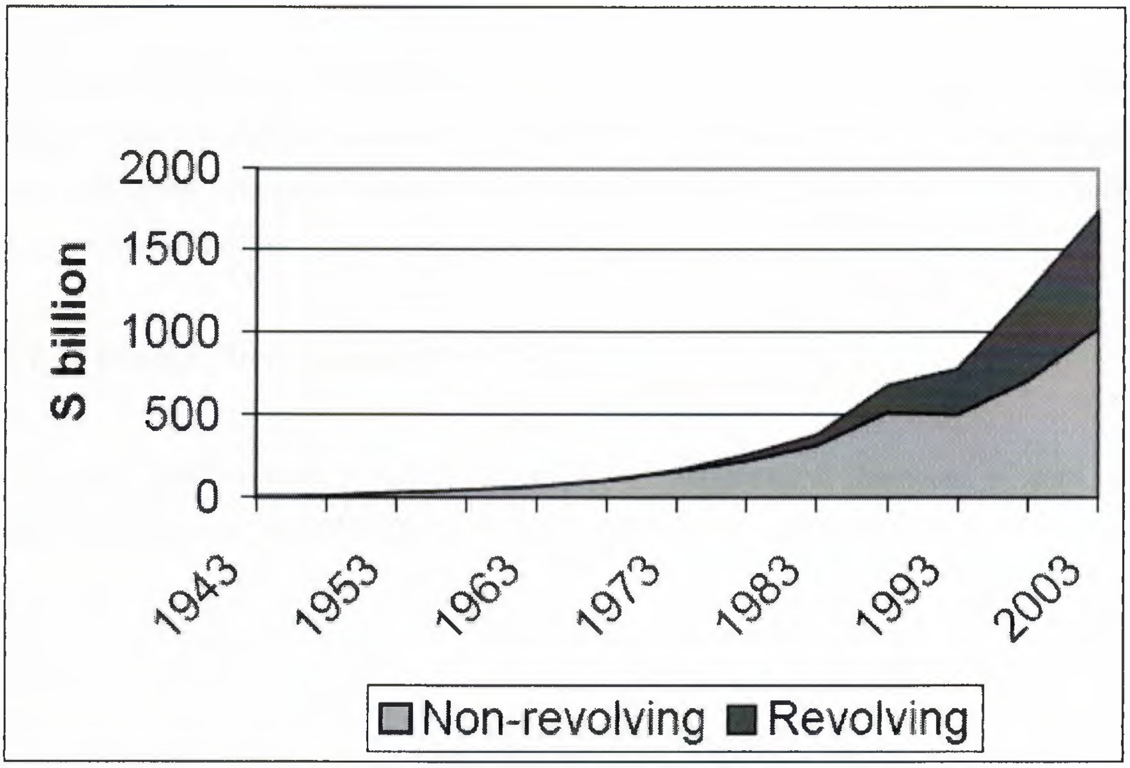


Figure 2.1. Outstanding consumer credit in US 1943-2003

In 1993 in the UK there were 1316 million transactions by plastic card of which 724 million were by credit card compared with 3728 million transactions by cheques. By 2002 plastic card had overtaken cheque usage with 4814 million transactions on plastic cards of which 1687 million were by credit card while there were only 2393 million cheque transactions. Moreover the newer forms of commercial channels like the internet are dominated by credit card usage. Between 1999 and 2002 the number of UK adults using the internet has increased from below 10 million to 26 million, while the number using cards to pay for internet purchase increased from 1.3 million to 11.8 million with a total transaction value of £9 billion. More than 70% of internet payments are by credit card and this percentage is increasing all the time.

The most popular client evaluation system approaches, namely statistical, fuzzy, neural network and neuro-fuzzy are identified in the next section.

2.2. Statistical Models

The popular statistical approaches to credit scoring models, namely Linear Discriminant Analysis and Logistic Regression are conceptually analyzed to show that the algorithms used will result with the probability which could only interpreted as binary values good or no good candidates for granting or not granting loan.

2.2.1. Linear Discriminant Analysis Approach

In Linear Discriminant Analysis technique a mathematical function is used as a discriminating function [3] of the form.

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \tag{2.1}$$

is used, with x_i being the variables describing the data set. The parameters a_i is the discriminating constant between the groups. The variable y is replaced by the weighted class numbers $c_1 = n_2 / (n_1 + n_2)$ and $c_2 = -n_1 / (n_1 + n_2)$ for multiple regressions where the end result is two distinct groups [3] representing the good and bad credit scores.

2.2.2. The Logistic Regression Approach

The Logistic Regression approach to linear discrimination says that p, the probability of default, is related to the application characteristics $X_1, X_2, \cdots X_m$ and hence

$$\log(p/(1-p)) = w_0 + w_1 X_1 + w_2 X_2 + \cdots w_m X_m \quad (2.2)$$

The right hand side of the equation gives a linear score and the lender decides what the cut off **c** will be so that those with score **c** or above are accepted and those with score below **c** are rejected [4]. Linear programming also leads to a score for each person and a cut-off **c** by trying to minimize the errors **e** where for the goods the score should satisfy

$$w_1 X_1 + w_2 X2 + \cdots + w_m X_m \geq c - e \quad (2.3)$$

while for the bads the score should satisfy

$$w_1 X_1 + w_2 X_2 + \cdots + w_m X_m \leq c + e \quad (2.4)$$

Since the above techniques relay on the applicant's characteristics and their interpretation, it is very important that the collected data on a given candidate is accurate and complete. The Table 2.1 below shows a typical candidate information collection used by the statistical loan assessment techniques. The primary resources are the candidate themselves and the public credit information firms.

Table 2.1. Information for consumer credit scoring

Information Resources	Application Forms Public credit information companies	
Information categories and examples	Basic Personal Information	Age, Sex, etc.
	Family information	Marriage status, Number of children, etc.
	Residential information	Status, Number of years at the current address, etc.
	Employment status	Occupation, Number of years in current occupation, etc.
	Financial status	Salary, other assets and expenses, etc.
	Security information	Form and value of securities, etc.
	Information on credit bureau reports	Past payment history, Number of inquiries for information on the applicant, etc.

The popular loan assessment techniques and the data collected for the evaluation of the candidates clearly show that there is a need to improve the interpretation of the probabilistic outcome where the clients are classified as good or bad distinctively.

Although the risk is measured with probabilistic methods using statistical data, it is only effective when great amount of data is collected. Even then the available data may not be sufficient to permit estimating reliably the frequencies of release of risk agents. In general the uncertain feature of risk is related with both randomness and fuzziness [2].

The information collected on a certain client is basically in two folds. Quantitative information like salary, assets, expenses and securities etc. are of course valuable information and can easily be used in statistical risk measurement techniques like Linear Discriminant Analysis and Logistic Regression. The problem arises in the second fold where the information collected from the experts concerned is mostly in linguistic form [1] and can only be interpreted using fuzzy logic.

2.2.3. Fuzzy Logic Approach

A retail loan evaluation system for clients using Fuzzy Logic (FL) was modeled by [7] where 120 real data is used (same data that is used in clustering and NFT2IS later in the thesis) collected in a local bank in Azerbaijan. The linguistic terms which are utilized for the inputs and output are shown in Table 2.2.

Table 2.2. Input-Output terms used in FL approach

Input	**Linguistic terms**
Income Level	Low/Medium/High
Credit History	Bad/Average/Good
Character	Bad/Average/Good
Employment	Short/Medium/Long
Collateral condition	Bad/Average/Good
Output	**Linguistic terms**
Credit Standing	Bad/Average/Good

Input variables "character", "collateral condition" and "credit history" take the values in the range 0 and 1. Input variable "employment" is expressed in years and takes values in the range 0 and 25 while variable "income level" is expressed in US dollars and takes values in the range 0 and 5,000. For input fuzzification, triangular and trapezoidal membership functions are used.

The following procedure is used for the client evaluation system.

1. Fuzzyfication. In the first step the information inputs are fuzzyfied to a certain degree of membership between 0 and 1 in linguistic terms.

2. Knowledge base. The second step consists of creating knowledge base in which all the expert knowledge of input relations and forming a judgmental conclusion is modeled by if-then rules as follows:

If (condition is fulfilled), **Then** (conclusion is valid)

There are several ways to define these rules. Mamdani type fuzzy inference system was used. In this context, the condition consists of several clauses than are connected with one another by a logical operator AND.

3. Aggregation. The next step involves aggregation which is used to combine the outputs of the several rules in order to produce one control output. For a Mamdani inference system, OR operator was used for aggregation.

4. Defuzzification was carried out on the bases of Center Of Gravity (COG).

The inference system described above has 243 rules three of which are listed below.

Rule No.1 ***If*** *Character is "bad" and Collateral condition is "bad" and Credit history is "bad" and Employment period is "short" and Income level is "low",* ***Then*** *Credit standing is "bad" .*

Rule No.215 ***If*** *Character is "good" and Collateral condition is "average" and Credit history is "good" and Employment period is "long" and Income level is "medium",* ***Then*** *Credit standing is "average".*

....

Rule No. 243 ***If*** *Character is "good" and Collateral condition is "good" and Credit history is "good" and Employment period is "long" and Income level is "high",* ***Then*** *Credit standing is "good".*

The system performance was 100% on the client rejects but several disadvantages are present. There are far too many rules in the system which makes the computation costly. Although the sample data is available, learning procedure is not possible from the data in this type of inference system. Furthermore number of rules exceeds the number of test data revealing the fact that one can never be sure that the uncertainty is resolved unless the number of rules reaches the Cartesian product of all inputs.

2.2.4. Neural Network Approach

Financial applications of neural networks (NN) typically focus on pattern matching, classification and forecasting. These functions include mortgage underwriting judgments credit card fraud detection, prediction of corporate bond ratings and the forecasting of credit risk from customer applications [9]. Multilayer perceptron (MLP) is one of the neural network models with broad applications. It is especially suitable for simple pattern classification. When it is used to classify two classes of patterns, this means the two classes of samples are separated by a hyperplane in a high dimension samples space. Rosenblatt proved that the algorithm is convergent if the two classes of patterns are linearly separable (i.e. there exists a hyperplane that separates the two class of samples). MLP have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm.

Basically, error back-propagation learning consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an activity pattern (input vector) is applied to the sensory nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the networks are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule. Specifically, the actual response of the network is subtracted from a desired (target) response to produce an error signal. This error signal is then propagated backward through the network, against the direction of synaptic connections. In credit risk analysis, a structure of MLP includes input layer, single hidden layer and output layer. The input layer consists of the nodes that represent financial indexes. These indexes usually selected by using Main Component Analysis, Profile Analysis, etc. The hidden layer usually uses logistic function or sigmoid function. The output layer generally has one node or two nodes. It produces results of credit risk analysis. Figure 2.2 shows distribution of the samples in the samples space which will be classified.

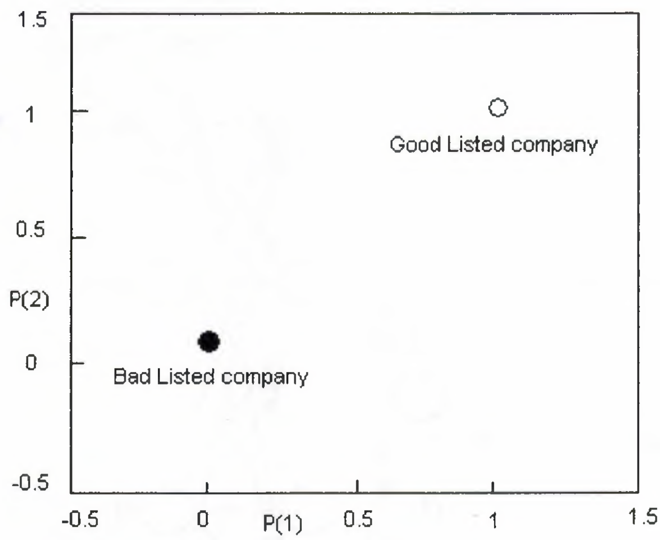


Figure 2.2. Distribution of samples to classify

Figure 2.3 shows a network structure of MLP with four inputs nodes, four hidden neurons, and one output nodes. According to the network structure in Figure 2.3, the neural network credit scoring model can be established as follows.

$$y=\sum_{j=1}^{4} v_j[g(\sum_{i=1}^{4} w_{ji}x_i)+b_j]+b \tag{2.5}$$

The model (2.5) can be expressed by vector as follows

$$y=V[g(W^T X)+B]+b \tag{2.6}$$

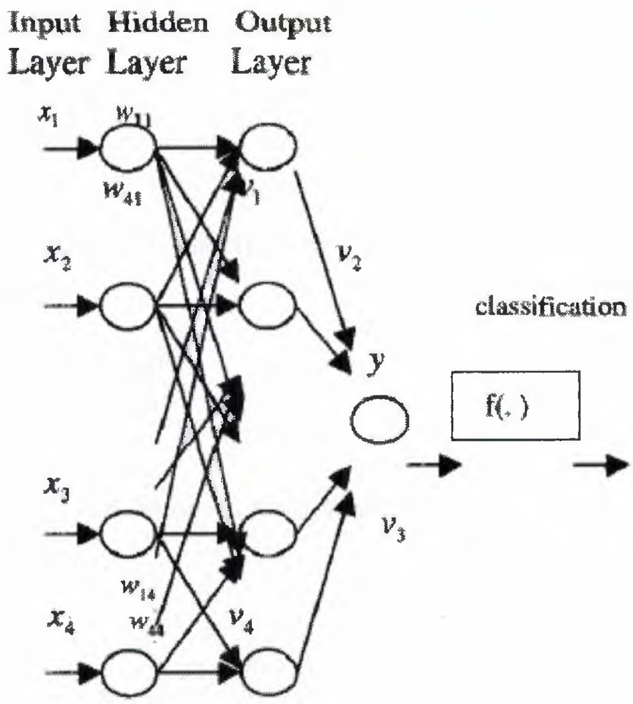


Figure 2.3. The network structure of MLP.

Where $W = (w_{ji}), (i, j = 1,2,3,4)$ is a vector of forward connected weights between the input layer and the hidden layer. $V = (v_1, v_2, v_3, v_4)$ a row vector of forward connected weights between the hidden layer and the output layer. $B = (b_1, b_2, b_3, b_4)^T$ is a vector of bias of the hidden layer and b is a bias of the output layer. $g(h)$ is a transfer function and can be defined by logistic function

$$g(h) = \frac{1}{1+\exp(-h)} \tag{2.8}$$

The classification function is a hardlim function. The hardlim function is defined by

$$a = f(y) = \begin{cases} 1 & y \geq 0 \\ 0 & y < 0 \end{cases} \tag{2.9}$$

Assume the error signal of the output layer in k th epoch is

$$e(k) = t(k) - y(k) \tag{2.10}$$

Then square of the error signal can be expressed by

$$\xi(k) = e(k)^2 = (t(k) - y(k))^2 \tag{2.11}$$

Therefore, the gradient of square of the error signal is

$$\nabla(\xi(k)) = \frac{\partial(e^2(k))}{\partial V(k)} = 2e(k)\frac{\partial e(k)}{\partial V(k)} = -2e(k)\frac{\partial y(k)}{\partial V(k)} \tag{2.12}$$

the partial derivative of $y(k)$ is obtained from model (2.6) as

$$\frac{\partial y(k)}{\partial V(k)} = (g(W(k)^T X) + B(k))^T \tag{2.13}$$

So the gradient of square of the error signal is also expressed by

$$\nabla(\xi(k)) = -2e(k)[g(W(k)^T X) + B(k)]^T \tag{2.14}$$

According to the least-mean-square (LMS) algorithm, the classification update of the connected weights is against the gradient direction. Let η be an update step, then the update of the connected weight can be expressed as

$$\begin{aligned} v(k+1) &= v(k) - \eta\nabla(\xi(k) \\ &= v(k) + 2\eta e(k)\left[g(W(k)^T X) + B(k)\right]^T \end{aligned} \tag{2.15}$$

According to the above statement, the learning algorithm of the neural network credit scoring model as follows:

1. Initialize both connected weight and bias of the neural network respectively (produced by random number). Here s is number of hidden neuron.

$$\begin{aligned} (W, B) &= initp(X, s) \\ (v, b) &= initp(s, t) \end{aligned} \tag{2.16}$$

2. For the value of t of target 1 (or 0). if the value of the algorithm classification a is the same, the iteration is stopped. Otherwise, it needs to update both connected weight and bias between the hidden layer and the output layer in the light of the following formula

$$V(k+1) = V(k) - \eta \nabla(\xi(k))$$
$$= V(k) + 2\eta e(k)\left[g(W(k)^T X) + B(k)\right]^T \tag{2.17}$$

Repeat the second step and continue the process until the error $e(k)$ satisfies the designed precision. Figure 2.4 shows the result of classification where the data samples are distinctly divided into two groups representing "Good" and "Bad" client scores. The NN credit scoring algorithms are generally good classifiers and have arround 95% success in accuracy[9] . Against its high accuracy NN classifiers have a disadvantage of not being transparant to the user and also difficult to see and understand how a particular decision is made.

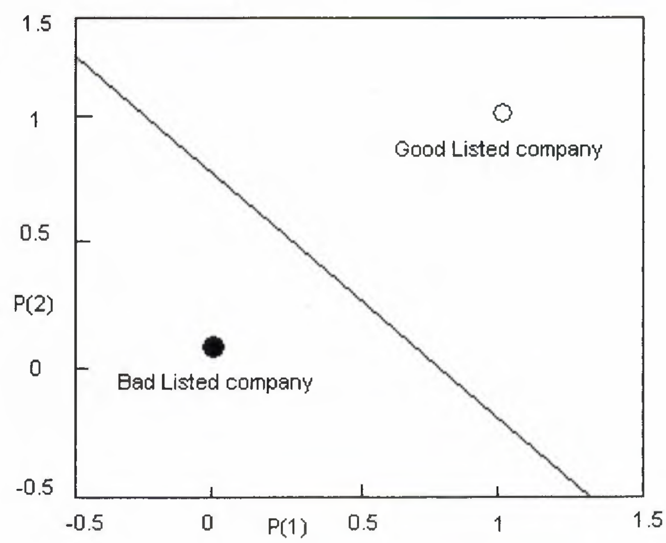


Figure 2.4. Result of the expected classification

2.2.5. Neuro-Fuzzy Approach

The publication on Soft Computing [1] introduces the Neuro-Fuzzy approach to loan assessment evaluation. For providing learning and automatic integrity reinforcement the fuzzy inference is implemented by a Neuro-Fuzzy network. The Neuro-Fuzzy network used is Radial Basis Function (RBF) neural network.The network consists of 3 layers of neurons. The input layer is fed by parameters specifying current customer attributes. The next layer performs normalization of these parameters values to fall into the certain range. Neurons in third layer calculate the distance measure Based on the values of distance measure, the final output, representing the rating value, is calculated.

$$y_j = \sum_i |F_{ji} - x_i| w_{ij} \tag{2.18}$$

The linguistic data provided by expert evaluation is used in fuzzy rules of the following type.

IF F_{11} / w_{11} AND F_{12} / w_{12} AND ... AND F_{1n} / w_{1n} AND ... AND F_{1N} / w_{1N}

THEN D= d_1

IF F_{21} / w_{21} AND F_{22} / w_{22} AND ... AND F_{2n} / w_{2n} AND ... AND F_{2N} / w_{2N}

THEN D= d_2

... ...

IF F_{r1} / w_{r1} AND F_{r2} / w_{r2} AND ... AND F_{rn} / w_{rn} AND ... AND F_{rN} / w_{rN}

THEN D= d_r

... ...

IF F_{R1} / w_{R1} AND F_{R2} / w_{R2} AND ... AND F_{Rn} / w_{Rn} AND ... AND F_{RN} / w_{RN}

THEN D= d_R

Where an element $F_{rn} = \{f_n = v_{rn}\}$ is called an attribute (or feature) and expresses the presence of some attribute (attribute or feature number *n*) in the input (object, event or situation) to be qualified for the output (object class, result event, or control), defined for rule r; f_n is a fuzzy variable taking a value from a set of input fuzzy constant (linguistic terms) $V = \{v_1, v_2, ..., v_M\}$; v_{rn} is a value from set V used in rule r for variable f_n; N is total number of variables; R is the number of fuzzy rules; M is the dimension of fuzzy constant set V; D is the combined output variable; d_r is a fuzzy contribution to output D from rule r; w_{rn} is the importance value of feature F_{rn}. Value of d_r in this case is fuzzy singleton, showing the confidence degree of output r. A simplified rule looks like:

IF
{<Candidate is financially sound>="VERY"}/W=0.6 AND ...
{<Personal guaranties>="GOOD"}/W=0.5 AND ...
{<Talking manner>="AVERAGE"}/W=0.6
THEN
<Loan Rating>="GOOD"

2.3. Review of existing work in clustering and fuzzy type 2 Logic System

There are many instances of upgrading to fuzzy type 2 (FT2) from type 1 as well as new areas of application where uncertainty can not completely be resolved. Fuzzy clustering is a common data mining technique to classify data for initial rule base construction.

In [24] the authors used FT2 sets for linguistic grades of membership. They used FT2 for learning the membership grades thru an adaptive network to evaluate cars where inputs reflects the car's details linguistically and are not quantitative or measurable.

i.e. car maintenance(low,med,hgh,vhgh).

Comfort(low,med,hgh).

The results were found to be satisfactory in the sense that this approach offers the capability to allow linguistic descriptors to be learnt by an adaptive network.

In [25] FT2 logic is proposed for plant monitoring and diagnostics. The concept of the fractal dimension is used to measure the complexity of the time series of relevant variables for the process. A set of type-2 fuzzy rules is used to represent the knowledge for monitoring the process. In the type-2 fuzzy rules, the fractal dimension is used as a linguistic variable to help in recognizing specific patterns in the measured data. The results were compared against the results of using only a traditional type-1 approach.

Experimental results show a significant improvement in the monitoring ability with the type-2 fuzzy logic approach.

Most conventional fuzzy time series models (Type 1 models) utilize only one variable in forecasting. Furthermore, only part of the observations in relation to that variable are used To utilize more of that variable's observations in forecasting,[26] proposes the use of a Type 2 fuzzy time series model. In such a Type 2 model, extra observations are used to enrich or to refine the fuzzy relationships obtained from Type 1 models and then to improve forecasting performance. The Taiwan stock index, the TAIEX, is used as the forecasting target. The study period extends over the 2000–2003 period. The empirical analyses show that Type 2 model outperforms Type 1 model.

[27] presents a connection admission control (CAC) method that uses a type-2 fuzzy logic system to handle linguistic uncertainties. The linguistic knowledge about CAC is obtained from computer network experts. A methodology for representing the linguistic knowledge using type-2 membership functions and processing surveys using type-2 fuzzy logic system is proposed. The type-2 fuzzy logic system provides soft decision boundaries, whereas a type-1 fuzzy logic system provides a hard decision boundary. The soft decision boundaries can coordinate the cell loss ratio (CLR) and bandwidth utilization, which is impossible for the hard decision boundary.

In [28] a new control scheme using type 2 fuzzy neural network and adaptive filter is proposed for controlling nonlinear uncertain systems.Using type 2 fuzzy neural network model combines the type-2 logic system and the neural network. The results shows that the type 2 fuzzy neural network has the ability of universal approximation.
i.e.. identifcation of nonlinearsysiems. A control scheme for nonlinear uncertain systems is introduced. In order to have a better performance of transient response with step input, an adoptive filter has been used to develop two-degree-of-freedom control scheme. The tuning parameters of filter and type-2 fuzzy neural network will change according to the needs by the learning algorithm.The effectiveness of the proposed controller has bee confirmed by some the simulated results. For control of semiconductor manufacturing process, even the system with uncertainty and disturbed by noise the adaptive control scheme performs well.

In pattern recognition authors of [29] used fuzzy type 2 for the classification problem. They used fuzzy type-2 fuzzy sets to handle both fuzzy and random uncertainties in pattern recognition problems. They integrateed fuzzy type-2 fuzzy sets with Markov processes for speech recognition and handwritten Chinese character recognition. Experimental results show that fuzzy type-2 fuzzy sets can improve the classification performance in practical applications.

In [30], a new approach is presented for MPEG variable bit rate (VBR) video modeling and classification using fuzzy techniques. It is demonstrated that a type-2 fuzzy membership function, i.e., a Gaussian membership function with uncertain variance, is most appropriate to model the log-value of I/P/B frame sizes in MPEG VBR video. The fuzzy c-means (FCM) method is used to obtain the mean and standard deviation of I/P/B frame sizes when the frame category is unknown. It proposed to use type-2 fuzzy logic classifiers (FLCs) to classify video traffic using compressed data. Five fuzzy classifiers and a Bayesian classifier are designed for video traffic classification, and the fuzzy classifiers are compared against the Bayesian classifier. Simulation results show that a type-2 fuzzy classifier in which the input is modeled as a type-2 fuzzy set and antecedent membership functions are modeled as type-2 fuzzy sets performs the best of the five classifiers.

[31] examines the application of clustering and Takagi-Sugeno (TS) fuzzy models to the problem of stock-market analysis. Different model structures are evaluated in a case study on the modeling of the Dutch AEX-price index. A scenario-model is used for examining 'what if '-scenario's and a prediction model searches for predictive components in relevant macro economic variables. It is found that TS models can be applied successfully in these areas, due to their capability of approximating general non-linear systems and to their transparency.

Modeling of an industrial drying process into a three-input one-output first order Sugeno system is discussed in [32]. An objective system model is identified from input-output data of the system by applying the subtractive clustering algorithm. The input-output data represents process parameters measured during the drying of starch in a jet spouted dryer. Minimum error models are obtained through enumerative search of clustering parameters. A set of checking data is used to verify the model output. The optimal model, as well as its output, is presented. The step size used in the clustering parameter search is varied and its influence on the modeling performance is presented. Models obtained by setting the same cluster radius for all data dimensions and models obtained by setting a cluster radius for each data dimension are computed and their performance is compared.

Machinability is one of the important properties of a material. It is about cutting the material with maximum metal removal, in shortest time, with best surface finish while having maximum tool life. The high quality of surface finish is very important in order to face the required accuracy and marketing needs. In [33] a technique for modeling a machining process of Alumic-79 with 2 and 4-flutes cutting head is introduced. The optimum parameters, which are feed rate, spindle speed and depth of cut, are found for **2-** flutes and 4-flutes cutting head to obtain a high quality surface finish. The modeling of a machining process using subtractive clustering based second order Sugeno modeling approach is presented. A parametric search on clustering parameters to find the best n-rule model with the least error is performed. Among the best n-rule models, the model that has an acceptable error is picked. Then adaptive-neuro-fuzzy inference system (ANFIS) is used to fine tune the selected model. The optimized machining process parameters (feed rate, spindle speed, and depth of cut) are then determined by using the surface plot of the machining parameters vs. the surface roughness.

In [34] Nine companies listed on China Stock Exchange in the year 2000 are chosen and the following six major financial indexes are considered: net assets yield, net profit per stock, receivables velocity, stock velocity, floating ratio and asset/debt ratio. Using fuzzy dynamic cluster analysis, these 9 listed compnnies are classified into three types: Good, Middle and Bad, then two most important financial indexes in direct ratio to the financial status: net assets yield and receivables velocity are identified. They are abstracted into a subject function representing this type through trapezium distribution. In doing so, a fuzzy cluster evaluation standard is established. Finally, by comparing the Listed Companies being scored with the fuzzy cluster evaluation standard, and according to the maximum subject principle, the credit scoring for the companies can he obtained.

The study in [35] presents a modified neural network based on subtractive clustering (NN-SC). It can be used to estimate the mark-up of construction bidding system. Neural fuzzy approaches are limited for complex and arbitrary in computation and structure. To overcome these drawbacks and have fuzzy inference and self-learning ability NN-SC is proposed. It uses subtractive clustering to generate rules and form rulebase. With rule inference steps, it is convenient to determine the degree of applicability for each rule. Therefore, it has high degree of transparency, compact structure and computational efficiency. And based on neural network, nonlinear mapping between input and output is accomplished. With the simulation, it is proven that the proposed network is valid and has good performance.

3. CLUSTERING AND RULE EXTRACTION

3.1. Client Data

Data obtained from a local bank is analyzed. Out of 6 input data (income, age, work experience, credit history, guarantors and collateral), collateral was ignored due to inaccessible value and overriding effect on all other parameters for decision making using expert knowledge.

The model presented in this paper is using a set of statistical data Table 3.1. For credit history 0 stands for Bad and 1 stands for good position for the client. Similarly client score 0 means denial of credit request and 1 means acceptance of the request.

Table 3.1. Client input-output data.

No	Income	Age	Employment	Guarantors	history	risk
1	1073	29	3	1	0	0
2	893	32	4	2	0	0
3	664	25	2	2	1	1
4	1348	34	2	2	1	1
5	250	20	1	2	1	0
6	400	24	3	1	1	1
7	140	25	1	2	1	0
8	524	39	5	2	1	1
9	662	32	4	1	1	1
10	1695	37	7	1	1	1
11	1743	47	9	1	1	1
12	231	26	2	2	0	0
13	1543	48	6	2	1	1
14	359	27	2	2	1	1
15	944	33	5	1	1	1
16	876	38	3	2	1	1
17	1114	32	5	1	1	1
18	586	28	3	2	1	1
19	1636	50	8	2	1	1
20	1351	36	6	1	1	1

21	277	23	2	2	1	0
22	584	30	2	0	1	0
23	471	25	3	2	1	1
24	355	22	1	1	1	1
25	1000	40	4	2	1	1
26	582	26	3	2	1	1
27	1583	45	10	1	1	1
28	1615	50	7	2	1	1
29	923	42	5	2	1	1
30	2200	38	6	2	1	1
31	344	22	2	2	1	1
32	1296	28	4	1	1	1
33	104	21	1	2	1	0
34	760	24	3	0	0	0
35	2650	56	5	2	1	1
36	713	27	4	1	1	1
37	539	29	3	2	1	1
38	1143	30	5	2	1	1
39	900	26	3	2	1	1
40	650	30	6	1	1	1
41	260	23	1	2	1	0
42	500	27	3	2	1	1
43	450	29	2	2	1	1
44	1126	34	5	2	1	1
45	972	38	8	2	1	1
46	350	22	1	1	1	0
47	1322	31	8	2	1	1
48	2800	40	7	1	1	1
49	3100	37	5	2	1	1
50	830	30	8	2	1	1
51	750	45	3	2	1	1
52	1817	30	7	2	1	1
53	1886	47	9	1	1	1
54	930	33	5	2	1	1
55	1200	39	4	2	0	0
56	1672	48	9	2	1	1
57	3400	52	8	1	1	1
58	710	27	8	2	1	1
59	150	24	2	2	0	0

60	1730	45	9	2	1	1
61	1435	50	7	2	1	1
62	987	34	5	2	1	1
63	420	24	3	2	1	1
64	680	30	4	2	1	1
65	1856	39	7	2	1	1
66	1257	43	9	2	1	1
67	1707	46	8	1	1	1
68	1236	38	5	2	1	1
69	617	29	3	2	1	1
70	381	25	2	2	1	1
71	942	42	5	2	1	1
72	1335	37	7	1	1	1
73	660	27	3	2	1	1
74	776	33	3	2	1	1
75	1355	37	6	2	1	1
76	1993	56	9	2	1	1
77	879	35	5	1	1	1
78	468	31	2	2	1	1
79	1004	45	8	2	1	1
80	900	34	5	2	1	1
81	180	25	2	2	1	0
82	1786	48	7	2	1	1
83	1716	37	6	2	1	1
84	349	26	2	2	0	0
85	1161	29	4	2	1	1
86	1701	42	9	2	1	1
87	354	27	3	2	1	0
88	885	32	4	2	1	1
89	350	35	2	0	1	0
90	1521	55	8	2	1	1
91	480	22	2	2	1	1
92	1125	42	5	2	1	1
93	1022	32	6	2	0	0
94	1165	44	9	2	1	1
95	1178	28	8	2	1	1
96	550	60	10	0	1	0
97	1946	29	4	2	1	1
98	1089	28	9	2	0	0

99	1987	39	6	2	1	1
100	461	27	3	2	1	0
101	1759	47	8	2	1	1
102	780	33	5	1	0	0
103	1854	55	7	1	1	1
104	809	25	3	2	1	1
105	400	24	1	1	1	0
106	1836	48	9	2	1	1
107	550	23	2	2	1	1
108	610	29	4	2	1	1
109	542	31	3	0	1	0
110	300	22	1	2	1	1
111	625	34	5	2	0	0
112	185	23	1	2	1	0
113	200	55	2	2	1	0
114	1299	34	6	2	1	1
115	732	37	4	2	1	1
116	1788	45	8	2	1	1
117	942	26	5	2	1	1
118	1647	50	7	2	1	1
119	589	24	3	2	1	1
120	1545	38	6	2	1	1

3.2. Clustering the Client Data and ANFIS Training

Against 5 inputs there is a single output reflecting the risk decided by the expert advice. Out of 120 client records, 80 are used for training and 40 for testing and checking.

The client data is subjected to the subtractive clustering procedure using Matlab. The algorithm is repeated for cluster radii 0.1 thru 0.9 while keeping the accept ratio, reject ratio, squash factor constant with 0.5, 0.15 and 1.25 respectively. Figure 3.1 shows the data points representing the clients with respect to coordinates 'Income' and 'Age'. With radius = 0.8, four clusters were found and their centers are marked on the data space.

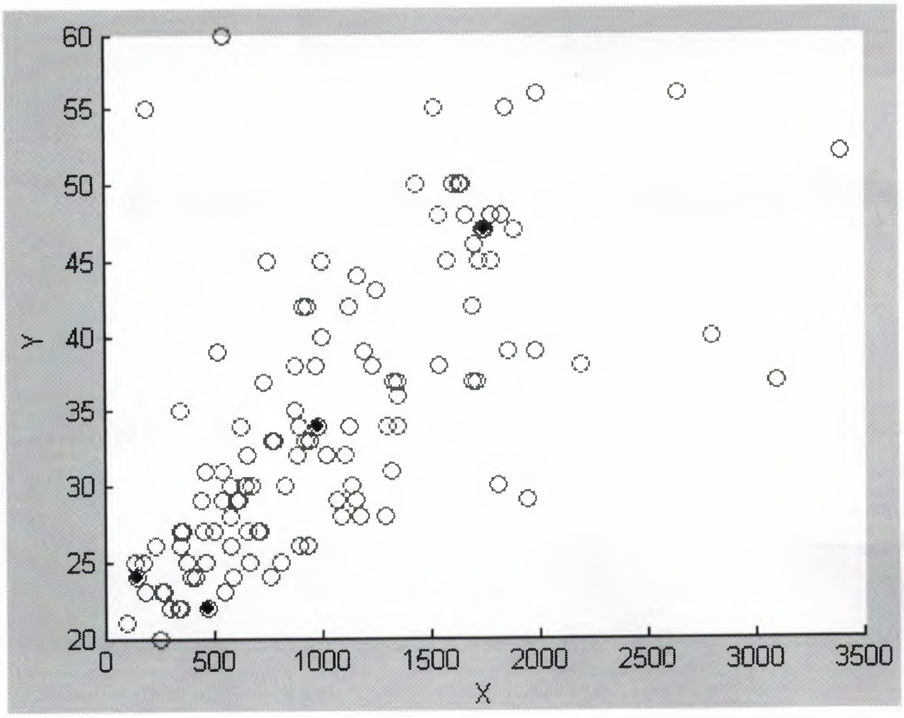


Figure 3.1. Clusters when r=0.8

Each run takes the input-output training data and generates a Sugeno-type FIS that models the data behavior. Table 3.2 reflects the different rule bases obtained.

The training of the FIS with radius = 0.8 at 200 epochs results with a training error of 0.11078 and testing error of 0.3142. The ANFIS graphical output shows the test points representing the FIS results over the actual output data (0,1). See Figure 3.2.

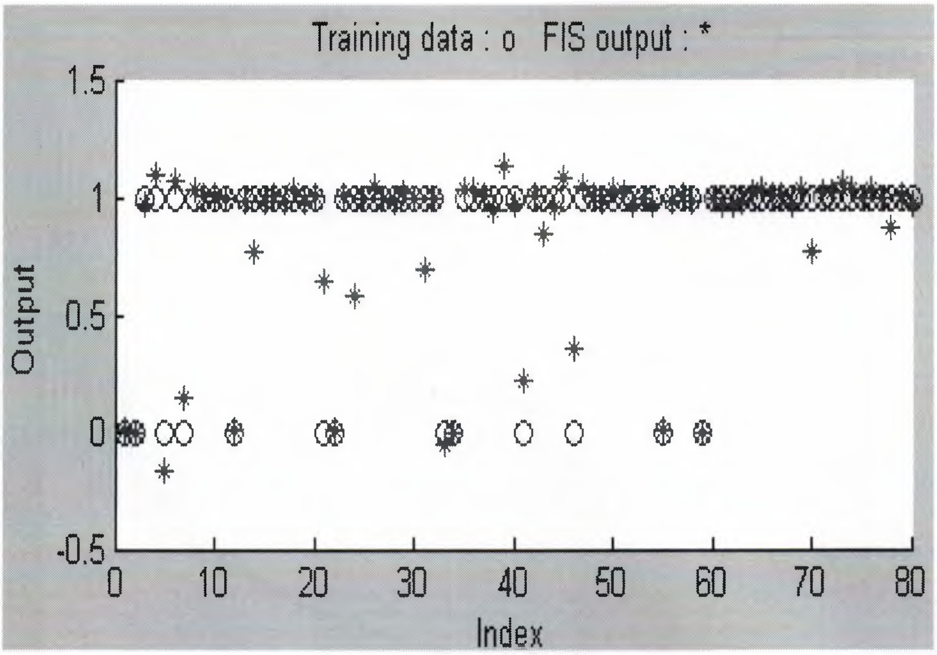


Figure 3.2. Testing of FIS

The training error plot against number of epochs is shown in Figure 3.3. At 200 epochs the error stabilizes to a value 0.11078. It is clear from the results that choosing radius very small or very large will result in either producing too many rules or poor accuracy, because if radius is chosen very small the density function will not take into account the effect of neighboring data points; while if taken very large, the density function will be affected and account all the data points in the data space. So a value between 0.4 and 0.8 should be adequate for the radius of neighborhood in order to have realistic, manageble and computationally efficient number of rules with good accuracy.

It is observed from Table 3.2 that when radius is taken as 0.8, a very simple rule base with only four rules and the highest accuracy of he experiment (96.67%) is acheived.

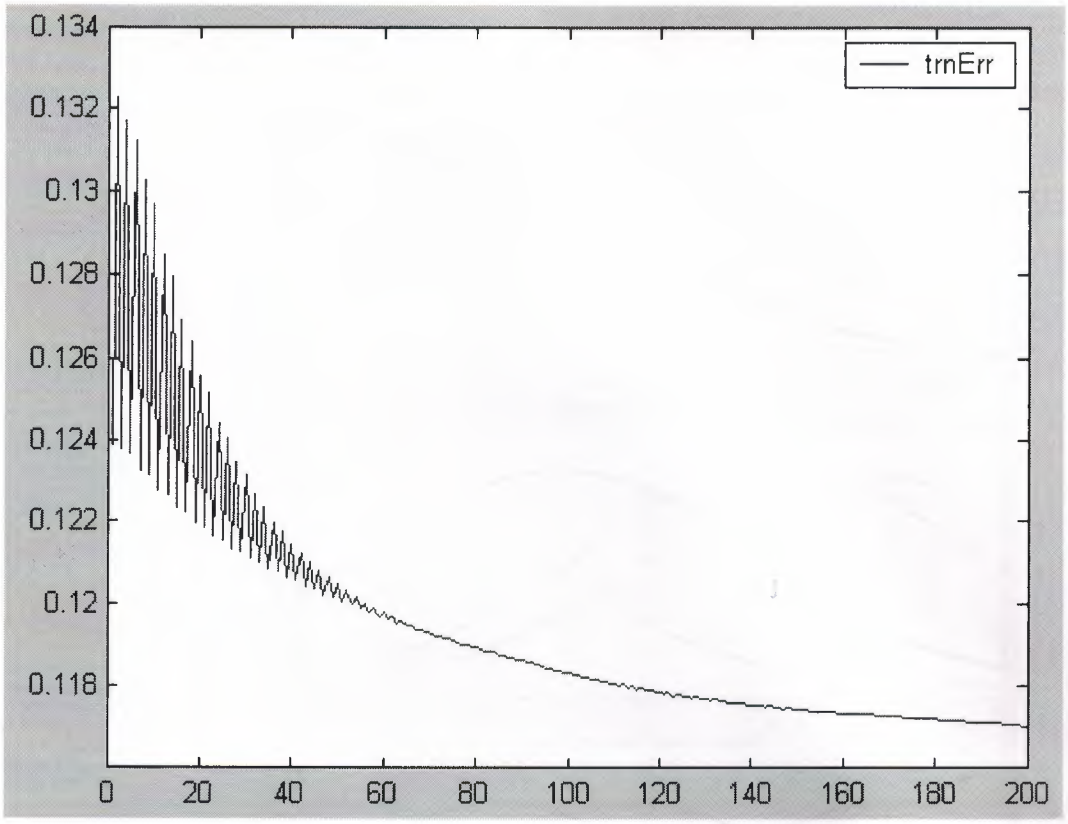


Figure 3.3. Training error at cluster radius = 0.8.

Table 3.2. The comparative test results

Cluster Radius	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Actual
No of Rules	61	13	10	7	6	6	4	4	3	NA
Training RMSE	0.00035	0.06433	0.07407	0.07605	0.08116	0.08284	0.14755	0.11079	0.12389	NA
Testing RMSE	0.4719	0.4171	0.3444	0.3565	0.3486	0.7331	0.3778	0.3142	0.3769	NA
Credit Approved	94	94	93	94	94	96	93	94	91	93
Credit Rejected	26	26	27	26	26	24	27	26	29	27
Unmatched	5	6	5	7	6	6	5	4	9	NA
Accuracy %	95.83	95.00	95.83	94.17	95.00	95.00	93.83	96.67	92.50	NA

3.3. Input Membership Functions.

The input membership functions obtained from the subtractive clustering using Matlab are of Gaussian type. Each input space shown in Figure 3.4 generalizes the input data submitted to the ANFIS training.

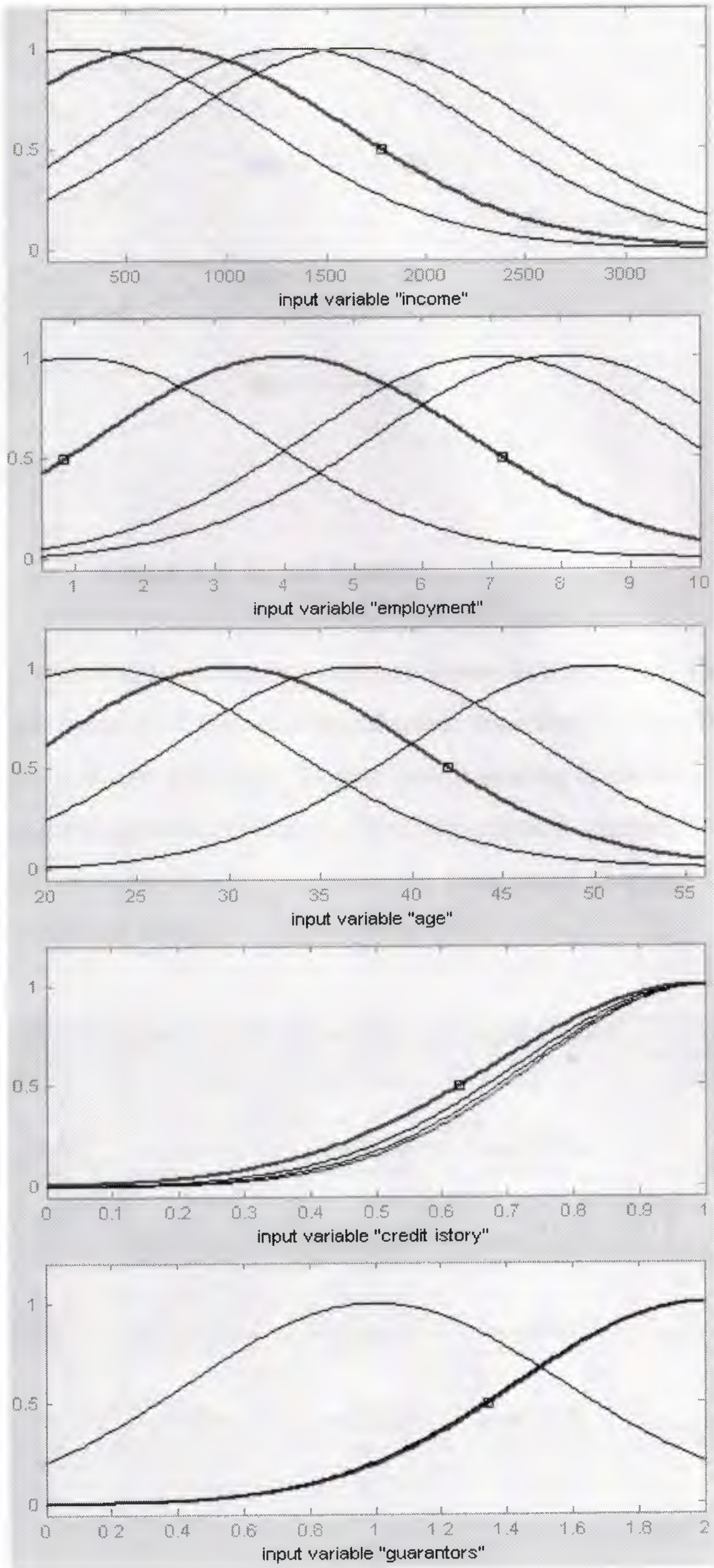


Figure 3.4. Gaussian Input Membership Functions

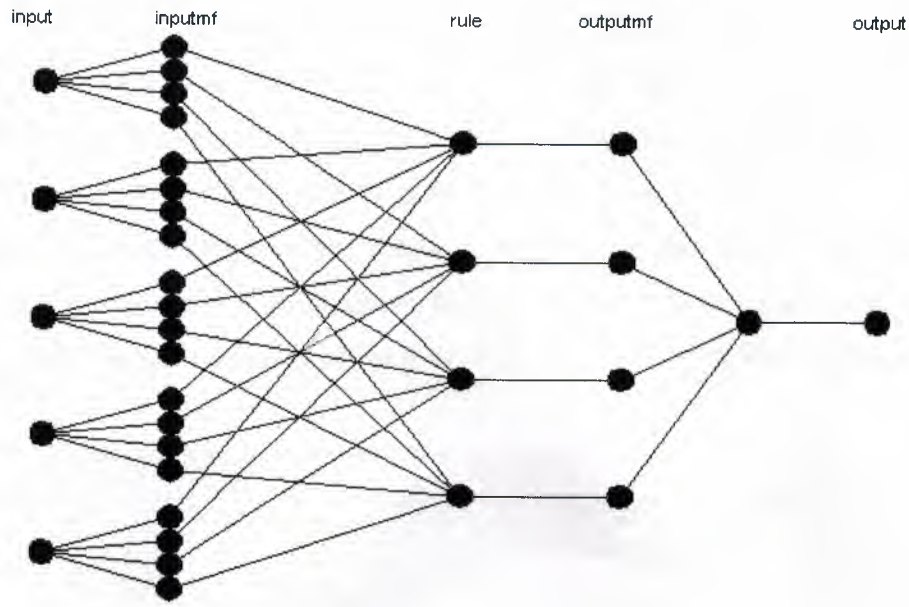


Figure 3.5. Model Structure

The model is constructed with 4 clusters hence 4 rules as shown in Figure 3.5. The model structure has 5 inputs each made of 4 Gaussian membership functions. 4 rules fired as a result of the training of the network. Firs order Sugeno type reasoning is conducted on the forth layer where the firing strengths are obtained. The crisp output is received on the 6^{th} layer after the aggregation process. Figure 3.6 shows the crisp input data and the crisp output risk measure of a particular client.

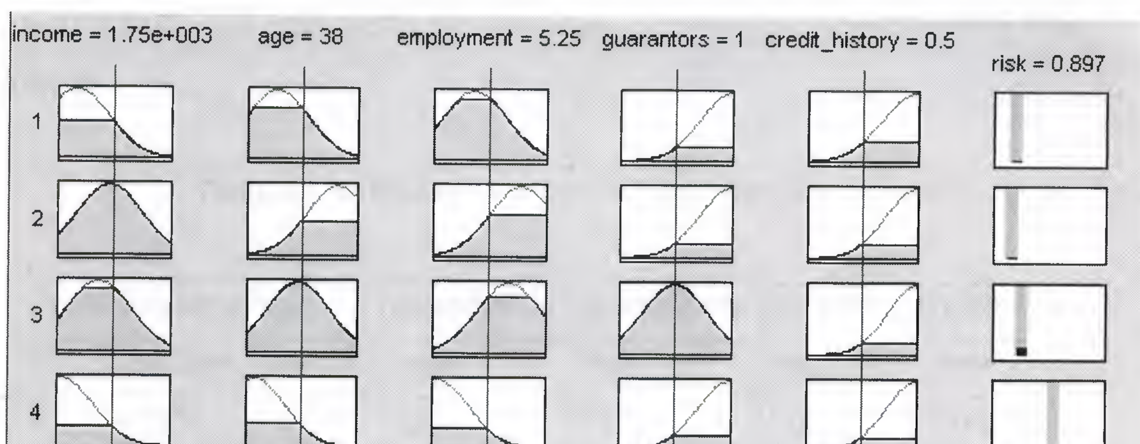


Figure 3.6. Rules

The surface plot is a three dimensional graphics tool in Matlab to show the shape of the FIS with three dimensional plots at a time. A particular instance of client age-income against risk is shown in Figure 3.7. A generalized idea can be obtained from the surface plot by observing the shape of the relationship between the given parameters. In this particular plot for example, the risk grows higher with low income and young age. (Here 0 represents high risk since we have taken 0 as "loan not granted" by the expert advice).

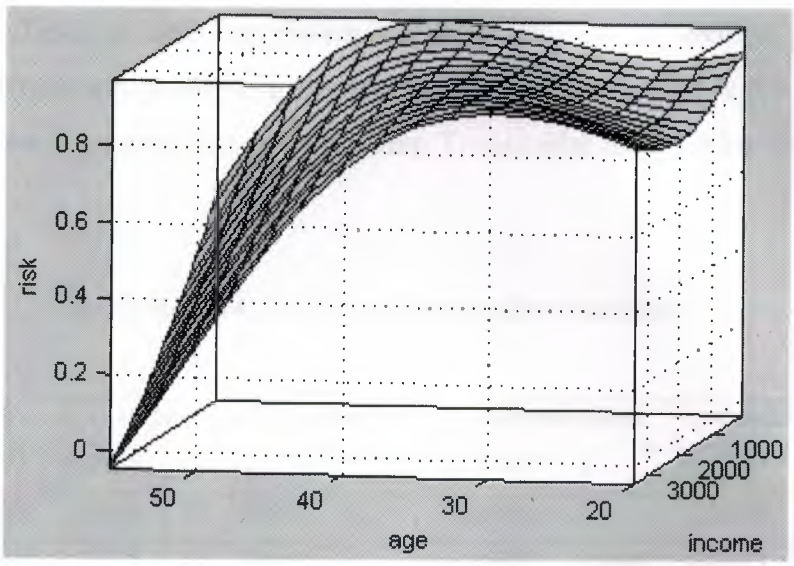


Figure 3.7. Surface plot of age-income v credit risk

The IF-THEN rules produced by the subtractive clustering and ANFIS training is as follows.

Table 3.3. If Then rules produced from subtractive clustering.

rule	income	age	experience	guarantors	cr_history	risk
1	avglow	avglow	avglow	Hgh	hgh	low
2	Hgh	hgh	hgh	Hgh	hgh	avglow
3	avghgh	avghgh	avghgh	Low	low	hgh
4	Low	low	low	Hgh	low	avghgh

Each row of the table contains the clusters representing the input-output space where the result of each client assessment belongs. These rules are obtained from the ANFIS editor by carefully naming the inputs and the outputs at membership function level after the training process.

3.4. Input membership function approximation

As it can be seen in Figure 3.4, two of the inputs (Guarantors and Credit history) have overlapping membership functions. These almost duplicate input functions have no effect on the FIS and therefore can be eliminated [14]. Working with Gaussian membership functions is difficult in both calculating similarity measure as well as defuzzification process. The parameters obtained in the ANFIS learning process Table 3.4 can be used to transform Gaussian membership functions into Trapezoidal membership functions Figure 3.8.

Table 3.4. Gaussian Membership functions

Income		Age		Experience		Guarantors		Credit History	
932.2	260	10.18	23	2.687	0.9999	0.5643	2	0.3047	0.9936
932.2	680	10.18	30	2.687	4	0.5656	2	0.2828	1
932.2	1335	10.18	37	2.687	7	0.5658	0.9997	0.2671	1.004
932.2	1636	10.18	50	2.687	8	0.5667	1.999	0.2736	1.003

The Gaussian membership functions are transformed into Trapezoidal membership functions using Matlab Membership Function-To-Membership Function conversion tool.

```
x=0:0.1:60;
mfp1 = [10.18 30];
mfp2 = mf2mf(mfp1,'gaussmf','trapmf');
plot(x,gaussmf(x,mfp1),x,trapmf(x,mfp2))
```

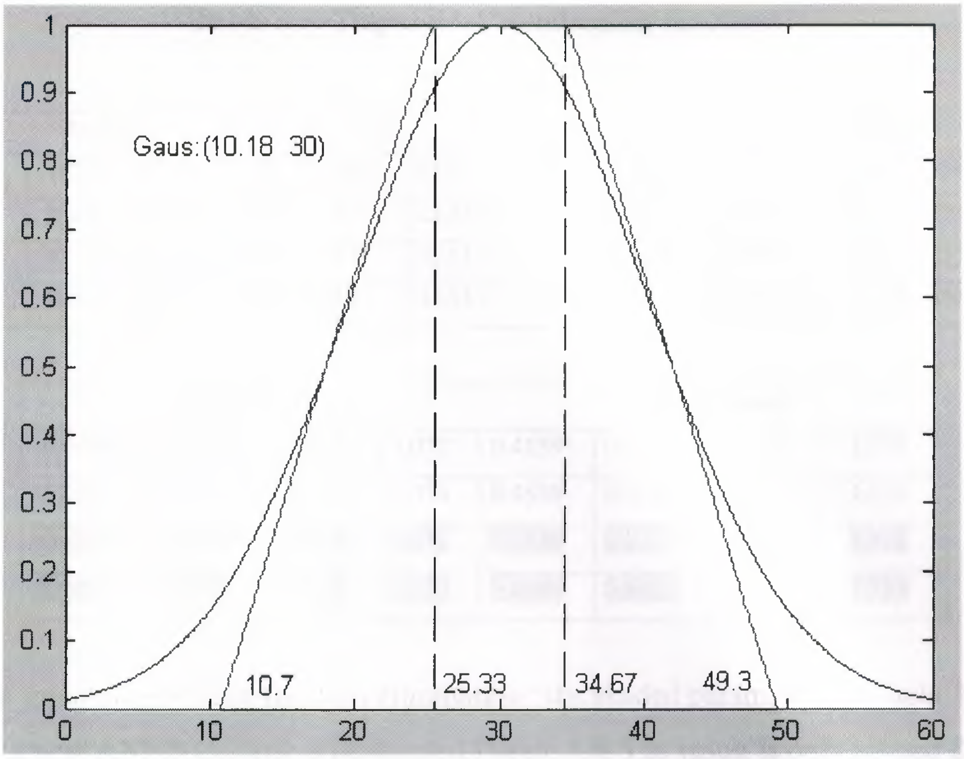


Figure 3.8. Gaussian to Trapezoidal membership function conversion

The new Trapezoidal function parameters are collected from the variable mfp2.

mfp2 = (10.7   25.33   34.67   49.3)

The function conversion process is conducted for all input membership functions and the results are tabulated as shown in Table 3.5.

Table 3.5. Trapezoidal Membership functions

Income				Age				Experience			
-1507	-167.9	687.9	2027	3.697	18.33	27.67	42.3	-4.094	-0.2336	2.233	6.094
-1087	252.1	1108	2447	10.7	25.33	34.67	49.3	-1.094	2.766	5.233	9.094
-432.3	907.1	1763	3102	17.7	32.33	41.67	56.3	1.906	5.767	8.233	12.09
-131.3	1208	2064	3403	30.7	45.33	54.67	69.3	2.906	6.767	9.233	13.09

Guarantors				Credit History			
-0.07304	0.7399	1.259	2.072	0.4159	0.8537	1.134	1.571
0.925	1.739	2.259	3.074	0.4638	0.8702	1.13	1.536
0.9278	1.740	2.260	3.072	0.4839	0.8770	1.128	1.521
0.9305	1.741	2.259	3.070	0.4980	0.8817	1.127	1.511

After the input membership function elimination "the shaded parameters in Table 3.5 process, a new ANFIS training is performed Figure 3.9. The result is only around 2% away from the maximum accuracy achieved with the FIS using the Gaussian membership functions originally extracted from subtractive clustering technique Table 3.6.

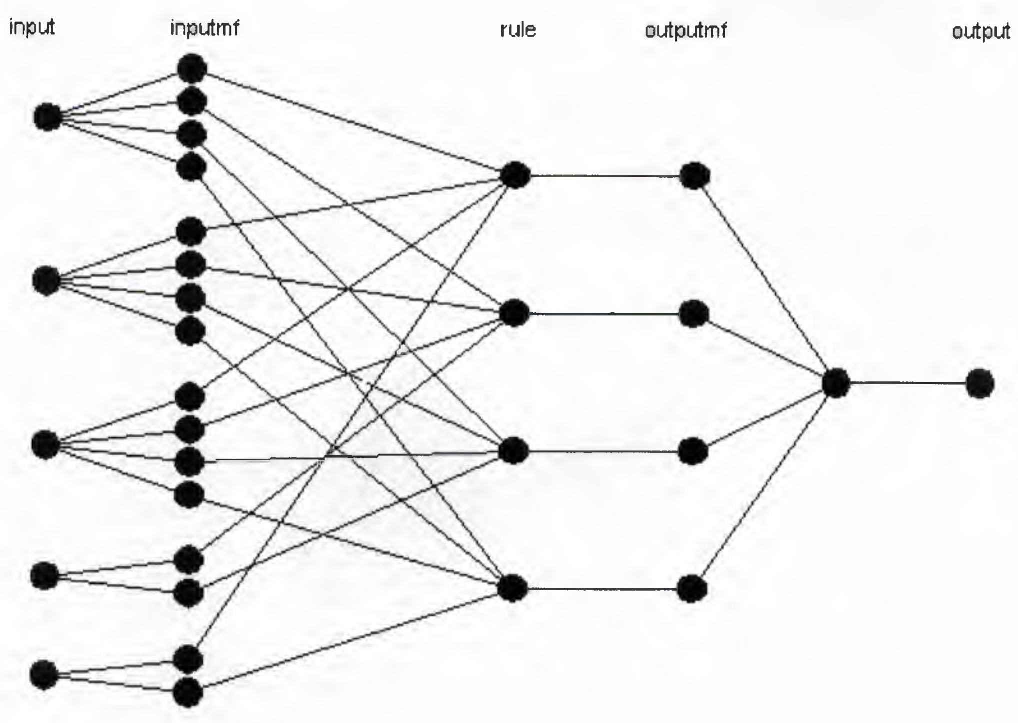


Figure 3.9. New model structure

Table 3.6. The result of FIS with trapezoidal input functions.

radius	unmatched	rules	trnRMSE	chkRMSE	Accuracy %
0.8	7	4	0.15159	0.49546	94.17

The graphical representation of the new rules and the surface plot is shown in Figure 3.10 and Figure 3.11 respectively.

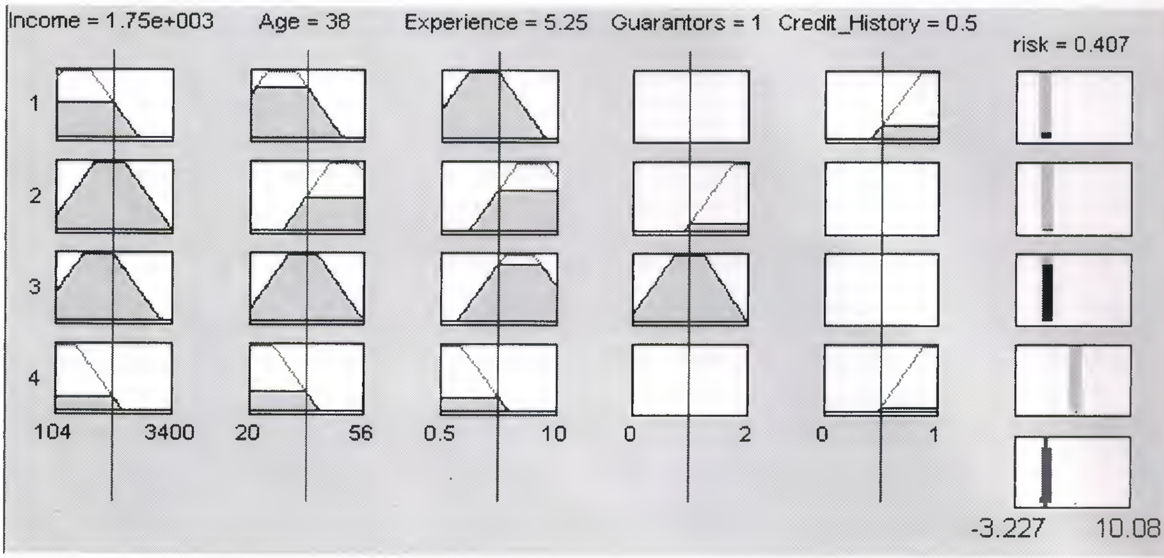


Figure 3.10. The new rules

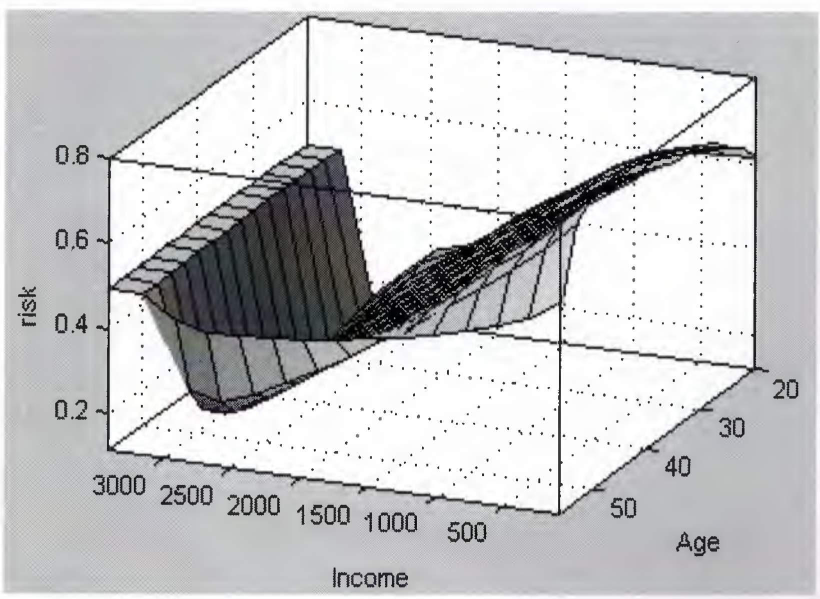


Figure 3.11. The new surface plot

The new FIS has the same number of rules but with trapezoidal membership functions. As described in Introduction section of this thesis, the new FIS obtained is now ready to be re-parameterized and upgraded to Neuro Fuzzy Type 2 inference system to remove further the uncertainty.

4. FUZZY TYPE 2 LOGIC SYSTEM

4.1. Fuzzy Logic System

A Fuzzy Logic System (FLS), includes fuzzifier, rules, inference engine, and defuzzifier [21]. Quite often, the knowledge that is used to construct the rules in a FLS is uncertain. Type-1 FLSs, whose membership functions are Type-1 Fuzzy sets, are unable to directly handle rule uncertainties. Type-2 FLSs, the subject of this paper, in which antecedent or consequent membership functions are Type-2 fuzzy sets, can handle rule uncertainties. A general formula for the extended up-star composition of Type-2 relations is given by Karnik and Mendel [19], [20]. Based on this formula, Karnik and Mendel [19], [20] established a complete Type-2 FLS theory to handle uncertainties in FLS rules. Similar to a Type-1 FLS, a Type-2 FLS includes fuzzifier, rule base, fuzzy inference engine, and output processor. The output processor includes type-reducer and defuzzifier; it generates a Type-l fuzzy set output (from the type-reducer) or a crisp number (from the defuzzifier). A Type-2 FLS is again characterized by IF-THEN rules, but its antecedent or consequent sets are now Type-2. Type-2 FLSs can be used when the circumstances are too uncertain to determine exact membership grades, such as when training data is corrupted by noise.

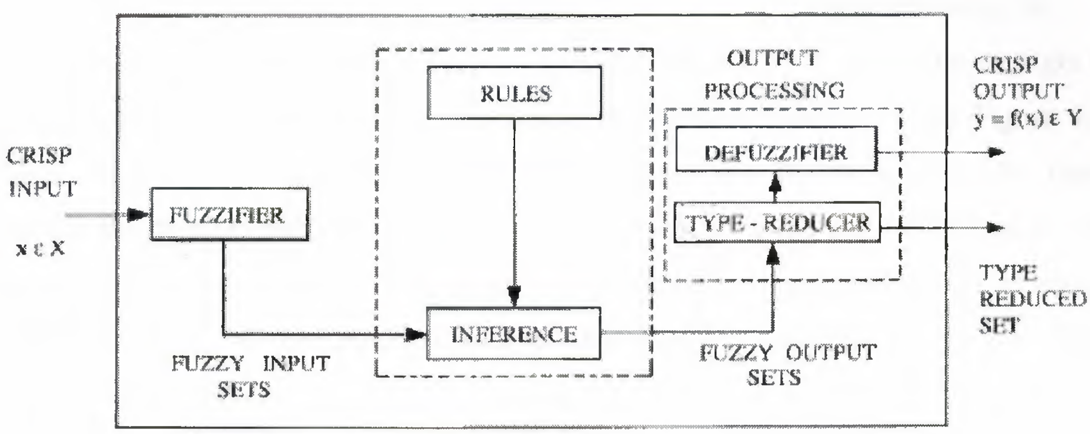


Figure 4.1. Fuzzy Type 2 FLS

General Type-2 FLSs are computationally intensive, because type-reduction is very intensive. Things simplify a lot when secondary membership functions (MF) are interval sets, in this case, the secondary memberships are either 0 or 1. When the secondary MFs are interval sets, the Type-2 FLS is called "Interval Type-2 FLS".

Interval Type-2 FLS is applicable [18] when:

- the data-generating system is known to be time-varying but the mathematical description of the time-variability is unknown.
- Measurement noise is nonstationary and the mathematical description of the nonstationarity is unknown.
- Features in a pattern recognition application have statistical attributes that are nonstationary and the mathematical descriptions of the nonstationarities are unknown;
- Knowledge is mined from a group of experts using questionnaires that involve uncertain words
- Linguistic terms are used that have a nonmeasurable domain.

4.2. Type-2 Fuzzy Sets

In this section, Type-2 Fuzzy sets and some important associated concepts are defined. By doing this, we provide a simple collection of mathematically well-defined terms that will let us effectively communicate about Type-2 Fuzzy sets. Imagine blurring the Type-1 membership function depicted in Figure 4.2.(a) by shifting the points on the triangle either to the left or to the right and not necessarily by the same amounts, as in Figure 4.2.(b). Then, at a specific point there no longer is a single value for the membership function; instead, the membership function takes on values wherever the vertical line intersects the blur. Those values need not all be weighted the same; hence, we can assign an amplitude distribution to all of those points. Doing this for all $x \in X$, we create a three-dimensional membership function (a Type-2 membership function) that characterizes a Type-2 Fuzzy set.

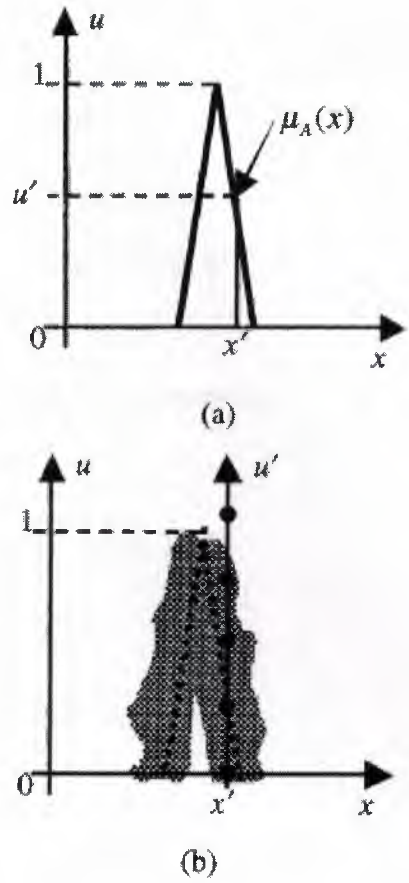


Figure 4.2. (a) Type-1 membership function and **(b)** blurred Type-1 membership function, including discretization at $x = x'$.

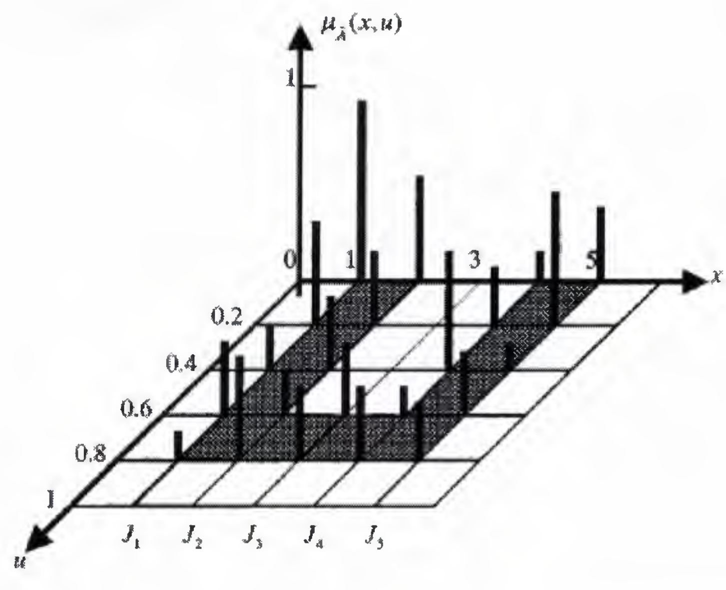


Figure 4.3. Example of a Type-2 membership function. The shaded area is the FOU.

Definition 1: A Type-2 Fuzzy set, denoted $\tilde{A}$, is characterized by a Type-2 membership function $\mu_{\tilde{A}}(x,u)$, where $x \in X$ and $u \in j_x \subseteq [0,1]$,

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \tag{4.1}$$

in which $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$. $\tilde{A}$ can also be expressed as

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x,u)/(x,u) \quad J_x \subseteq [0,1] \tag{4.2}$$

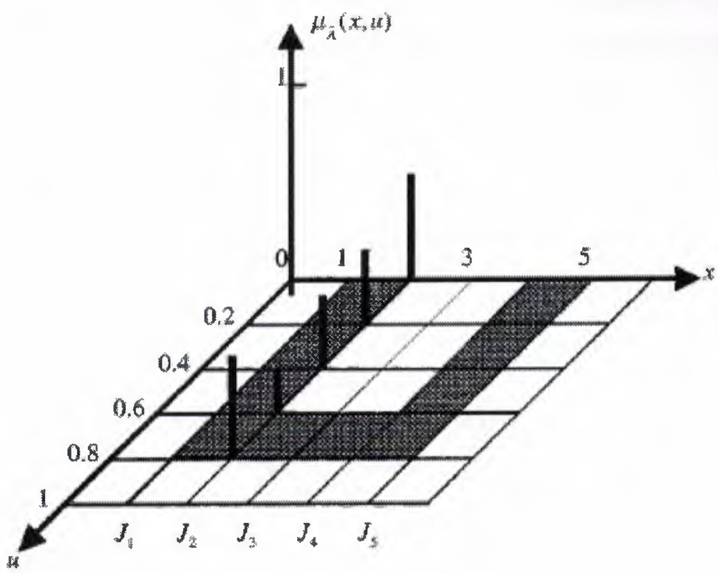


Figure 4.4. Example of a vertical slice for the Type-2 membership function .

where $\iint$ denotes union over all admissible x and u. For discrete universes of discourse is $\int$ replaced by $\sum$.

In *Definition 1*, the first restriction $\forall_u \in j_x \subseteq [0,1]$ that is consistent with the type-1 constraint that $0 \leq \mu_A(x) \leq 1$, i.e., when uncertainties disappear a type-2 membership function must reduce to a type-1 membership function, in which case the variable u equals

$\mu_A(x)$ and $0 \le \mu_A(x) \le 1$. The second restriction that $0 \le \mu_{\tilde{A}}(x,u) \le 1$ is consistent with the fact that the amplitudes of a membership function should lie between or be equal to 0 and 1.

Definition 2: At each value of x, say $x = x'$, the 2-D plane whose axes are u and $\mu_{\tilde{A}}(x,u)$ is called a vertical slice of $\mu_{\tilde{A}}(x,u)$. A secondary membership function is a vertical slice of

$\mu_{\tilde{A}}(x,u)$. It is $\mu_{\tilde{A}}(x = x', u)$ for $x \in X$ and $\forall u \in j_{x'} \subseteq [0,1]$, i.e,

$$\mu_{\tilde{A}}(x = x', u) \equiv \mu_{\tilde{A}}(x') = \int_{u \in J_{x'}} f_{x'}(u)/u \quad J_{x'} \subseteq [0,1] \tag{4.3}$$

Based on the concept of secondary sets, we can reinterpret a Type-2 Fuzzy set as the union of all secondary sets, i.e., using (4.3), we can re-express in a vertical-slice manner, as

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid \forall x \in X\} \tag{4.4}$$

or, as

$$\tilde{A} = \int_{x \in X} \mu_{\tilde{A}}(x)/x = \int_{x \in X} \left[\int_{u \in J_x} f_x(u)/u \right] \Big/ x \tag{4.5}$$

$J_x \subseteq [0, 1]$.

Definition 3: The domain of a secondary membership function is called the primary membership of x. In (2.20), j_x is the primary membership of x, where $j_x \subseteq [0,1]$ for $\forall x \in X$.

Definition 4: The amplitude of a secondary membership function is called a secondary grade. In (2.20), $f_x(u)$ is a secondary grade; in (1), $\mu_{\tilde{A}}(x',u')(x' \in X, u' \in j_{x'})$ is a secondary grade. If and are both discrete (either by problem formulation, as in Example 1, or by discretization of continuous universes of discourse), then the right-most part of (2.20) can be expressed as

$$\begin{aligned}\tilde{A} &= \sum_{x\in X}\left[\sum_{u\in J_x} f_x(u)/u\right]\Big/ x\\ &= \sum_{i=1}^{N}\left[\sum_{u\in J_{x_i}} f_{x_i}(u)/u\right]\Big/ x_i\\ &= \left[\sum_{k=1}^{M_1} f_{x_1}(u_{1k})/u_{1k}\right]\Big/ x_1+\cdots+\left[\sum_{k=1}^{M_N} f_{x_N}(u_{Nk})/u_{Nk}\right]\Big/ x_N. \end{aligned} \tag{4.6}$$

In this equation, also denotes union. Observe that has been discretized into values and at each of these values has been discretized into values. The discretization along each does not have to be the same, which is why we have shown a different upper sum for each of the bracketed terms. If, however, the discretization along each is the same, then

$$M_1 = M_2 = \cdots = M_N \equiv M.$$

Definition 5: Uncertainty in the primary memberships of a Type-2 Fuzzy set, , consists of a bounded region that we call the footprint of uncertainty (FOU). It is the union of all primary memberships, i.e.,

$$\mathrm{FOU}(\tilde{A}) = \bigcup_{x\in X} J_x \tag{4.7}$$

The shaded region in Figure 4.4 is the FOU. The term *footprint of uncertainty* is very useful, because it not only focuses our attention on the un certainties inherent in a specific Type-2 membership function, whose shape is a direct consequence of the nature of these uncertainties, but it also provides a very convenient verbal description of the entire domain of support for all the secondary grades of a Type-2 membership function. It also lets us depict a Type-2 Fuzzy set graphically in two-dimensions instead of three dimensions, and in so doing lets us overcome the first difficulty about Type-2 Fuzzy sets-their three-dimensional nature which makes them very difficult to draw. The shaded FOUs imply that there is a distribution that sits on top of it—the new third dimension of Type-2 Fuzzy sets. What that distribution looks like depends on the specific choice made for the secondary grades. When they all equal one, the resulting Type-2 Fuzzy sets are called Interval Type-2 fuzzy sets. Such sets are the most widely used Type-2 Fuzzy sets to date.

Definition 6: Fordiscrete universes of discourse X and U, an embedded Type-2 set A_e has N elements, where A_e contains exactly one element from $j_{x_1}, j_{x_2}, \ldots, j_{x_N}$, namely $u_{1,}, u_2, \cdots, u_N$, each with its associated secondary grade, namely

$f_{x1}(u_1), f_{x_2}(u_2), \cdots, f_{x_N}(u_N),$, i.e.,

$$\tilde{A}_e = \sum_{i=1}^{N} [f_{x_i}(u_i)/u_i]/x_i \quad u_i \in J_{x_i} \subseteq U = [0,1]. \tag{4.8}$$

Set A_e is embedded in $\tilde{A}$, and, there are a total of $\prod_{i=1}^{N} M_i A_e$.

Definition 7: For discrete universes of discourse X and U, an embedded Type-1 set A_e has N elements, one each from $j_{x_1}, j_{x_2}, \ldots, j_{x_N}$, namely , i.e., $u_{1,}, u_2, \cdots, u_N$ i.e.

$$A_e = \sum_{i=1}^{N} u_i/x_i \quad u_i \in J_{x_i} \subseteq U = [0,1]. \tag{4.9}$$

Set A_e is the union of all the primary memberships of set A_e in (4.8), and, there are a total of $\prod_{i=1}^{N} M_i A_e$.

Definition 8: A Type-1 fuzzy set can also be expressed as a Type-2 Fuzzy set. Its Type-2 representation is $(1/\mu_F(x))/x$ or $(1/\mu_F(x))/x, \forall_x \in X$, for short. The notation$1/\mu_F(x)$ means that the secondary membership function has only one value in its domain, namely the primary membership $\mu_F(x)$, at which the secondary grade equals 1.

4.3. The Structure Of Neuro Fuzzy Type-2 Inference System

The structure of the Neuro Fuzzy Type 2 Inference System (NFT2IS) is shown in Figure 4.5. Layer 1 contains nodes accepting crisp signals, Layer 2 contains fuzzifiers that map input signals to fuzzy Type-2 terms used in the rules. Layer 3 consists of nodes representing rules. Each rule nodes performs Min operation on the outputs (interval valued membership degrees) of the previous layer incoming links. Layer 4 consists output terms membership functions of type-1. Layer 5 compute the fuzzy output signal for the output variables. Layer 6 does defuzzification using the Center-of-Gravity (COG) defuzzification method.

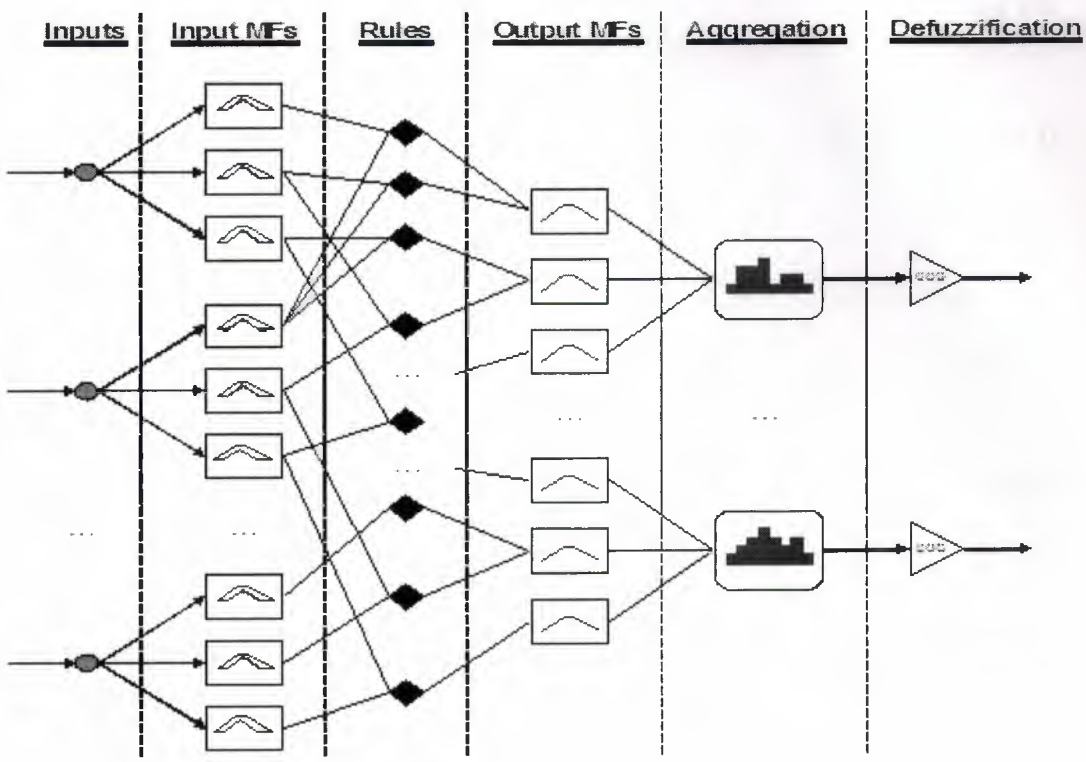


Figure 4.5. Structure of Neuro Fuzzy Type 2 Inference System

4.4. Fuzzification and Inference Procedure

The NFT2IS in this thesis uses 5 Type-2 input variables and 5 Fuzzy Type-1 output variables. The input variable's Fuzzy Type 2 terms are described as:

$$\widetilde{A} = \{x / \mu_x\}, x \in X \subset \Re \tag{4.10}$$

$$\mu_x = \{m/1\}, m \in M_x \subset [0,1] \tag{4.11}$$

where

$$M_{xL} = \text{lowerof}([m_{x1}, m_{x2}], [m_{x3}, m_{x4}]) \tag{4.12}$$

$$m_{x1} = \max\left(\min\left(1, \frac{RL - x}{RL - ML}\right), 0\right) \tag{4.13}$$

$$m_{x2} = \max\left(\min\left(1, \frac{RR - x}{RR - MR}\right), 0\right) \tag{4.14}$$

$$m_{x3} = \max\left(\min\left(1, \frac{x - LL}{ML - LL}\right), 0\right) \tag{4.15}$$

$$m_{x4} = \max\left(\min\left(1, \frac{x - LR}{MR - LR}\right), 0\right) \tag{4.16}$$

and we calculate the lower of two intervals [a,b] and [c,d] (the operator "lowerof" used above) as follows

$$\text{lowerof}([a,b],[c,d]) = \begin{cases} [a,b], if\left(\dfrac{a+b}{2} < \dfrac{b+c}{2}\right) \\ [c,d], elsewise \end{cases} \tag{4.17}$$

LL, *LR*, *ML*, *MR*, *RL*, *RR* ($LL \le LR \le ML \le MR \le RL \le RR$) are parameters defining the "shape" of Fuzzy Type-2 membership functions. An example of Fuzzy Type 2 input value defined in this way ([0.25, 0.75], [1.25, 1.75], [2.25, 3.00]) is shown in Figure 4.6. As it can be seen, a Fuzzy Type 2 number can be composed on the basis of three intervals [*LL*,*LR*] (a left interval, indicated by letter L in the figure), [*ML*,*MR*] (a medium interval, indicated by letter M in the figure), and [*RL*,*RR*] (a right interval, indicated by letter R in the figure): [*LL*, *LR*], [*ML*, *MR*], [*RL*, *RR*]. As can be seen from Figure 4.6, input term membership functions can be considered as interval valued membership functions (interval membership values for two values of x are shown: x=1 and x=2.5).

The output variable's Fuzzy Type-1 terms are ordinary Fuzzy Type-1 trapezoidal fuzzy numbers:

$$B = [L, ML, MR, R] = [[L, L], [ML, MR], [R, R]] \tag{4.18}$$

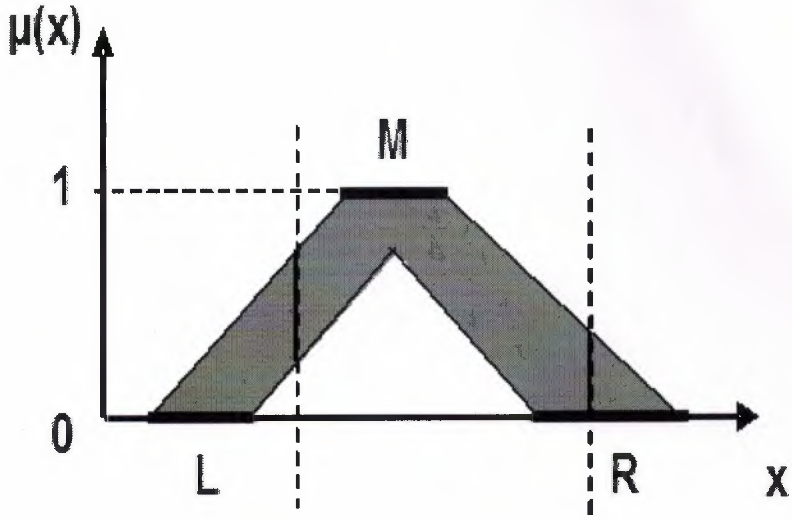


Figure 4.6. A Fuzzy Type 2 term value

Zadeh's implication to compute output membership functions is used. After the implication is performed, we get two piecewise linear membership functions for every output variable:

$$\tilde{y}_i = \{y / [\mu_{Li}(y), \mu_{Ri}(y)]\} \tag{4.19}$$

Type reducing is performed on the basis of center of gravity (COG) defuzzification procedure:

$$\text{COG}(\tilde{y}_i) = \{y/[\text{COG}(\mu_{Li}(y)), \text{COG}(\mu_{Ri}(y))]\} = \{y/[y_{Li}, y_{Ri}]\} \tag{4.20}$$

The final defuzzification is performed as follows:

$$y_i = \frac{y_{Li} + y_{Ri}}{2} \tag{4.21}$$

4.5. Fuzzy Type 2 Input Membership Functions

The input variable parameters which are now in trapezoidal form Figure 4.7, can be converted to Fuzzy Type II parameters.

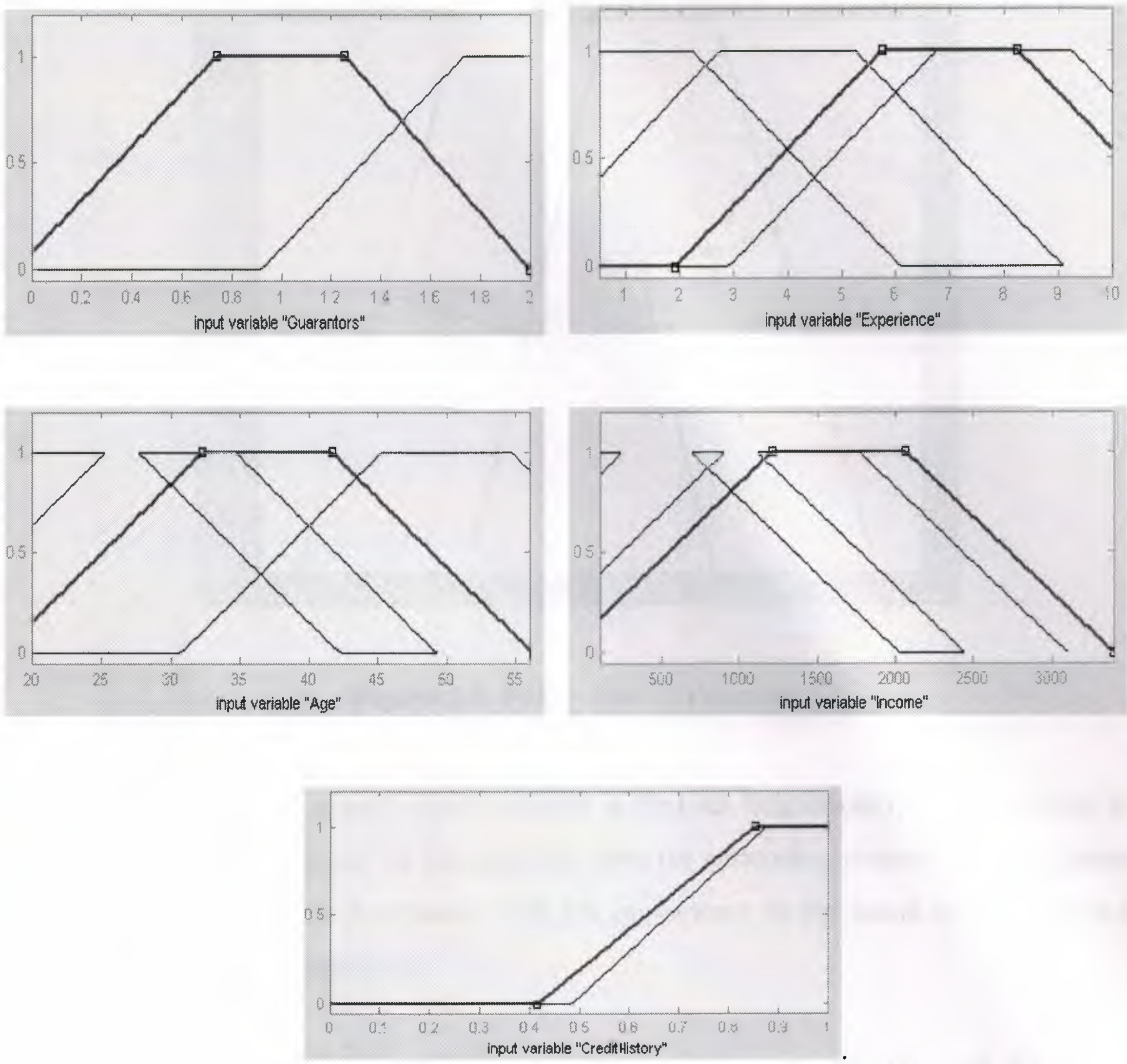


Figure 4.7. Trapezoidal Membership Functions

Keeping the existing Fuzzy Type I parameters of the input membership functions at the center, Type 2 parameters are set by extending the function's boundaries in and out by equal amounts (a=b=c=d) as shown in Figure 5.8.

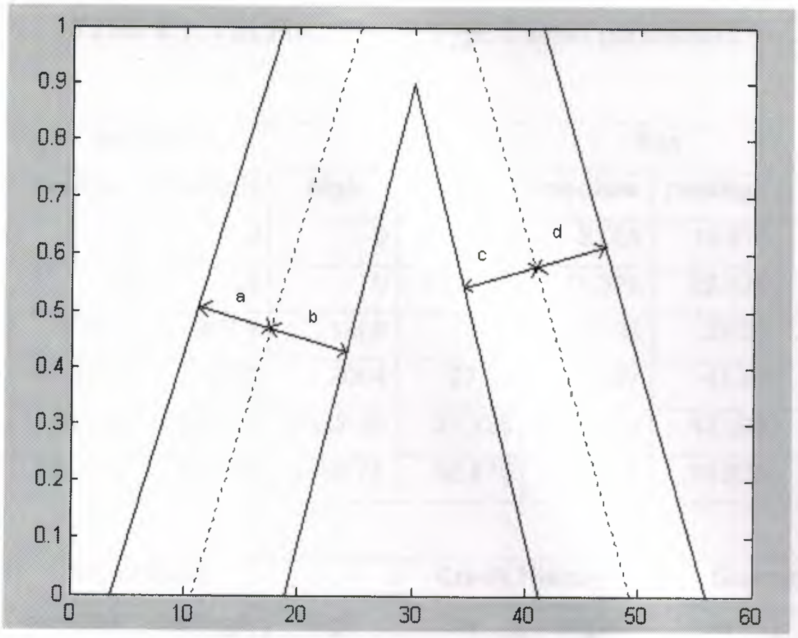


Figure 5.8. Fuzzy Type II Function.

The size of extension on each input variable is first set heuristically, not exceeding the percentage FIS lost accuracy. In this case 5%.Then the network is trained and the accuracy is calculated. The process is repeated with 5% increments on the initial extensions for as long as the accuracy is improved.

Ex: For input age (Average-low) Fuzzy Type 2 Parameters *LL*, *LR*, *ML*, *MR*, *RL*, *RR* are obtained by extending *L*, *ML*, *MR*, *R* Fuzzy Type I parameters as follows.

$(L, ML, MR, R)_{avglow}$ = [10.7, 25.33, 34.67, 49.3]

$(LL,LR,ML,MR,RL,RR)_{avglow}$ = [(10.7- 0.6), (10.7+0.6), 25.33, 34.67, (49.3-0.6) , (49.3+0.6)]

$(LL,LR,ML,MR,RL,RR)_{avglow}$ = [10.1, 11.3, 25.33, 34.67, 48.7, 49.9]

The final Fuzzy Type 2 input membership functions are obtained by extending the original Fuzzy Type 1 inputs by 25% as shown in Table 4.1.

Table 4.1. The Final Fuzzy Type 2 input parameters

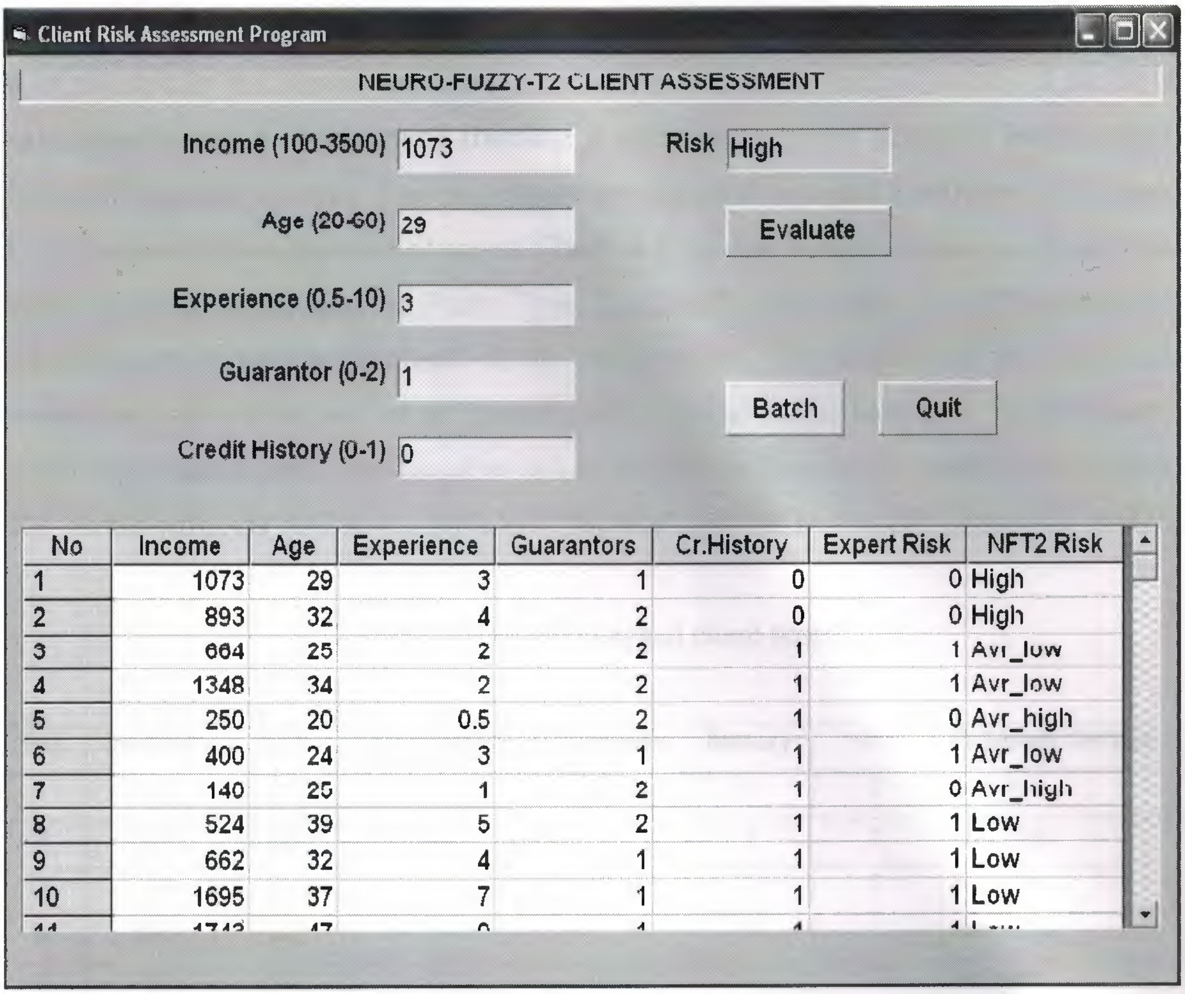
Income				Age			
low	medlow	medhgh	high	low	medlow	medhgh	high
0	0	0	0	2.77275	8.025	13.275	23.025
0	0	0	0	4.62125	13.375	22.125	38.375
0	252.1	907.1	1208	18.33	25.33	32.33	45.33
687.9	1108	1763	2064	27.67	34.67	41.67	54.67
1520.25	1835.25	2326.5	2552.25	31.725	36.975	42.225	51.975
2533.75	3058.75	3877.5	4253.75	52.875	61.625	70.375	86.625

Experience				Credit History		Guarantors	
low	medlow	medhgh	high	low	high	low	high
0	0	1.4295	2.1795	0	0	0	0
0	0	2.3825	3.6325	0	0	0	0
0	2.766	5.767	6.767	1	1	1	1
2.233	5.233	8.233	9.233	1	1	1	1
4.5705	6.8205	9.0675	9.8175	3	3	3	3
7.6175	11.3675	15.1125	16.3625	3	3	3	3

4.6. The NFT2IS software.

Using Microsoft Visual Basic 6, programming language and Microsoft Excel spreadsheet program, a software is developed to perform the inferencing procedure on the given crisp inputs and return defuzzified output. The model input parameters, type conversions, and defuzzification formulation is built on Microsoft Excel sheets to provide easy access and modifications as well as give an inside view of the system. The software developed works with the Excel sheet data and formula to perform the inferencing and give out linguistic results on a user friendly environment. The code of the program and the related Excel sheets are provided in the Appendix.

The software works in batch mode evaluating a list of clients as well as in user mode where the details of a single client are submitted for evaluation. The screen shot of the software is shown in Figure 4.9.



No	Income	Age	Experience	Guarantors	Cr.History	Expert Risk	NFT2 Risk
1	1073	29	3	1	0	0	High
2	893	32	4	2	0	0	High
3	664	25	2	2	1	1	Avr_low
4	1348	34	2	2	1	1	Avr_low
5	250	20	0.5	2	1	0	Avr_high
6	400	24	3	1	1	1	Avr_low
7	140	25	1	2	1	0	Avr_high
8	524	39	5	2	1	1	Low
9	662	32	4	1	1	1	Low
10	1695	37	7	1	1	1	Low

Figure 4.9. The NFT2IS software output in batch mode

The program output contains the client detail inputs as well as the expert system decision on the client. The expert system decision is either 0 (Bad client) or 1 (Good client). The NFT2IS output is in given in four categories using linguistic terms Low_risk, Average_low_risk, Average_high_risk and High_risk. Each linguistic term represents the cluster that the client belongs.

The client score less than 2 points out of 10 is regarded as high risk clients and therefore their applications are rejected. Clients with score between 2 and 4 are regarded as average-high risk and perhaps require expert advice to reject. Client scores between 4 and 6 are regarded as average low risk. Client scores above 6 are regarded as low risk. Clients with average low and low risk scores can be granted their loan.

Observing the list of client evaluation results Appendix A, it is found that two of the clients were rejected by the experts due to their inadequate collateral which is not one of the input parameters we used in this thesis (because it overrides all other attributes and therefore removed from the system). The two clients are regarded as sound candidates for a loan. Five clients that have unmatched scores (Table 4.2) against expert decision are to do with their "income". Narrowing the Fuzzy Type 2 [*LL*, *LR*], [*ML*, *MR*], [*RL*, *RR*] parameters will make the overall performance of the model worse. The clients with Avr_high risk whose loan application are set as "questionable" by the model have low "Employment" and/or low "Guarantors" and therefore can be decided in favor of the model by the expert. The clients with Avr_low scores have low "Income" and can be decided against the model.

Table 4.2. The mismatched client scores.

No	Income	Age	Employment	Guarantors	history	risk	Program Output
1	277	23	2	2	1	0	Avr_low
2	355	22	1	1	1	1	Avr_high
3	180	25	2	2	1	0	Avr_low
4	300	22	1	2	1	1	Avr_high
5	200	55	2	2	1	0	Avr_low

4.7. User-driven rule base design

The rule base constructed with combined techniques, clustering and fuzzy type 2 resulted with 95.83 % accuracy when tested against expert decision. The result is within the acceptable range[17] with some losses of accuracy resulted from the ANFIS training and conversion of Gaussian membership functions to trapezoidal membership functions of inputs. The membership function simplification of inputs thru elimination [13], also caused some losses in accuracy. A new rule base can be obtained by modifying the input-output membership functions and setting up new rules that can increase the accuracy. The new rule base is aimed at classifying the client data into two groups. Two groups distinguishing the high risk clients and low risk clients. We already know from subtractive clustering that the data is classified into four groups hence four rules can be extracted Table 4.3.

Table 4.3. User-Driven rule base.

rule	income	age	experience	guarantors	cr_history	risk
1	Hgh	Avg	Hgh	Hgh	Hgh	Low
2	Hgh	Avg	Avg	Hgh	Hgh	Low
3	Avg	Avg	Hgh	Hgh	Hgh	Avglow
4	Avg	Avg	Avg	Hgh	Hgh	Avglow

The rules from the subtractive clustering also tells us that no client receives a low risk score if guarantors and credit history is low. Therefore clients with high or average income, age and experience inputs can receive low risk score.

The input parameters are distributed according to the rules given in table 4.3 such that they aim at finding the clients with low risk scores. Thru experimental runs, the rule base and the Fuzzy Type 2 input membership function parameters can be adjusted to obtain results with 100% success on client rejects. Table 4.4 shows the final input parameters.

Table 4.4. User-Driven rule base input parameters

Income	Low	0	0	150	200	250	300
	Med	290	350	1400	1500	2000	2200
	Hgh	1400	2000	2200	3000	4000	5000
Age	Low	0	0	0	0	18	20
	Med	18	21	30	45	55	58
	Hgh	56	57	59	60	70	80
Experience	Low	0	0	0	0	0.5	1
	Med	0.95	1	4	5	6	8
	Hgh	5	7	8	10	14	18
Guarantors	Low	0	0	0	0	0	0
	Hgh	0	0	1	1	3	3
Cr. History	Low	0	0	0	0	0	0
	Hgh	0	0	1	1	3	3

The output obtained from the training of the proposed NFT2 inference system is plotted against the expert decision Figure 4.10.

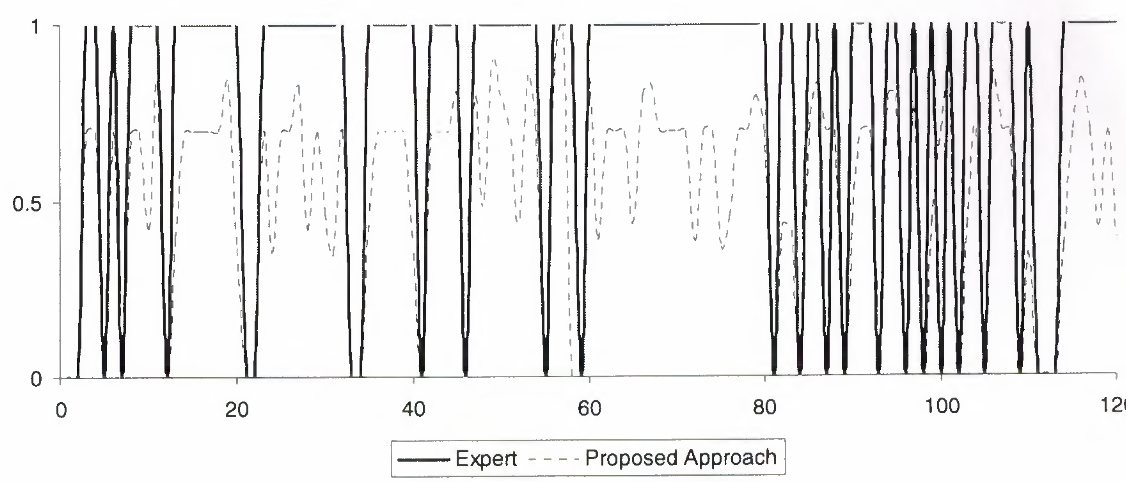


Figure 4.10: Expert decision against proposed approach results

CONCLUSION

The Neuro-Fuzzy-Type-2 inference system (NFT2IS) is modeled to handle the classification problem in client assessment procedure. The model uses subtractive clustering based system identification with Sugeno reasoning mechanism to classify the input-output data for initial rule extraction. The rules obtained are refined and trained using feed forward neural network with fuzzy type 2 inputs. The Fuzzy Type 2 input membership functions gave the model the flexibility and effectiveness to define the uncertain input boundaries. The rule base designed is very compact and computationally very efficient. NFT2IS is applied on real data with five inputs and an output obtained from a bank in Azerbaijan. The model returns a clear output that can easily distinguish between a 'good' and 'bad' client for the management to act upon. Accuracy over 95% is achieved with data-driven rule base, and 100% accuracy is obtained with user-driven rule base when compared with expert decision.

Further study in clustering procedure may be considered where uncertain cluster boundaries exist. Fuzzy Type 2 logic system can give better classification and hence more effective initial rule base.

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APPENDIX A: NFT2 program output

No	Income	Age	Employment	Guarantors	history	risk	Program Output
1	1073	29	3	1	0	0	High
2	893	32	4	2	0	0	High
3	664	25	2	2	1	1	Avr_low
4	1348	34	2	2	1	1	Avr_low
5	250	20	1	2	1	0	Avr_high
6	400	24	3	1	1	1	Avr_low
7	140	25	1	2	1	0	Avr_high
8	524	39	5	2	1	1	Avr_low
9	662	32	4	1	1	1	Avr_low
10	1695	37	7	1	1	1	Low
11	1743	47	9	1	1	1	Low
12	231	26	2	2	0	0	High
13	1543	48	6	2	1	1	Low
14	359	27	2	2	1	1	Avr_low
15	944	33	5	1	1	1	Avr_low
16	876	38	3	2	1	1	Avr_low
17	1114	32	5	1	1	1	Avr_low
18	586	28	3	2	1	1	Avr_low
19	1636	50	8	2	1	1	Low
20	1351	36	6	1	1	1	Low
21	277	23	2	2	1	0	Avr_low
22	584	30	2	0	1	0	High
23	471	25	3	2	1	1	Avr_low
24	355	22	1	1	1	1	Avr_high
25	1000	40	4	2	1	1	Avr_low
26	582	26	3	2	1	1	Avr_low
27	1583	45	10	1	1	1	Low
28	1615	50	7	2	1	1	Low
29	923	42	5	2	1	1	Avr_low
30	2200	38	6	2	1	1	Low
31	344	22	2	2	1	1	Avr_low
32	1296	28	4	1	1	1	Avr_low
33	104	21	1	2	1	0	Avr_high
34	760	24	3	0	0	0	High
35	2650	56	5	2	1	1	Low

36	713	27	4	1	1	1	Avr_low
37	539	29	3	2	1	1	Avr_low
38	1143	30	5	2	1	1	Avr_low
39	900	26	3	2	1	1	Avr_low
40	650	30	6	1	1	1	Avr_low
41	260	23	1	2	1	0	Avr_high
42	500	27	3	2	1	1	Avr_low
43	450	29	2	2	1	1	Avr_low
44	1126	34	5	2	1	1	Avr_low
45	972	38	8	2	1	1	Low
46	350	22	1	1	1	0	Avr_high
47	1322	31	8	2	1	1	Avr_low
48	2800	40	7	1	1	1	Low
49	3100	37	5	2	1	1	Low
50	830	30	8	2	1	1	Avr_low
51	750	45	3	2	1	1	Avr_low
52	1817	30	7	2	1	1	Avr_low
53	1886	47	9	1	1	1	Low
54	930	33	5	2	1	1	Avr_low
55	1200	39	4	2	0	0	High
56	1672	48	9	2	1	1	Low
57	3400	52	8	1	1	1	Low
58	710	27	8	2	1	1	Avr_low
59	150	24	2	2	0	0	High
60	1730	45	9	2	1	1	Low
61	1435	50	7	2	1	1	Low
62	987	34	5	2	1	1	Avr_low
63	420	24	3	2	1	1	Avr_low
64	680	30	4	2	1	1	Avr_low
65	1856	39	7	2	1	1	Low
66	1257	43	9	2	1	1	Low
67	1707	46	8	1	1	1	Low
68	1236	38	5	2	1	1	Avr_low
69	617	29	3	2	1	1	Avr_low
70	381	25	2	2	1	1	Avr_low
71	942	42	5	2	1	1	Avr_low
72	1335	37	7	1	1	1	Low
73	660	27	3	2	1	1	Avr_low
74	776	33	3	2	1	1	Avr_low

75	1355	37	6	2	1	1	Low
76	1993	56	9	2	1	1	Low
77	879	35	5	1	1	1	Avr_low
78	468	31	2	2	1	1	Avr_low
79	1004	45	8	2	1	1	Low
80	900	34	5	2	1	1	Avr_low
81	180	25	2	2	1	0	Avr_low
82	1786	48	7	2	1	1	Low
83	1716	37	6	2	1	1	Avr_low
84	349	26	2	2	0	0	High
85	1161	29	4	2	1	1	Avr_low
86	1701	42	9	2	1	1	Low
87	354	27	3	2	1	0	Avr_low
88	885	32	4	2	1	1	Avr_low
89	350	35	2	0	1	0	High
90	1521	55	8	2	1	1	Low
91	480	22	2	2	1	1	Avr_low
92	1125	42	5	2	1	1	Avr_low
93	1022	32	6	2	0	0	High
94	1165	44	9	2	1	1	Low
95	1178	28	8	2	1	1	Avr_low
96	550	60	10	0	1	0	High
97	1946	29	4	2	1	1	Avr_low
98	1089	28	9	2	0	0	High
99	1987	39	6	2	1	1	Avr_low
100	461	27	3	2	1	0	Avr_low
101	1759	47	8	2	1	1	Low
102	780	33	5	1	0	0	High
103	1854	55	7	1	1	1	Low
104	809	25	3	2	1	1	Avr_low
105	400	24	1	1	1	0	Avr_high
106	1836	48	9	2	1	1	Low
107	550	23	2	2	1	1	Avr_low
108	610	29	4	2	1	1	Avr_low
109	542	31	3	0	1	0	High
110	300	22	1	2	1	1	Avr_high
111	625	34	5	2	0	0	High
112	185	23	1	2	1	0	Avr_high
113	200	55	2	2	1	0	Low

114	1299	34	6	2	1	1	Avr_low
115	732	37	4	2	1	1	Avr_low
116	1788	45	8	2	1	1	Low
117	942	26	5	2	1	1	Avr_low
118	1647	50	7	2	1	1	Low
119	589	24	3	2	1	1	Avr_low
120	1545	38	6	2	1	1	Low

APPENDIX B: Microsoft Visual Basic 6 Program Source Code

```
Dim XL As Excel.Application
Dim WB As Excel.Workbook
Dim WS As Excel.Worksheet

Private Sub Command1_Click()
Set WS = WB.Worksheets("income")
WS.Range("A2").Value = Text1.Text
Set WS = WB.Worksheets("age")
WS.Range("A2").Value = Text2.Text
Set WS = WB.Worksheets("experience")
WS.Range("A2").Value = Text3.Text
Set WS = WB.Worksheets("guarantors")
WS.Range("A2").Value = Text4.Text
Set WS = WB.Worksheets("cr_history")
WS.Range("A2").Value = Text5.Text
Set WS = WB.Worksheets("rules")
If Val(WS.Range("E5").Value) < 0.25 Then
   Text6.Text = "High"
   ElseIf Val(WS.Range("E5").Value) < 0.35 Then
   Text6.Text = "Avr_high"
   ElseIf Val(WS.Range("E5").Value) < 0.6 Then
   Text6.Text = "Avr_low"
   ElseIf Val(WS.Range("E5").Value) < 0.8 Then
   Text6.Text = "Low"
End If
End Sub

Private Sub Command2_Click()
WB.Close
XL.Quit
Set XL = Nothing
```

```
Set WB = Nothing
Set WS = Nothing
End
End Sub

Private Sub Command3_Click()
res_r = 0
For n = 2 To 121
Set WS = WB.Worksheets("data")
income = WS.Cells(n, 1)
age = WS.Cells(n, 2)
experience = WS.Cells(n, 3)
guarantors = WS.Cells(n, 4)
cr_history = WS.Cells(n, 5)
res = WS.Cells(n, 6)
Set WS = WB.Worksheets("income")
WS.Range("A2").Value = income
Set WS = WB.Worksheets("age")
WS.Range("A2").Value = age
Set WS = WB.Worksheets("experience")
WS.Range("A2").Value = experience
Set WS = WB.Worksheets("guarantors")
WS.Range("A2").Value = guarantors
Set WS = WB.Worksheets("cr_history")
WS.Range("A2").Value = cr_history
Set WS = WB.Worksheets("rules")
If Val(WS.Range("E5").Value) < 0.2 Then
   Text6.Text = "High"
   ElseIf Val(WS.Range("E5").Value) < 0.4 Then
   Text6.Text = "Avr_high"
   ElseIf Val(WS.Range("E5").Value) < 0.6 Then
   Text6.Text = "Avr_low"
   ElseIf Val(WS.Range("E5").Value) < 0.9 Then
   Text6.Text = "Low"
```

```
End If
MSFlexGrid1.AddItem Str(n - 1) & Chr(9) & income & Chr(9) & age & Chr(9) &
experience & Chr(9) & guarantors & Chr(9) & cr_history & Chr(9) & res & Chr(9) &
Text6.Text
b = FormatNumber(WS.Range("E5").Value, 5)
Set WS = WB.Worksheets("data")
WS.Cells(n, 7) = b
Next
End Sub

Private Sub Form_Load()
Form1.Caption = "Client Risk Assessment Program"
MSFlexGrid1.Rows = 1
MSFlexGrid1.Cols = 8
MSFlexGrid1.Clear
MSFlexGrid1.Col = 0
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
MSFlexGrid1.Text = "No"
MSFlexGrid1.Col = 1
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
MSFlexGrid1.Text = "Income"
MSFlexGrid1.Col = 2
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
MSFlexGrid1.Text = "Age"
MSFlexGrid1.Col = 3
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
MSFlexGrid1.Text = "Experience"
MSFlexGrid1.Col = 4
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
```

```
MSFlexGrid1.Text = "Guarantors"
MSFlexGrid1.Col = 5
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
MSFlexGrid1.Text = "Cr.History"
MSFlexGrid1.Col = 6
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
MSFlexGrid1.Text = "Expert Risk"
MSFlexGrid1.Col = 7
MSFlexGrid1.Row = 0
MSFlexGrid1.CellAlignment = flexAlignCenterCenter
MSFlexGrid1.Text = "NFT2 Risk"
MSFlexGrid1.ColWidth(0) = 900
MSFlexGrid1.ColWidth(1) = 1400
MSFlexGrid1.ColWidth(2) = 900
MSFlexGrid1.ColWidth(3) = 1600
MSFlexGrid1.ColWidth(4) = 1600
MSFlexGrid1.ColWidth(5) = 1600
MSFlexGrid1.ColWidth(6) = 1600
MSFlexGrid1.ColWidth(7) = 1600
Set XL = New Excel.Application
Set WB = XL.Workbooks.Open("c:\theses\references\risk_T2.xls")
End Sub

Private Sub Text1_KeyPress(KeyAscii As Integer)
If KeyAscii = 13 Then
Text2.SetFocus
End If
End Sub

Private Sub Text2_KeyPress(KeyAscii As Integer)
If KeyAscii = 13 Then
Text3.SetFocus
```

```
End If
End Sub

Private Sub Text3_KeyPress(KeyAscii As Integer)
If KeyAscii = 13 Then
Text4.SetFocus
End If
End Sub

Private Sub Text4_KeyPress(KeyAscii As Integer)
If KeyAscii = 13 Then
Text5.SetFocus
End If
End Sub

Private Sub Text5_KeyPress(KeyAscii As Integer)
If KeyAscii = 13 Then
Command1.SetFocus
End If
End Sub
```

APPENDIX C: Microsoft Excel Worksheets

income	range		low	medlow	medhgh	high
1545	104-3400	LL	0	0	0	0
		LR	0	0	0	0
		ML	0	252.1	907.1	1208
		MR	687.9	1108	1763	2064
		RL	1520.25	1835.25	2326.5	2552.25
		RR	2533.75	3058.75	3877.5	4253.75

lowerof	low	medlow	medhgh	high
A	0	0.148789	0.369591	0.459984
B	0.535661	0.775984	1	1
C	1	1	1	1
D	1	1	0.876347	0.748546

AB	AB	AB	AB
0	0.148789	0.369591	0.459984
0.535661	0.775984	1	1
0.267831	0.462386	0.684795	0.729992

age	range		low	medlow	medhgh	high
38	20-60	LL	2.77275	8.025	13.275	23.025
		LR	4.62125	13.375	22.125	38.375
		ML	18.33	25.33	32.33	45.33
		MR	27.67	34.67	41.67	54.67
		RL	31.725	36.975	42.225	51.975
		RR	52.875	61.625	70.375	86.625

lowerof	low	medlow	medhgh	high
A	0	0	0.147186	0.437332
B	0.590158	0.876458	1	1
C	1	1	1	0.671371
D	1	1	0.812224	0

AB	AB	AB	AB
0	0	0.147186	0.437332
0.590158	0.876458	1	1
0.295079	0.438229	0.573593	0.718666

experience	range		low	medlow	medhgh	high
6	0.5-10	LL	0	0	1.4295	2.1795
		LR	0	0	2.3825	3.6325
		ML	0	2.766	5.767	6.767
		MR	2.233	5.233	8.233	9.233
		RL	4.5705	6.8205	9.0675	9.8175
		RR	7.6175	11.3675	15.1125	16.3625

lowerof	low	medlow	medhgh	high
A	0	0.13375	0.445883	0.535444
B	0.300394	0.874955	1	1
C	1	1	1	0.832788
D	1	1	0.618313	0.422723

AB	AB	AB	AB
0	0.13375	0.445883	0.535444
0.300394	0.874955	1	1
0.150197	0.504352	0.722942	0.767722

guarantors	range		low	high
2	0-2	LL	0	0
		LR	0	0
		ML	1	1
		MR	1	1
		RL	3	3
		RR	3	3

lowerof	low	high
A	0.5	0.5
B	0.5	0.5
C	1.0	1.0
D	1.0	1.0

AB	AB
0.5	0.5
0.5	0.5
0.5	0.5

cr_history	range		low	high
1	0-1	LL	0	0
		LR	0	0
		ML	1	1
		MR	1	1
		RL	3	3
		RR	3	3

lowerof	low	high
A	1.0	1.0
B	1.0	1.0
C	1.0	1.0
D	1.0	1.0

CD	CD
1.0	1.0
1.0	1.0
1.0	1.0

W	MIN(R)			
0.9	0.438229			
0.8	0.499975		**Risk**	**0.6040**
0.3	0.499975			
0.1	0.150197			