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Case Study

The Use of Multi-Objective Meta-Heuristic Algorithm GENETIC ANFIS in Rating the Loans Granted to Real Customers of Bank Melli Iran

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ABSTRACT

The present study is aimed to Rating the loans granted to the real customers of Bank Melli Iran in accordance with the credit factors of the customers using the multi-objective meta-heuristic algorithm of genetics-adaptive neuro-fuzzy network system (GENETIC-ANFIS). This research is a qualitative-quantitative design and exploratory based on purpose in terms of purpose and descriptive in terms in terms of data collection and analysis method and survey. Qualitative data was collected via the research of Rezaei et al. (2022) and the decision-making team of the banking field, and quantitative data was collected through 1178 real customers of Bank Melli of Mazandaran province during the years 2012 to 2021 based on 14 types of loans. According to the rating of granted loans, the risk of each loan was measured separately for 4 personal, environmental, economic and credit factors. In Mudharabah loans, Musyarakah, debt purchase, Istisna and salaf, the economic factor showed the highest sensitivity. Also, the behavior of the research meta-heuristic model has indicated 78% reliability in the accuracy and interpretability of the model compared to genetic algorithm, neural network, fuzzy logic and neural-fuzzy network models.

1 Introduction

Due to the great financial crisis around the world in the last four decades (e.g. the US savings and loan crisis in the 1980s to the European debt crisis in 2008) and the regulatory and supervisory concerns considered in Basel III, credit risk assessment is a major issue in risk management for lending institutions, including the banking industry [1-2]. Without distinguishing between good and bad customers, banks and financial institutions are not able to continue and develop. An important technique to evaluate

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credit risk is the validation model. According to [3], credit scoring is one of the most important methods to compare good customers with bad customers in the financial services industry. Normally, in order to grant small loans to real customers who are the majority of the loan applicants, banks need a detailed assessment and validation of each real customer, which is costly for banks and because the real customers have different jobs and are the major applicants for bank loans, the same evaluation of all jobs and various loans can be a wrong method in validating customers. Also, a real customer may have obtained a good credit rating in the primary validation of the bank, but because of various personal, social and economic factors such as economic recession or sanction, he demonstrates a different credit behavior. For example, we can refer the sanctions in our country (Iran), when the conditions were abnormal and many predictions were not true. Thus, it is important that basically the behavior of real customers is dynamic in nature; this means that it changes over time and is not static, and this should be mentioned in the presentation of the credit risk assessment model of real customers. In its proposed method, the current study considers the customer as a dynamic element whose behavior changes over time, and presents a model that, with the different conditions and under uncertain conditions and in accordance with the new loans received, predicts the real customer's credit correctly and with very minimal error.

To calculate the expected and unexpected losses and then determine whether their capital is sufficient or not, banks need the customer default probability. Most researches focus on single classifier models. These models are divided into two groups based on their techniques: models that apply statistics and models that use artificial intelligence. There are various statistical methods, including linear discriminate analysis [4], logistic regression [5], and the nearest neighbor search [6-7]. Also, artificial intelligence techniques such as support vector machine [8-9], decision tree [10-11], adaptive boosting [12], there are different artificial neural networks such as feed-forward neural networks, back-propagation, multilayer perceptron, fuzzy neural approach and deep neural networks and probabilistic neural networks [13-14]. Also, the existing theoretical literature recommends methods based on optimization with meta-heuristic algorithms [15-17]. Meta-heuristic algorithms, such as genetic algorithms, work in search spaces and are very exact, because nature, physics and humans are inspired by them [18]. The adaptive neuro-fuzzy system is a synthesized learning model combining the advantages of neural-artificial network and fuzzy logic and has capabilities such as superior computing ability, specialized knowledge of fuzzy logic, and supervised learning ability of neural-artificial network as one of the available soft computing techniques. Although, the adaptive neuro-fuzzy systemis used for efficient prediction modeling of nonlinear problems, the adaptive neural-fuzzy system performance prediction model depends only on the proper selection of its training parameters (assumption and result) which are often evaluated by trial and error method. It is really difficult and time –consuming to adjust these parameters through the trial and error method [19]. Therefore, derivative optimization and meta-heuristic algorithms are mostly used to train the parameters of the adaptive neuro-fuzzy system to achieve effective prediction models. Recently, few researchers have employed nature-inspired algorithms to adjust the parameters of adaptive neuro-fuzzy systems. There are various artificial intelligence algorithms, each of which has its own set of adjustment parameters to obtain the given level of intelligence. In addition, the performance of genetic algorithm is unknown in terms of computational time for learning and predicting unknown data. The genetic algorithm repeats the natural evaluation in search of optimal solutions. Considering the non-linear nature of credit rating models and their linguistic nature, the computations and complexity of using these models are increasing the importance of these models day by day. Meta-heuristic tools such as neural networks, fuzzy logic, genetic algorithms, etc. are suitable for controlling and managing non-linear issues. These systems have high prediction accuracy with their special computations and very low time consumption while covering all weaknesses of statistical methods and linear models, and have very high flexibility in dealing with problems [1].

In this research, 5 systems and algorithms are used for credit rating of facilities provided to customers; three algorithms are individual, one algorithm is combinatorial, and one algorithm is heuristic and evolutionary. The reason for choosing these 5 algorithms is the proximity of the parameters of these models to the criteria of the credit rating problem of customers and facilities. The artificial neural network algorithm, which was created utilizing the function of the human brain, was established for learning, generalization and decision making. In this research, this algorithm is used to create an appropriate network structure, determine layers, select parameters and search for local optimization that will be used in the testing and training process. The main reason for choosing this algorithm is to learn the training process to appropriately determine the factors related to customers [14].

Fuzzy systems that emerge based on the theory of fuzzy sets will express the conditions of uncertainty and doubt that exist in ambiguous concepts and variables in mathematical language and based on the degree of membership. The main reason for choosing this logic is to create an if-then knowledge base for the judgment of experts in the research [2]. Genetic algorithms are an optimization and search technique based on genetic principles and natural selection. In this research, using the population, it is sought to optimize the objective function and also minimize the cost function. The main reason for choosing this algorithm is weighting the layers and optimizing the objective function [7]. One of the models with high predictive ability is neuro-fuzzy hybrid models. These models perform better than neural networks and fuzzy systems because they simultaneously consider the ability to learn and use if-then rule bases in their structure. That is because they incorporate the best features of neural networks and fuzzy systems together. This model has been used in facility classification [19].

The adaptive neuro-fuzzy algorithm, despite its widespread application, has drawbacks such as getting stuck in local optimization. Evolutionary algorithms have great ability to perform global searches and avoid getting stuck in local optimization. The metaheuristic and evolutionary genetic-neuro-fuzzy algorithm does not require knowledge of parameter values. This algorithm is based on the dynamics of the model and parameter values have no effect on the system. The reason for using this algorithm is that it does not rely on expert and specialist opinions in determining the final model. This algorithm has been used in the final ranking of individual customers based on facilities provided.

The current study presents a main approach to design classification based on fuzzy rules, which is equipped with an effective mechanism to optimize the balance between accuracy and interpretability. This means that classification based on fuzzy rules characterized by various optimized levels obtains a balance, including systems with high accuracy and better interpretability (based on current approaches) to support decision-making. Obviously, such dimensions have not yet been investigated in the literature on financial decision-making.

According to the mentioned concepts, this research attempts to design a meta-heuristic algorithm that can accurately and with high interpretability implement the credit rating of real customers based on the granted loans.

The remainder of this article is organized as follows: Section 2 reviews the literature related to the importance of new credit ratings, multi-objective classification techniques, definitions of loans given to real customers and definitions of applied algorithms of this study. Section 3 examines the research method and meta-heuristic algorithm based on the integration of adaptive neuro-fuzzy network system and genetic algorithm as well as multi-objective classification based on fuzzy rules with genetic learning approach. Section 4 deals with the behavior output of existing algorithms, the training data output, the comparison of prediction models, the classification of loans, their ranking and the details of the main findings of the study. Section 5 is dedicated to the conclusions, limitations, and study recommendations for future studies.

2 Theoretical Frameworks

2.1 Multi-Objective Classification Techniques

Credit classification techniques are usually evaluated in terms of three dimensions: accuracy, transparency and interpretability, and their computational efficiency (classification speed) [20-21]. Accuracy (the ability to accurately present the modeled decision-making process and create the most accurate decisions) is a basic requirement for certain reasons. Even a small increase in the number of correct decisions leads to a considerable reduction in costs.

Transparency and interpretability (the ability to justify and provide an understandable and complete explanation of the decisions, including the selection of the most essential inputs) are of great importance for both decision makers and applicants. The decision-maker can improve his knowledge and expertise in the relevant decision-making field, and the applicant can get an understandable and clear explanation of the decisions. This is especially important when the applicant's credit is rejected, as based on the regulations of some countries, vague and unclear reasons for credit rejection are illegal [22].

As far as classification speed is concerned, based on the researches done by [20], an immediate decision is much more attractive to a borrower than waiting a few days. If credit decisions are made immediately by different computer systems, the difference between them in classification speed is meaningless in terms of practical issues. Large credit scoring databases are available, for example, according to a study done by [20], databases with hundreds of thousands of applicants with more than a hundred characteristics are quite common, while functional scoring databases containing information about the behavior of previous refunds can be even larger. It is obvious that a lot of knowledge about different aspects of financial decision-making is hidden in such data sets. Therefore, the development of effective financial knowledge discovery tools in such data or financial data mining methods has a strong logic. Knowledge discovery tools are capable of automatically revealing understandable and valid patterns, trends and decision-making mechanisms hidden in financial data. As long as the representation of such data is taken into consideration, more useful structures are conditional rules and fuzzy linguistic conditional rules [23]. Rule extraction techniques provide classification models with clear advantages, first, they are understandable and therefore easily used in financial applications, for example, in applications where packages must be completely transparent and clear, second, the extracted rules only sacrifice a small amount of accuracy compared to the black box models that were created from them [24].

2.2 Types of Loans Granted to Real Customers

According to the circulars and notices, Bank Melli gives 14 types of loans to real customers, including: Mudharabah, Musyarakah, installment sale of raw materials, Murabahah, Jaala, debt purchase, Musyarakah, Muzara’ah, Qardhul Hassan, Salaf, Ijarah to own, housing installment sale, Istisna, production installment sale, which are briefly defined as follows:

Table 1: Types of Loans Granted to Real Customers

No.	Loans granted to the customers	Definition
1	Mudharabah	A contract whereby one of the parties (the owner) is responsible for providing capital (cash). On the condition that the other party (the agent) does business with it and both parties share the profit.
2	Musyarakah	It is the combination of cash or non-cash shares of the company belonging to several real or legal entities in a common way for the purpose of benefiting according to the contract.
3	installment sale of raw materials	It is the transfer of the same entity at a known price, in such a way that all or part of the said price is received in equal or unequal installments on the due date or due dates.
4	Murabahah	It is a contract by which the supplier informs the applicant of the total price of goods and services and then by adding an extra amount or percentage, it is given in cash, credit or installments, in equal or unequal installments for an applicant based on the due date or due dates.
5	Jaala	It is the obligation of a person (*jaal*) or an employer to pay an amount with a known wage (*jaal*) in exchange for performing a certain act according to the contract that performs the act.
6	Debt purchase	It is a contract whereby a third party buys the debtor's long-term debt from the creditor in cash for less than its nominal amount.
7	Masakat	It is a transaction between the owner of fruitful trees (trees using their leaves, flowers, fruits, etc.) and the agent who is responsible for training, watering and maintaining the trees.
8	Muzara'ah	It is a contract whereby one of the parties gives a certain land to the other party for a certain period of time to cultivate it and shares the crops.
9	Qardhul Hassan	It is a contract whereby the bank (as the lender) lends a certain amount to real and legal entities (as the borrower) to meet the needs as mentioned in the contract.
10	Forward contract (salf)	Advance cash payment of products of production units at a certain price.
11	Ijarah to own	It is the renting contract in which it is conditioned that the lessee will own the same leased property at the end of the lease period if he complies with the conditions mentioned in the contract.
12	housing installment sale	The bank can sell such houses in installments in order to facilitate the presentation of housing via the granting of banking loans based on the written request and commitment of the applicants.
13	Istisna	It is a contract whereby one of the parties commits to build or deliver a certain project or product with the required specifications for a certain amount and to deliver it in a certain time.
14	production installment sale	Installment sales contract based on the needs of working capital for a maximum one-year production period.

Source: Bank Melli Iran transactions and credit loans Instructions (Circulation 20b), [25].

2.3 Genetic Algorithm

The genetic algorithm, developed by Holland in 1975, is one of the most recognized types of evolutionary algorithms. This algorithm starts the search with a population of random initial solutions. Whenever the final criteria are not met, it produces new populations with genetic operators such as crossover, mutation and selection. With each repetition of these three genetic operators, a generation is created. Initial populations are defined as strings and each string is described by a chromosome. The crossover operator combines the genes of two parents with each other and two new children are created. In the mutation operator, a sudden change occurs in the gene [26].

In the selection operator, populations are evaluated using the fitness function. Populations with lower fitness are removed and populations are moved to the optimal response. There are different population selection methods to implement genetic operators, they are: rank selection, tournament selection and roulette wheel selection. Finally, after several generations, the genetic algorithm gradually goes near the optimal solution. The condition for stopping the algorithm is to go through a certain number of repetitions, which is determined by the user before starting the algorithm.

2.4 Adaptive Neuro -Fuzzy Network System

Fuzzy set theory is a complete and perfect tool to model vagueness and uncertainty (or imprecision) originating from mental phenomena that are neither random nor accidental. Humans are mostly involved in the decision analysis process. The logical method in decision-making should consider individuals'' mentality, not just using objective probability measurements. This attitude towards uncertainty and vagueness in human behavior has led to the study of a relatively new field in decision analysis: fuzzy decision making [27]. Fuzzy inference systems are one of the most widely used and common systems designed for fuzzy reasoning. Furthermore, fuzzy reasoning, which is also called approximate reasoning, is a type of inference method that obtains conclusions from a set of fuzzy if-then rules and known facts. Fuzzy inference system is a common computational framework based on the concept of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning [28].

3 Literature Review

Credit risk assessment is necessary for risk control. Thus, validity assessment is of great importance for researchers. Beaver [29] was a pioneer to use univariate analysis tools to predict financial stress on a firm-by-firm basis. In order to analyze credit risk, Messier and Hansen [30] developed expert systems and Dezai et al. [31] introduced a neural network model. Hashemi et al. [32] proposed heterogeneous intelligent system to predict asset patterns of the bank. In addition, Earky [33] considered a set of financial ratios to predict corporate bankruptcy and the default probability or non-repayment using the logistic regression model. West [34] examined the validity scoring accuracy of five neural network models: multilayer perceptron, mixture-of-experts, radial basis function, learning vector quantization, and fuzzy adaptive resonance. Martens et al. [22] introduced Trepan and G-REX methods to develop support vector machine rule extraction methods to determine credit scores. On the other hand, Pavlenko and Chernyak [35] showed how the probability diagram is applied to model and measure credit risk concentration. Zhang [36] proposed a vertical bagging decision trees model for credit scoring. Bellotti and Crook [37] tested the support vector machines against the traditional methods on a large credit card database. Finally, Zhang [38] presented a multi-criteria optimization classification based on kernel, fuzzification and penalty factors. Abbasi and Rahimi [39] addressed the design of an expert system for credit rating of individual customers of banks using a neuro-fuzzy network. Moslemi et al. [40] examined bank risk reporting ranking using data envelopment analysis. Fatemi Moghaddam et al. [41] identified financial factors affecting risk management in Iranian banks using the Delphi-fuzzy technique. Tajik et al. [42] presented an intelligent model for credit risk of individual bank customers using a machine learning algorithm. Finally, Roshandel et al. [43] measured the credit risk of Iranian banks using KMV-Merton and Z-Score models.

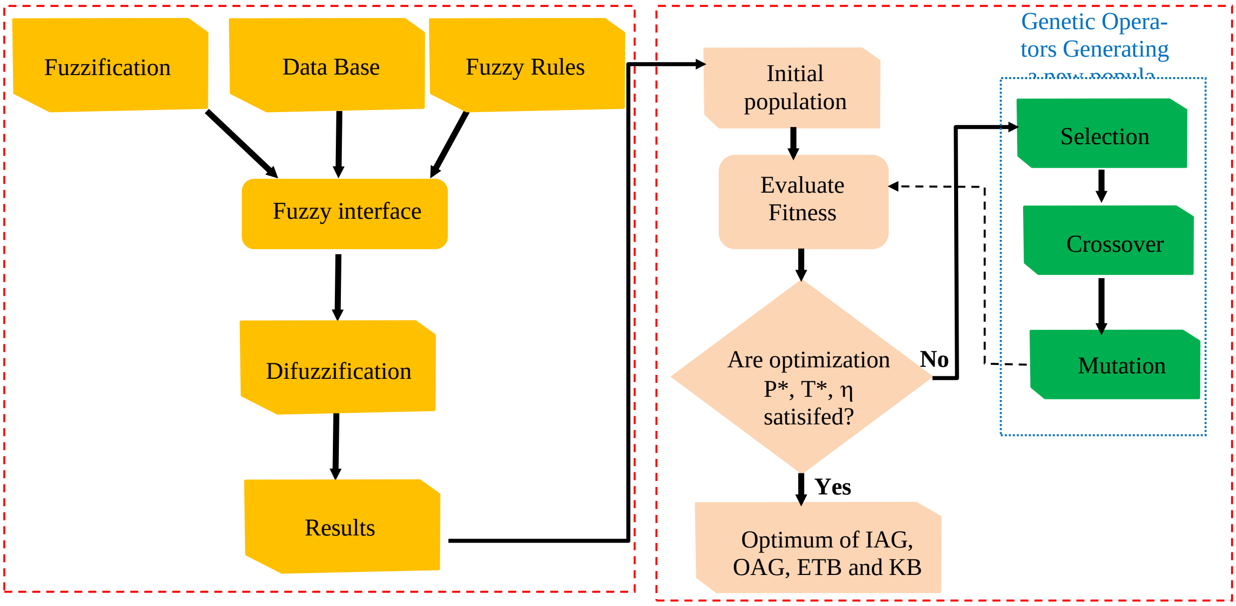
Many local and international researches were conducted on customers' credit risk. Thus, the present study attempts to deal with researches that are both new and compiled in recent years, and mostly focus on real customers, credit risk and artificial intelligence techniques in the field of banking.

Derakhshani et al. [44] designed a quick warning system for the credit risk of 400 real customers and

7500 legal customers of the bank using neural network models, survival probability function and support vector machine and found that the considered components in this study that based on personality, financial and economic characteristics, have significant effects on the probability of customer default and credit risk calculation. Moradi et al. [45] examined the information of 2,840,000 real customers of three governmental banks for 32 three-month periods from 2010 to 2017 and concluded that their innovative model with a sensitivity of 92.1% and a detection level of 89.1% has high efficiency and performs better and has higher efficiency compared to probit, logit, and neural network models. Paridari et al. [46] used the financial transactions of 1123735 real customers of Kargaranwellfare Bank in six time periods (monthly) with the aim of segmentation and dynamic ranking of customers by K-means algorithms and self-organizing neural networks (SOM) and found that of the total customers examined, 56% are mobile customers with a consistent structure, in this group 15% are dynamic customers with a growing value trend, 82% are dynamic customers churn, and 3.6% are ordinary and dynamic loyal customers with the ability to increase value, 1.2% of customers are among low-value dynamic customers with an unstable and intermittent growth pattern. Torabian et al. [47] used the information of variables such as gender, age, loan support and amount of loans for 94487 real customers of Saderat Bank of Tehran during the period 2014 to 2018 and found that the variables of age and education are effective on credit status and rating of customers, while other variables mentioned above have a significant relationship with the customer's credit condition. Basser et al. [48] evaluated the credit risk using the fuzzy classification method based on clustering and demonstrated that the proposed model of this research is useful in predicting the credit risk of customers compared to other models. Khalili and Rostgar [49] examined the optimal cost-sensitive credit scoring with a hybrid performance metric for bank customers using data from Iran, Germany and Australia and 5 nearest neighbor models, support vector machine, decision tree, Adaboost , the neural network and 9 scenarios. They concluded that the proposed research method provides very good scoring performance. Song et al. [50] predicted loan default using credit rating and multi-objective group learning scheme and showed that the proposed algorithm of this research is better than the credit rating models recommended in other studies. Stefania et al. [51] examined a research “credit risk scoring model based on discriminant analysis. The results of the data from Colombia indicated that the function presented in this research could detect the credit risk of granted loans.

4 Research Methodology

This research is exploratory in terms of purpose, and it is descriptive and survey in terms of data collection and analysis. In this research, the credit rating of 14 loans granted to real customers of Bank Melli of Mazandaran province was performed in 4 groups of credit factors that were previously identified in Rezaei et al.'s [52] study. Personal, environmental, economic and credit factors were previously identified by experts, and 14 loans given to customers were extracted from the financial statements of Bank Melli of Mazandaran province during the period 2012 to 2021. The number of customers who were obtained from the financial statements by total count sampling method was 1178. Ten-year loans data for all real customers, including good and bad customers, are classified in 5 fuzzy spectrums. These 5 spectrums including very low risk, low risk, medium risk, high risk and very high risk were extracted by the researcher for each customer based on the granted loans. Then, these scores, which were coded from 1 to 5 (1 for very low risk and 5 for very high risk) were given to the MATLAB software and based on the 5 models of this research (1-neural network, 2-fuzzy, 3 -genetics, 4- adaptive neural- fuzzy, 5-genetics-ANFIS), the outputs of the predicted models were extracted based on the criteria of accuracy and interpretability. Also, the classification of loans granted to customers was performed based on accuracy and interpretability criteria. Finally, the experts in Rezaei et al.'s [52] research, besides some new experts in the field of banking, were interviewed for the credit scoring of real customers for each loan. The risk of each loan was measured separately for 4 personal, environmental, economic and credit factors. Scores from 1 to 10 are used for the risk assessment for each loan, as scores of 1 are for very low risk and 10 for very high risk.In this study, prediction was performed using neural-fuzzy-genetic network model in three stages: 1- model design, 2- data preparation and 3- model execution. In the design of neural-fuzzy-genetic network model, the multi-layer feed-forward network with the hybrid learning algorithm of error back propagation and least squares (LS-BP hybrid) and Sugeno fuzzy [53] inference system has been applied. The number of hidden layers is 3 and the sigmoid model input function and linear output function are considered. Moving average function is also applied for de-fuzzification. In the stage of data preparation, initial processing was performed on 300 data states. The data should be normalized and for normalization, it has been done like artificial neural network. In order to model ANFIS, first the data with scores between 1 and 10 were entered into the software. According to the rules of the neural-fuzzy network, 75% of the data related to the training data and 25% of the total data related to the test data have been entered into the model. In the model execution stage, a suitable neural network is implemented through the continuous change of the number of layers and the number of neurons of the hidden layers, and also through different membership functions and their number, a suitable fuzzy system has been used. The final goal of the model is to reduce the training error. In all ANFIS models, dimensions and credit scoring of each dimension, the average training error is less than the threshold (0.5) and this indicates that the model has high efficiency. The following Figure (Figure 1) shows the data processing in the fuzzy and genetic system.



(a) Artificial Neural Fuzzy Inference Network (ANFIS) **(b) Genetic Algorithm (GA)**

Fig. 1: The Data Processing Stages, Artificial Neuro-Fuzzy Network Output and Genetics Algorithm

In each learning trial, the best approximation of the Pareto front is obtained. The Pareto front is the set of Pareto optimal solutions: they are characterized by different levels of interpretability-accuracy balance. By obtaining a set of solutions in the form of the best approximation of the Pareto front, first a credit classification solution based on fuzzy rules with the characteristic of the highest accuracy $Q_{ACC}^{(tst)}$ in the test data set is obtained ($Q_{ACC}^{(lrn)}$is defined for the learning data set) second, it is selected with the characteristic of the highest interpretability of $Q_{INT}$from the Pareto front. Then the average results from K tests are calculated. Such a test is referred to as single k multi-layer crossover validation (single k-fcv). The single k-fcv test is repeated ten times for different divisions of the original data set into K subsets. In addition, in order to minimize the bias associated with the initiation of the method, each of the mentioned k-fcv tests has been repeated ten times for randomly selected initial values of the parameter in our method. Therefore, a total of 100 individual k-fcv tests were performed for each K. Besides, in order to increase the reliability of the performance evaluation and for comparative delivery with the alternative methods reported in the research literature, four values of K have been considered: k=10 (the learning to test ratio 1:9), k= 5 (ratio 1:4), k=3 (ratio 2:1) and k=2 (ratio 1:1). A non-model ratio of 1:2.6 has also been considered for the data set.

In all the tests, the genetic learning process was performed via one thousand generations (during 1000 generations), the initial population had 10000 individuals, the tournament selection was 2, and the mutation and crossover probabilities were 0.7 and 0.5, respectively.

The classification performance of fuzzy rules is assessed in terms of its accuracy and interpretability. The main criterion to measure accuracy is $Q_{ACC}^{(lrn)}$ for learning data and $Q_{ACC}^{(tst)}$ is defined mathematically for test data. The classification accuracy of fuzzy rules can also be expressed as the percentage of correct decisions: $ACC^{(lrn)} = Q_{ACC}^{(lrn)}.100\%,\ \ ACC^{(\mathrm{tst})} = Q_{ACC}^{(\mathrm{tst})}.100\%.$, Some other measurements of accuracy regarding learning and test data can be classified into two categories, as the true positive ratio (TPR) or sensitivity and true negative ratio (TNR) or the characteristic defined as follows:

$$TPR = \frac{TP}{TP + FN}, TNR = \frac{TN}{TN + FP} \tag{1}$$

Where TP (True positive) is the number of correctly classified positive cases, TN (True negative) is the number of correctly classified negative cases, and FP (False positive) and FN (False negative) are the number of false negative and positive items of the class, respectively. It is clear the accuracy of the aforementioned sum is

$$Q_{ACC} = (TP + TN) / (TP + FN + TN + FP) \tag{2}$$

The main measurement criterion is the interpretability of Q_{INT}. In addition, there are some other indicators of interpretability, such as the number of rules (R) in the basis of the rule, the number of indicators (n_{ATR}) used by the classifier, the number of Persian collections (linguistic terms) that indicate the classifier indices (n_{FS}) and the number of indices used in each rule ($n_{ATR/R}$). During the genetic learning, the assessment of specific individuals (fuzzy knowledge bases) in the framework of the Pittsburgh-type approach, should be performed in each generation. For this reason: 1) a fuzzy set theory representation of the set of linguistic rules 1) should be formulated and 2) a fuzzy estimation inference scheme should be employed. Generally, there are two different interpretations of if-then rules. First, it refers to the combination-based approach, it deals with special rules as independent local forms and is compiled separately. In the second case, which is called the logical or application-based approach, these rules are called fuzzy restricting rules and, therefore, are based on the minimum feature principles that are collected separately. Fuzzy models are learned from a set of input-output pairs, which are independent local examples of system behavior. Therefore, the relationship-based model is more compatible with the nature of learning data compared to the logical model and is used exclusively (e.g. [50] model with soft t to combine many records and records with results related to rules and also Max software for collecting rules). As far as the fuzzy estimation inference is concerned, two schemes are used in the literature (for example, the combined rule of inference and reasoning based on similarity); both of which can be used in our approach. Thus, by using the Mamdani model [54] as mentioned before, we obtain the input numerical data $x' = (x'_1, x'_2, \ldots, x'_n)$ of the response of the fuzzy set B, which is known by the membership function

$\mu_{B'}(y),\ y \in Y = \{y_1, y_2, \ldots, y_c\}$:

$$\mu_{B'}(y) = \max_{r=1,2,\ldots,R} \mu_{B'^{(r)}}(y) = \max_{r=1,2,\ldots,R} \min\left[\alpha^{(r)}, \mu_{B_{(\sin gl.)j^{(r)}}}(y)\right], \tag{3}$$

Where

$$\alpha^{(r)} = \min_{\substack{i=1,2,\ldots,n,\\ sw_i^{(r)} \neq 0}} \alpha_i^{(r)}, \tag{4}$$

And

$$\alpha_i^{(r)} = \begin{cases} \mu_{A_{i,sw_i^{(r)}}}(x'_i), & \text{for } sw_i^{(r)} > 0, \\ \mu_{\bar{A}_{i,sw_i^{(r)}l}}(x'_i), & \text{for } sw_i^{(r)} < 0. \end{cases} \tag{5}$$

$\alpha^{(r)}$ Is the degree of activity of the r[th] fuzzy rule by the input numerical data x', while $\alpha_i^{(r)}$ for i as we have $sw_i^{(r)} \neq 0$ for the degree of activation of certain characteristics in that rule. Normally, a non-fuzzy response y' is required from classification based on fuzzy rules, which is calculated as follows:

$$y' = \arg\max_{y \in Y} \mu_{B'}(y).$$

Figure 2 shows an overview of the combination of genetic algorithm and fuzzy-adaptive neural system.

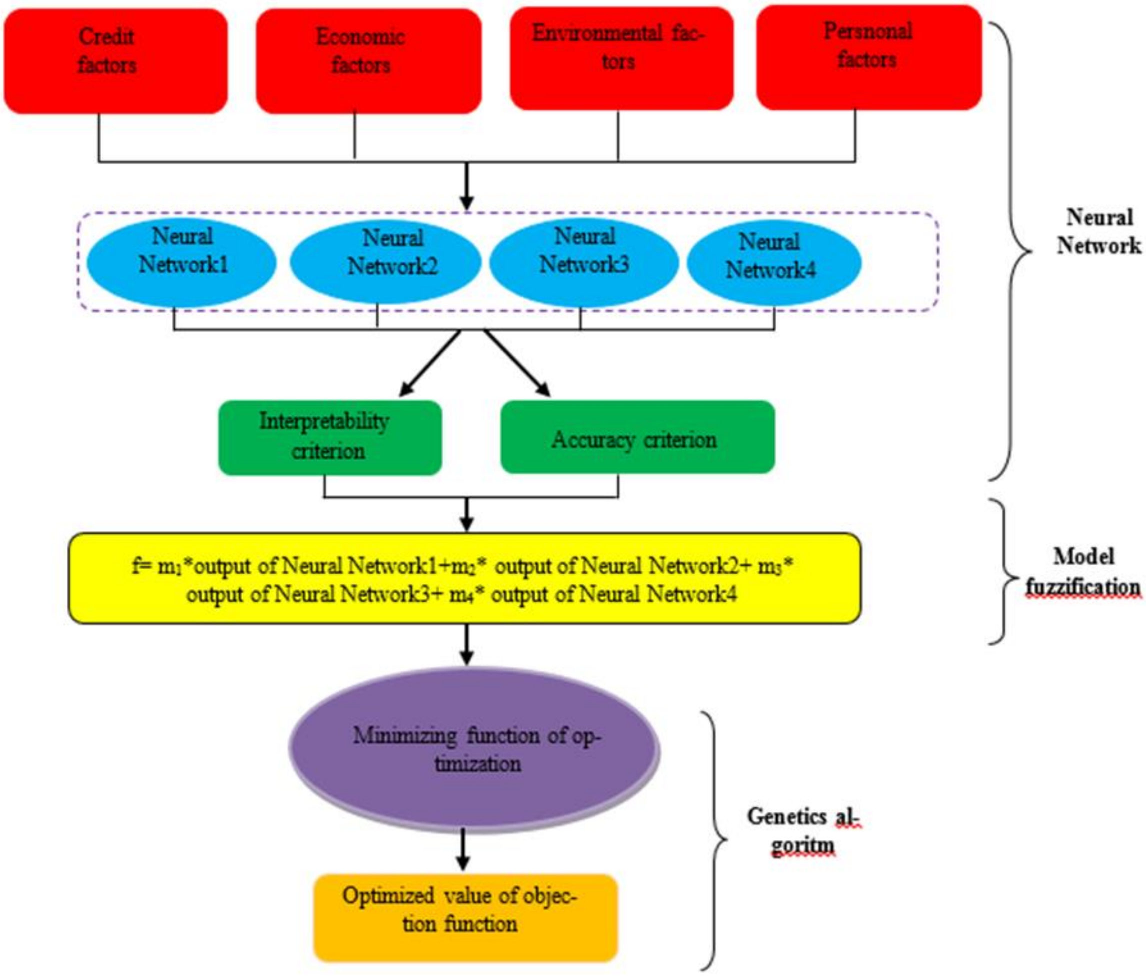


Fig. 2: The output of artificial fuzzy neural networks and genetic algorithm

5 Findings

5.1 The Figure of the Model's Behaviors

First, the output of the prediction model diagram used in this study is shown. Figure 3 shows the neural network training data output, neural network performance and genetic algorithm performance. In the composition of the neural network model, 70% of the data are used as training, 15% as testing and 15% as validation. Based on each epoch, the error of the validation data is calculated and finally the training is stopped. According to the middle Figure, the green diagram indicates the efficiency and performance of the network, and is increased after crossing with the network error, according to the neurons of the hidden layer (blue diagram). Also, based on the behavior of the genetic algorithm, the best behavior of the model according to the selection, mutation and crossover is increasing the production of generation (red) to predict the best behavior of the model.

Figure 4 shows the data output of the fuzzy logic training, the performance output of the adaptive neuro-fuzzy system and the output of the learning and training curves of the combination of the genetic algorithm and the neuro-fuzzy technique. In the left Figure, all the fuzzy logic rules in the training data are shown. As shown in the Figure, as the number of rules is increased, the model error is decreased. The middle figure demonstrates the speed of the neuro-fuzzy network. In this Figure, as the speed is increased, the behavior of the network is also decreased. This means that the model error has been considerably decreased and the accuracy of the model has been properly actualized. The right Figure shows the combination of genetic algorithm and neuro-fuzzy model for all four ANFIS. Here, the accuracy of the training data, which the model already knows, is about to 100% and is completely normal. But the important result, which is the accuracy of the test data, was higher than 95%, which is a very good result.

Figure 5 shows the three-dimensional behavior of four ANFISs. According to the rule of the neuro-fuzzy network, if the speed is increased, the acceleration should have a downward behavior, but if the distance is increased, the acceleration behavior is ascending. The three-dimensional shape is the same continuous (smoothed) structure made of rules. We can have them for any value of any combination of speed or distance. Figure (5) demonstrates ANFIS levels and ANFIS function after training. This Figure is the same level created between input variables (personal, environmental, credit and economic factors) and output variables (credit scoring) obtained by using ANFIS model.

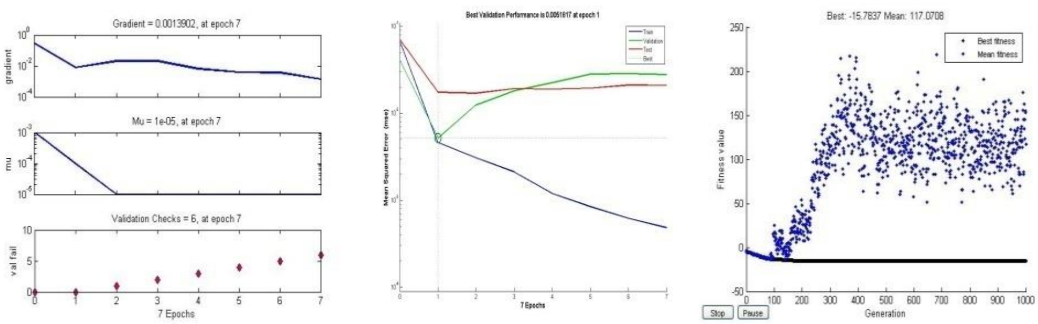


Fig. 3: The output of neural network training data (right), output of neural network performance (middle), output of genetic algorithm performance (left)

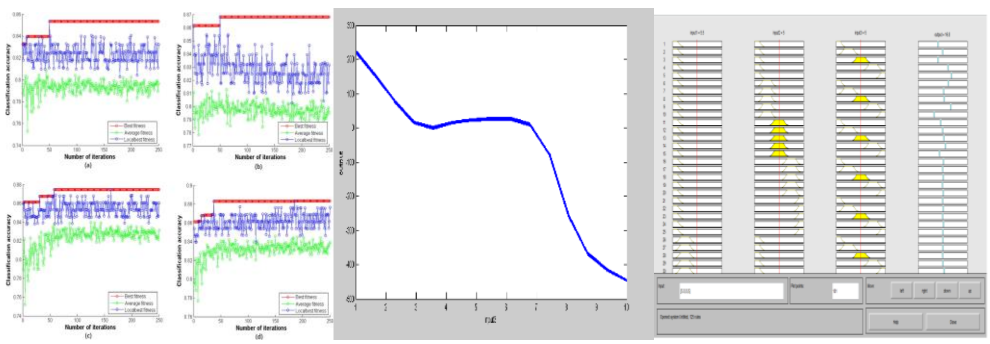


Fig. 4: Output of fuzzy logic training data (right), output of adaptive neuro-fuzzy system performance (middle), output of learning and training curves of combination of genetic algorithm and neuro-fuzzy technique (left)

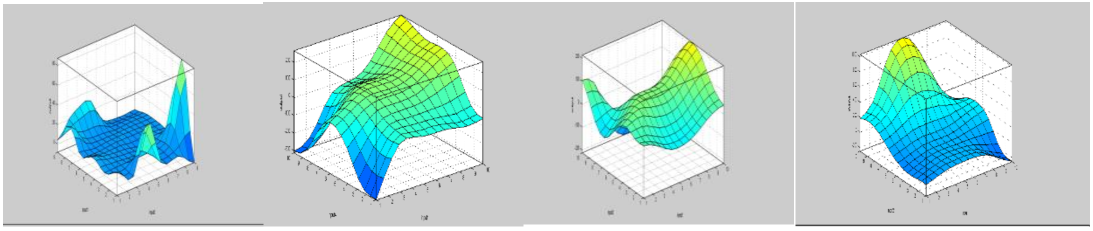


Fig. 5: Levels created between input and output variables in different ANFIS (1 to 4 from right to left respectively)

5.2 Comparison of Prediction Models

As shown in Table 2, the average interpretability of the model should approach 4 according to the number of ANFISs. In other words, any model that is close to 4 has a higher interpretability. In the above table, the combination of genetic algorithm with neuro-fuzzy model with the number of 3.28 has higher interpretability than other models. Also, the accuracy of the model combining the genetic algorithm with the neuro-fuzzy model is 87%, which shows the high accuracy of the model in predicting the classification of real customers' loans.

Table 2: Comparison of The Behavior of the Models Used in the Research Based on the Criteria of Accuracy and Interpretability

Model	**Symbol**	**The interpretability mean of the model**	**Percentage of model precision**
Fuzzy logic	FIS	2.45	0.74
Neuro- artificial network	ANN	2.81	0.77
Genetics algorithm	GA	2.85	0.79
Adaptive neuro-fuzzy network	ANFIS	3.21	0.84
The combination of genetics algorithm with the neuro-fuzzy model	GA-ANFIS	3.28	0.87

5.3 Classification of loans

Based on the data of loans granted to Bank Melli of Mazandaran Province during the years 2012 to 2021 and based on the proposed GA-ANFIS model, the output of the two-objective customer credit scoring function is shown in Table 3.

Table 3: Classification of Credit Loans of Real Customers According to Accuracy and Interpretability Criteria

-----------	**Objective function**		**Interpretability criteria**				**Accuracy criteria**	
Type of loan	**1-Q_{INT}=Q_{CPLX}**	$\mathbf{1-Q_{ACC}^{lrn}}$	**R**	**n ATR**	**n FS**	**n ATR/R**	**ACC(lrn)**	**ACC(tst)**
Mudharabah	0/1621	0/1609	4	4	4	1/6	%85/5	%85/6
Musyarakah	0/256	0/211	4	4	4	1/7	%89/6	%91/1
installment sale of raw materials	0/1821	0/1711	4	3	2	1/6	%86/5	%87/4
production installment sale	0/1824	%1804	4	3	3	1/6	%87/5	%89/9
housing installment sale	%1123	%1108	4	4	3	½	%82/5	%83/2
Ijarah to own	0/1299	%1251	4	4	3	½	%82/3	%82/9
jaala	0/1521	0/1499	4	4	2	1/3	%84/1	%84/2
Qardhul Hassan	0/1359	0/1321	4	3	3	½	%82/9	%83/7
Muzara'ah	0/922	0/825	4	3	3	½	%79/5	%80/2
Masakat	0/1025	0/921	4	4	3	1	%80/3	%81/9
Debt purchase	0/1609	0/1601	4	4	3	1/5	%85/2	%85/9
Murabahah	0/1599	0/1521	4	4	3	1/3	%84/9	%85/4
Istisna	0/1108	0/1059	4	4	2	1/1	%81/7	%82/2
Forward contract(salf)	0/1601	0/1599	4	3	2	¼	%84/9	%85/2

This function is the balance between interpretability and accuracy based on complexity of fuzzy rules (QCPLX) and complexity of model learning accuracy (Q_{ACC}^{lrn}). in interpretability criterion, all fuzzy rules, the number of fuzzy sets and the number of active fuzzy characteristics and in the accuracy criterion, Learning accuracy and test accuracy are considered as input. As shown in Table 3, the Musyarakah loan with the highest balance and the Muzara'ah loan had the lowest balance of objective function between interpretability and accuracy criteria.

5.4 Credit Scoring of Customers

After predicting different behaviors and having access to a final model in the form of a combination of genetic algorithm and neuro-fuzzy model, as well as the high accuracy of the mentioned model, now we should consider the credit ranking of the real customers, as the risk score of each loan for each ANFIS-GA or agent is shown in Table 4. This table shows how risky each loan is in each factor. Based on the range of risks from 1 to 10 (as every loan is inherently risky, zero is not used in the range and the risk range is defined between 1 and 10), in Mudharabah loans, Musyarakah, debt purchase, Istisna and salaf, the economic factor has the highest sensitivity. Also, in installment sales loans, Jaala and Mudharabah, the credit factor has the highest sensitivity, and in the loans of the housing sector, Ijarah to own, Qardhul Hassan, Muzara'ah and Musyarakah, the personal factor has the highest sensitivity.

Table 4: Credit scoring of real customers of Bank Melli Iran

Loan/factors	Personal factors	Environmental factors	Economic factors	Credit factors
Mudharabah	3.77	3.68	4.5	4.18
Musyarakah	4.83	5.5	7.25	6.5
installment sale of raw materials	3.44	3.62	5.83	6.62
production installment sale	5.22	5.25	6.16	7.06
housing installment sale	4.18	1.93	2.83	2.27
Ijarah to own	4.125	1.68	1.73	3.82
jaala	2.38	2.62	3.33	4.68
Qardhul Hassan	3.11	0.17	2.16	2.62
Muzara'ah	2	0.13	1.33	1.68
Masakat	1.83	0.25	1.35	1.63
Debt purchase	2.78	2.62	4.5	4.37
Murabahah	2.75	2.43	3.66	4.72
Istisna	2.88	2.5	4.18	3.16
Forward contract(salf)	1.94	1.37	5.93	4.83

Table 6 indicates the risk classification of real customer loans of Bank Melli Iran. As shown in this table and Table 5 which shows the range of scoring of these loans based on risk, Muzara'ah, Masakat, Istisna, and housing loans are considered low risk for customers in accordance to the opinion of the experts.

Table 5: Spectrum of ANFIS-GA Score

Impact severity	Score
Very low	1-2
Low	2.1-3.9
Medium	4-4.9
Much	5-7
Very much	Above 7.1

Also, Ijarah to own loans, Qardhul Hassan, Jaala, Murabahah and Salf have medium risk and debt purchase, Mudharabah, installment sale of production equipment, machinery and utilities, installment sale of raw materials, spare parts and work tools and participation have high risk.

Table 6: Risk Classification of Real Customer Loans of Bank Melli Iran

Credit ranking of loan	Loan	Credit ranking score	Risk classification
1	Muzara’ah	2.85	Low
2	Masakat	3.74	Low
3	Istisna	3.95	Low
4	Housing sector	3.99	Low
5	Ijarah to own	4.05	Medium
6	Qardhul Hassan	4.25	Medium
7	jaala	4.36	Medium
8	Murabahah	4.74	Medium
9	Forward contract (salf)	4.92	Medium
10	Debt purchase	5.05	Much
11	Mudharabah	5.21	Much
12	Installment sale of production, machineries and utilities equipment	5.36	Much
13	installment sale of spare parts and working tools	5.55	Much
14	Musyarakah	5.69	Much

6 Discussion and Conclusions

The present study was aimed to score the loans granted to the real customers of Bank Melli of Mazandaran province, which was done using genetic-neural-fuzzy meta-heuristic algorithm. In this research, the preliminary results of Rezaei's et al. [48] research and a semi-structured interview from a team of experts in the banking field were used to analyze and predict the quantitative data of 1178 real customers who received 14 types of loans during the years 2012 to 2021.The general results of this paper showed that the economic factor has the highest sensitivity in Mudharabah, Musyarakah, debt purchase, Istisna and salf loans. Also, in installment sales loans, Jaala and Mudharabah, the credit factor has the highest sensitivity, and in the housing sector, Ijarah to own, Qardhul Hassan, Muzara’ah and Masakat, the personal factor has the highest sensitivity.The results of the granted loans showed that in the Musyarakah loan, the credit factor has the highest non-repayment risk. In the Musyarakah loan regarding the investment by real customers, due to the subject of civil partnership and also the of contract that is made between the bank and the customer based on the clauses of the contract, the requirement for validation before granting the loans to the customer is of great importance and the bank does not pay the company's share to the customer in a single payment in cash, but it is paid several times, and in each payment, some kind of collateral validation, loan amounts, etc. are performed that if any of the credit requirements are not met, the payment is stopped and granting this loan depends on the credit factor. Also, the personal factor in the Musyarakah loan has little risk in the repayment of the loans by the customer. The main cause for the low risk of personal factors can be found in the low weight elasticity of these factors in the validation of the bank. For example, whether a person is employed or not is not effective on the bank's validation in granting loans in the matter of participation, and it considers mostly the content of the investment in the contract.

The results of this study demonstrated that the proposed algorithm can effectively optimize the parameters of the adaptive neuro-fuzzy system for the proper evaluation of the training and test data with minimum prediction errors. It is stated that the proposed approach can improve the superiority of the initial population by minimizing the number of evaluation and prediction error values. The above research studies have shown the importance of optimizing the parameters of adaptive neuro-fuzzy system for improved prediction modeling. Besides, very few researchers have used parameter-adjusted adaptive neural-fuzzy system approaches for predictive modeling of developed manufacturing processes such as additive production and non-traditional machining processes. Credit classification is a crucial component of vital financial decision-making such as credit rating and bankruptcy prediction. The performance of different credit classification methods is usually evaluated in terms of accuracy, interpretability and speed of decision making. Ranking accuracy reflects its ability to correctly demonstrate the decision-making process, while interpretability is the ability to provide concise and comprehensible explanations and justifications for the proposed decision. Fuzzy linguistic ranking rules are perfectly suitable for financial knowledge due to the ease of human understanding and high adaptability.In this study, an approach is proposed for the automatic design of rule-based ranking based on fuzzy rules from credit data. Since the balance between accuracy and interpretability is somewhat contradictory, a multi-objective evolutionary optimization algorithm has been used in the fuzzy ranking process. The proposed method in a separate test produced a set of optimal Pareto solutions that are the best estimates of the optimal solutions of the decision-making problem in mind. The characteristic of the proposed solutions is the diversity in the amount of accuracy and interpretability exchange. Moreover, the proposed method is strongly competitive with other models in terms of decision speed and has a relative advantage. Immediately after genetic learning and combining results with fuzzy rules, new decisions are obtained.

In this study, a method has been proposed that optimizes the requirements of accuracy and interpretability from the beginning in the same phase of ranking data. Most existing ranking methods for credit data are almost exclusively focused on accuracy issues. In previous studies, developing concise and comprehensible explanations and justifications for proposed decisions were either not considered in the ranking design process or generally ignored; thus, this study has improved and resolved previous shortcomings. The proposed method of this study is an effective tool for selecting features and even discovering numeric feature domains that are necessary for the decision-making process. It also identifies the necessary subsets within the absolute selected feature domains.The results of this research in rating with meta-heuristic algorithm and intelligent approaches combined with the results of [40], [41], [42], [44], [46]. It is similar.Based on the results of the study, it is recommended that banks can issue securities to cover a part of credit risk based on (or support) the collaterals they receive from customers for granting loans, whether the loans are overdue and in default or not and the loans that are in the current situation, and by selling the securities attempt to bring the money to the bank credit cycle. It is suggested that by paying attention to the risk associated with each of the banking contracts, banks can offer loans in the form of lower risk contracts to reduce the credit risk to their customers, and in fact, present a type of contract conversion. It is suggested that researchers in future studies compare the proposed model with other optimization models such as the Ant algorithm and its hybrid models to predict credit risk and analyze the results in order to discover the most optimal solutions. It is recommended that banks can build databases and information systems containing financial and credit data of customers and design a software system to implement the proposed model for credit risk estimation and decrease the adverse effects of customer scoring.

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