Accuracy and Interpretability in Hybrid Intelligent Algorithms in Rating the Effective Factors on Investment Firms in Various Crises

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Submit: 24/12/2024 Accept: 18/02/2025

ABSTRACT

The current study is aimed to design a rating model of effective factors on investment firms in various crises. All the related factors on investment firms and theoretical literature have been discussed in a study done by Pourbijan et al. (2025). The questions of experts have been classified into 5 fuzzy groups. These 5 items (very low risk, low risk, medium risk, high risk, and very high risk) were extracted by the researcher for the experts. Then, the scores from 1 to 5 (score 1: very low risk and score 5: very high risk), were given to MATLAB software. Also, based on the 5 models of this study (1-neural network, 2-Fuzzy, 3-Genetic, 4-Adaptive F, 5-Genetic-ANFIS), the outputs of the predicted models were extracted based on the accuracy and interpretability criteria. As shown in the results, the combination of the genetic algorithm with the Neural-Fuzzy model with the number 5/28 has more interpretability than the other models. Also, the accuracy of the model in the combination of the genetic algorithm with the Neuro-Fuzzy model was 87%, which indicates the high accuracy of the model in prediction. In rating factors with crisis, in the industry factor, the financial crisis has the highest sensitivity. Also, in the credit and economic conditions, the credit and economic crisis showed the highest sensitivity. Also, according to the experts, management characteristics and internal control quality have low risk for firms. Also, financial variables of the capital market, industrial factors and competitive situation have high risk and credit and economic situation showed very high risk. The results of rating firms based on risk show that investment firms can adapt to crisis conditions that sometimes occur in the market better than other listed firms. Thus, investment in these firms, with features such as: professional management, diversification of securities and risk reduction, high liquidity, economies of scale and cost reduction, and providing diverse services to owners of investment units and shareholders, can be introduced as two secure and profitable investment methods instead of savings and direct investment to all classes of society, especially the households who are the main owners of actual savings and potential assets, and on the other hand, we can guide the liquidity and savings of the society to a dynamic and beneficial market for the country's economy.

Keywords: Crisis, Investment Firms, Genetic Algorithm, Artificial Neural Network, Fuzzy Logic, Adaptive Neuro-Fuzzy Network Technique

1. Introduction

Since the Great Depression of the 1930s, the current crisis is the worst situation. This was the interpretation of *Kristalina Georgieva***,** Managing Director of the International Monetary *Fund*. Also, this institution predicted that the world economy would decrease by 3 percent due to the Corona crisis; that is, the most severe economic recession in the past century. What economic crises has the world encountered over the past century, and when did these crises occur, and what are the related effects? "The Economy's world" newspaper has examined at least 10 of the world's major crises after the Great Depression. The world economy has seen many economic crises in the past century (e.g. post World War II to the 2008 financial crisis; the oil crisis of the 1970s to dot-com crisis). However, two features have distinguished the Corona crisis from other crises: the first is the geographical domain of the crisis. In most previous crises, the largest economy around the world, the US and developed countries were highly affected, and the other countries were not affected by the crisis. The Corona crisis can also be considered the crisis in the real sector of the economy. However, a review of previous crises indicates that the financial and credit sectors were the main drivers of the crisis. In the last century, the world has experienced different economic crises, and the economic policies used to overcome the crises have been different based on time period and depth of the recession resulting from the crisis, the reasons for the crisis, and the extent of the crisis in different countries. However, the Corona crisis is a new form of economic crisis that had no similar example in the world economy. Unlike past crises that took place due to a set of factors such as a decrease in effective demand, expansionary monetary policies in the pre-crisis periods, or the crisis of forming bubbles in the capital markets and the credit sector of the economy, the Corona crisis has directly focused on the real sector of the economy and its supply side. Resolving this emerging crisis requires innovation in economic policymaking as well as trade and political relations at the global level. Therefore, examining past crises can provide a clear view of the destructive mechanisms of recessionary crises and the effect of economic policies. (World Economy Newspaper, November 2021, No. 5322).

The spread of the coronavirus has led to severe negative reactions in stock markets in different countries. Also, the side effects of this virus have caused the sharp decline of the price of many macroeconomic variables around the world. These cases have attracted the widespread attention of analysts and investors to the negative impacts of the spread of this virus on stock markets (Sanei-far et al., 2010). In financial markets, the behavior of investors is one of the important issues in finance, in which standard finance emphasizes the rational behavior of economic agents and the existence of arbitrage and behavioral finance focuses on behavioral errors and limitations in arbitrage in financial markets (Vakilifard et al., 2013). Nowadays, the problems caused by sanctions, the Covid-19 virus, and structural economic problems have caused people to feel desperate, because social groups such as working and entrepreneurial groups, consumers, producers, and different age groups of men and women have considerable economic problems. Indeed, the type of despair in society is different and it is not possible to talk about a single phenomenon. Young people are more prone to despair in the individual and collective domains. This also exists in developed countries where progress and development are much evident. When issues and problems such as sanctions, the spread of the Covid-19 virus, and unemployment are taken into consideration, these phenomena certainly lead to social despair, and social despair influences the work process of individuals and investors. The entrepreneurial investors are those who have risk-taking behaviors. The darker the future horizon for these groups, the less risk-taking they are. Thus, their level of risk-taking, such as investment is decreased and they turn towards negative risk. This issue has different impacts on consumers. In fact, despair and uncertain horizons cause that the producer takes his money to the abroad; or not to make new investments, but the consumer also shows a special behavior.

In recent years, various studies have been performed on the assessment of the performance of firms and investment funds. All of these researches (e.g: Pahlavan et al.,2025; Iravani et al., 2024; Aghabeigi and Khodadadi, 2022; Kwon et al., 2020; Grahamet al., 2020; Alimoradi et al. 2019; Sadat Nasiri, and Soleimani Amiri, 2019; Mambini et al., 2019; Saghafi et al., 2018; Babbar and Sehgal, 2018; Mansourimoayyed, 2018; Mamta and Ojha, 2017; Mousavi et al. 2015; Tariverdi et al., 2013; Sedighi et al., 2013; Chen et al., 2011; Mamoghli and

Daboussi,2009, etc.) focused on evaluating the performance of these firms with quantitative variables, so other quantitative variables affecting this performance and qualitative variables have been neglected. Using theoretical basics and expert opinions, the present study seeks to identify all the dimensions and factors affecting the performance of investment firms in the Iranian capital market. Also, in previous researches, all of them have examined the performance of the firms using the data envelopment analysis model or linear and parametric models, and other models have not been employed in the measurement. Thus, as a second step, this research attempts to measure and rank these factors with different data mining models, including: data envelopment analysis, neural network-fuzzy logic-adaptive neuro-fuzzy approach, and finally compares these models with each other for better assessment.

Given the special role of investment firms in the market and the widespread acceptance of these firms by capital market activists and investors around the world, their performance is of great importance to two groups of users: the first group is potential investors who are looking for a suitable place for investment. Second, people who are currently investors in one or more firms and want to know whether they have performed the right thing or not; thus, assessing the performance of investment firms is important so that stock traders can make the required decisions about holding, selling, or buying shares of these firms at the appropriate time. Investors are inclined to know about the performance of investment firms. The more information is available and the more skillful to use the available information, the more precise the evaluation of the performance of organizations will be. In the absence of adequate knowledge of the various activities of the company and the lack of a suitable criterion for measuring the performance of each branch, good decisions cannot be made. If investors suffer losses from the consequence of their decisions, they can exit the market. One of the important outcomes of investors leaving the market may be the shrinkage of the market and the limitation of the capital injected into the market. In this case, the capital market is not able to help the economy by injecting the necessary resources for the development of infrastructure. Therefore, evaluating the performance of investment firms is one of the most important debates for investors, and identifying and analyzing all branches of the activities of investment firms' is necessary for performance evaluation. According to empirical studies, the total activities of investment firms in Iran are divided into three general branches: stock market investment, non-stock market investment, and investment in other assets (projects) (Mashayekh, 2003). The diversity of these activities and the difficulty of accessing information on these activities have led to the researchers and scientific literature neglect other branches of investment firms' activities and focus merely on the stock market investment branch; therefore, the current study addresses this issue and seeks to examine all branches of investment firm activity. Also, the existing theoretical literature presents optimization-based techniques with meta-heuristic algorithms (Chacko et al., 2020; Jadhav et al., 2018; Lubis et al., 2021; Pławiak et al., 2020). Metaheuristic algorithms, like genetic algorithms, operate in search spaces and are exact because they are inspired by nature, physics, and humans (Lopez and Maldonado, 2019). Adaptive neural-fuzzy system is a hybrid learning model that combines the advantages of artificial neural networks and fuzzy logic, and has capabilities such as superior computational capability, fuzzy logic expertise, and supervised learning capability of artificial neural networks, and is considered as one of the existing soft computing techniques. Although adaptive neural-fuzzy system is applied to efficiently model the prediction of nonlinear problems, the performance of adaptive neural-fuzzy system prediction model depends only on the appropriate selection of its training parameters (assumption and outcome), which are often examined by trial and error. Exact adjustment of these parameters via trial and error is usually time-consuming and difficult (Aghbashloo, Tabatabaei, Nadian, Davoudnia and Soltanian, 2019). So, derivative optimization algorithms and metaheuristic algorithms are basically used to train the parameters of adaptive neuro-fuzzy systems to achieve effective predictive models. In recent years, a few researchers have used nature-inspired algorithms to adjust the parameters of adaptive neuro-fuzzy systems. There are numerous artificial intelligence algorithms, each with its own set of adapting parameters to obtain the given level of intelligence. Furthermore, the performance of the genetic algorithm is unknown in terms of computational time to learn and predict unknown data.

The genetic algorithm iterates natural evaluation in searching optimal solutions.

This research aims to present a fundamental approach for designing the rating and ranking of factors affecting investment companies based on fuzzy rules. The proposed approach is equipped with an effective optimization mechanism to balance accuracy and interpretability. This means that the fuzzy rule-based classification, optimized at different levels of such a balance, results in high-accuracy and better interpretability systems (compared to current approaches), supporting decision-making for all stakeholders. It is evident that such dimensions have not yet been explored in the financial decision-making literature. Additionally, ranking the factors affecting investment companies based on financial, credit, and economic crises is another innovative aspect of this research. This ranking can significantly assist stakeholders and investors in multi-criteria decision-making in times of crises.

The current study presents a fundamental approach to design fuzzy rule-based classifiers, which is equipped with an effective mechanism to optimize the balance between accuracy and interpretability. This means that fuzzy rule-based classifiers defined by different optimized levels of such balance, including high-accuracy systems with better interpretability (based on current approaches) for decision support, are obtained. It is evident that such dimensions have not yet been examined in the literature related to financial decision-making.

The rest of this study is organized as follows: Section 2 defines the literature related to company Rating, definition of investment firms and crisis. Section 3 is dedicated to the research methodology and meta-heuristic algorithm based on the combination of adaptive fuzzy neural network system and genetic algorithm, as well as multi-objective fuzzy rule-based classification with genetic learning approach. Section 4 includes the output of existing algorithm behaviors, training data output, comparison of prediction models, loans classification and ratings and details of the main results of the study. Conclusion, limitations of the study and suggestions for future research are presented in section 5.

Theoretical basics and review of literature

Company Rating: Rating is a type of calibration giving credit to a company. Rating can be regarded a criterion, capability, and competence that is defined by the management and planning organization and assigned to a company based on pre-defined standards and rules (Ebrahimi et al., 2016).

Investment firms: Investment firms are similar to equity investment funds to some extent, but with different approaches and goals. An investment firm was established in accordance with Article 21 of the securities market law. If we want to directly refer to it, we should say that its main goal is to purchase and sell shares of listed and non-listed firms (Alimoradi et al., 2019).

Crisis: An organizational crisis takes place when an unpredicted event occurs in an organization and endangers the security and peace of the organization. This unpredicted event has various types, it may be caused by internal and external factors (Fu et al., 2019).

Research Background

Aghabeigi and Khodadadi (2023) in a study “Financial risk assessment of investment firms in Tehran Stock Exchange (TSE) with D-CRITIC and EDAS fuzzy decision making method based on a new scoring function) found that the Pythagorean Fuzzy Set (PFS) (which is depicted by membership and non-membership degrees, is a new and effective tool to deal with ambiguity and uncertainty. A new Pythagorean Fuzzy Scoring Function is presented to solve the comparison problem in the current study. Besides, the composite weights that reflect both subjective and objective preferences are also given. Then, the weights of the criteria and the distance correlation between pairs of criteria are calculated using D-CRITIC, and the financial risk prioritization of firms is also computed by the EDAS (evaluation based on distance from the mean solution) method based on the new scoring function. This method is useful when we have contradictory criteria. Finally, the feasibility of the algorithm to assess the financial risk of four investment groups with the six criteria and the relevant sensitivity analysis is discussed.

Farhadi Sartangi et al. (2023) in a study “Design and implementation of a digital ecosystem risk analysis model Based on ANP and Qubit, Case Study in FMCG Investment Holding) concluded that by evaluating the current state of the model parameters, the business risk of the FMCG investment holding was computed and a solution was provided and the effectiveness of branding management was optimized in the investment holding using Matlab software and genetic algorithm.

Heidari Moghadam et al. (2023) in a study “the Intelligence of mutual fund investors during the Capital Market Depression and Boom” collected data from 34 funds between 2012 and 2020 to examine the intelligence of cash. In this regard, the boom and bust periods of the capital market were distinguished from each other and the ability of investors in each of these periods was examined to determine whether investors acted differently in different market periods. Also, real and legal investors were separated from each other so that the performance of each can be examined separately. The risk-adjusted return of funds was calculated using the Carhart four-factor model to examine the intelligence of investors, and the results of the study indicated that investors were much inclined to invest and the market acted intelligently when money entered the market during the boom state and when money was withdrawn during the recession period.

Ziaei Shirkalai et al. (2022) examined a study “Evaluation of the efficiency score of investment holdings considering undesirable variables using the FDH model (Free Disposal Hull): data envelopment analysis approach). The models presented in this study, besides calculating the total efficiency score in a network system can calculate the efficiency of each stage separately in the presence of undesirable factors without any additional calculations and present it to system managers. Also, to show the accuracy of the proposed model, it has been compared with the base model, as we identify less efficient units compared to the computational accuracy model. Based on the results, despite the fact that some units are considered overall efficient, they are considered inefficient due to inefficiency in some stages, and only the national industrial holding company has been considered as the only efficient unit, considering that it is efficient in both stages.

Mirzapoor et al. (2022) examined the relationship between company Ranking and audit quality in firms listed on the TSE). Audit quality was measured using four criteria: discretionary accruals, auditor change, audit fee, and auditor opinion type, and accounting firms were ranked using market value and income. Also, financial leverage, return on assets, sales change, and net loss were considered in the research model as control variables. The research sample consisted of 118 firms in the period from 2011 to 2018. The results of the test using composite regression indicated that there was a negative and significant relationship between the company's rank and discretionary accruals and the auditor's opinion. On the other hand, there was a positive and significant relationship between the company's rank and audit fees and the change of auditor. Also, with the improvement of the rank of listed firms based on the current value and sales volume, the audit quality was improved.

Khanipoor et al. (2021) used Delphi methods (expert consensus) and case studies and library studies to extract and analyze data. The study aimed to identify the sources of risk of the subsidiaries of a holding company (active in Iran’s cement industry), prioritize the risks and finally draw a map of the risks of each company for the exploitation of the parent company.

In their study “Investment sensitivity to domestic and foreign mutual funds: New evidence from emerging markets”, Kagalayan and Machokoto (2024) used a large panel of firm-year data from eight emerging African countries to show that firms’ fixed investment spending is more sensitive to foreign funds, especially debt, than to domestic funds. Patel et al. (2024) in their study “Investment style stability and fixed income mutual fund performance in India” investigated investment style, style consistency and its relationship with risk-adjusted performance of Indian fixed income mutual funds using a sample of 242 funds based on 16 groups over a period from April 2015 to March 2020. It was found that (a) fund managers perform security selection, but their security selection ability fails to improve risk-adjusted returns; (b) higher style consistency leads to better risk-adjusted performance; and (c) investment style and style consistency have a significant effect on fund performance.

In a study, Patel et al. (2023) examined performance persistence and style stability of fixed income mutual funds – a longitudinal study in India and evaluated the performance of Indian fixed income mutual funds using a comprehensive sample over a ten-year period from April 2010 to March 2020. They found that the persistence of performance of 190 fixed income funds across 16 fund categories was less consistent in style. It was found that a significant section (73%) of the funds had weak performance.

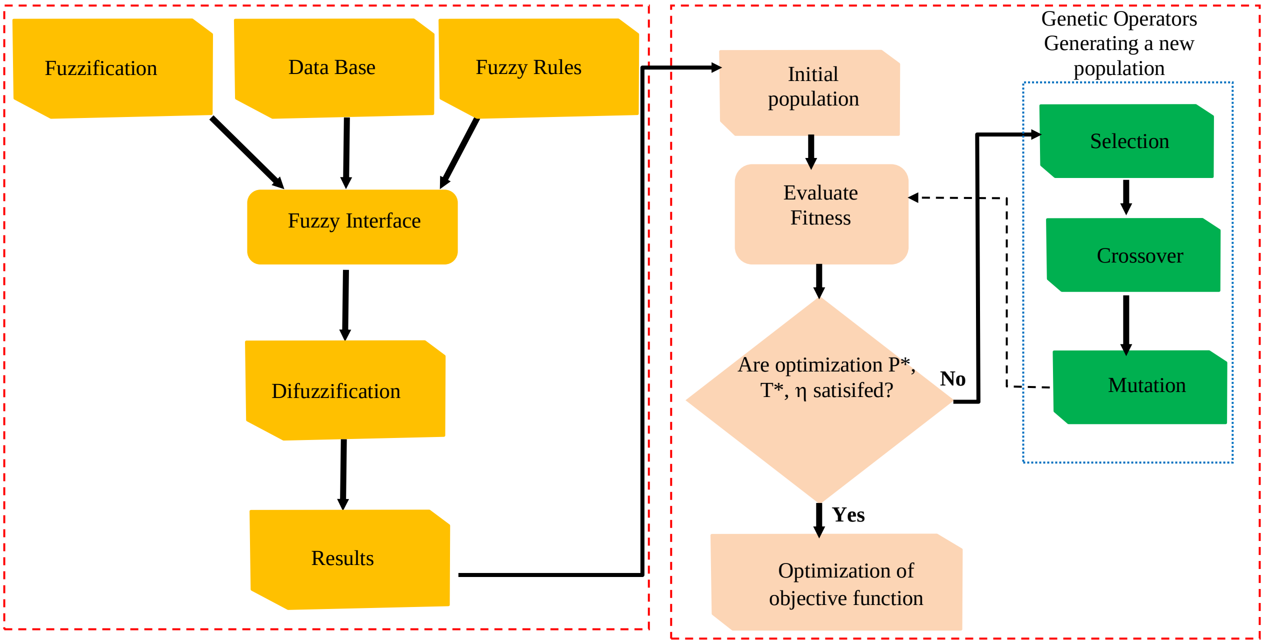
Yu et al. (2023) in a study "predict credit ratings of decarbonized firms: A comparative evaluation of machine learning models", used 355 Eurozone firms from 2010 to 2019, they showed that the classification and regression tree had the highest accuracy to predict credit ratings.

Sariyer and Taskin (2022) performed a study "Clustering firms based on environmental, social and governance ratings). They used data from firms listed on the Turkish Stock Exchange and applied cluster analysis to show that firms with higher ratings do not necessarily have high performance. The results of the cluster analysis indicate that firms with higher environmental and social scores have lower profitability.

Kwon et al. (2020) in a study "Mutual fund investment in private firms" used data from private firms from 2000 to 2019 and concluded that firms search for excess capital attempt to postpone public listing, mutual funds search for higher risk-adjusted returns and initial public offerings, and venture capitalists seek new investors to justify higher valuations.

Research Methodology

This research is exploratory in terms of purpose and descriptive and survey in terms of data collection and analysis. The Rating of investment firms is performed based on 6 groups of credit factors that were previously identified in the study of Pourbijan et al. (2025). The experts' questions are classified into 5 fuzzy groups. These 5 items such as very low risk, low risk, medium risk, high risk, and very high risk, were extracted by the researcher for the expert. Then, these scores, which were coded from 1 to 5 (score 1 for very low risk and score 5 for very high risk), were entered into the MATLAB software and, in accordance with the 5 models of this study (1-Neural Network, 2-Fuzzy, 3-Genetic, 4-Adaptive Neural-Fuzzy, 5-Genetic-ANFIS), the outputs of the predicted models were extracted based on accuracy and interpretability criteria. The effective factors on investment firms were also classified based on accuracy and interpretability criteria. Finally, the experts mentioned in the study by Pourbijan et al. (2025) and several new experts in the field of investment were again surveyed and interviewed. Scores ranging from one to ten were the risk assessment range for each factor, with scores of 1 for very low risk and 10 for very high risk. In this study, the Neural-Fuzzy-Genetic Network model was predicted in three stages: 1-model design, 2-data preparation, and 3-model implementation. A multilayer feed-forward network with a hybrid learning algorithm of error back propagation and least squares (LS-BP hybrid) and a fuzzy Sugeno inference system were used in the design of the neural-fuzzy-genetic network model. The number of hidden layers was 4, and the input function of the sigmoid model and the linear output function were also taken into consideration. The moving average function was also applied for defuzzification. In the data preparation stage, initial processing was carried out on 600 data states. The data should be normalized and for normalization, the same procedure has been followed as for the artificial neural network. For ANFIS modeling, data with scores between 1 and 10 were first 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 were entered into the model. In the model execution stage, by changing the number of layers and the number of neurons in the hidden layers continuously, the best neural network and also via different membership functions and their number, the best fuzzy system was implemented. The final goal of the model is to mitigate the training error. In all ANFIS dimension models and ANFIS Rating models for each dimension, the average training error is calculated as less than the threshold (0.5), which indicates that the model has high efficiency. The figure below (Figure 2) indicates the data processing in the fuzzy and genetic system. Figure 2 shows all the research steps with fuzzy multi-criteria decision-making techniques (Jang, 1993 , 1996).



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

Fig. 1: The data processing stages, artificial neuro-fuzzy network output and genetics algorithm

Classification Optimization based on designed Fuzzy rules and Genetic Algorithm

In each learning experiment, the best approximation of the Pareto front is obtained. The Pareto front is the set of Pareto-optimal solutions: they are distinguished by different levels of interpretability-accuracy trade-off. By achieving a set of solutions in the form of the best approximation of the Pareto front, first a valid classification solution based on fuzzy rules that has the highest accuracy characteristic $Q_{ACC}^{(tst)}$in the test dataset (as defined by $Q_{ACC}^{(lrn)}$for the learning dataset) and secondly with the highest interpretability characteristic $Q_{INT}$is selected from the Pareto front. Then the average of the results from K experiments is computed. Such an experiment is called K-single cross-validation (single k- fcv). The single k- fcv experiment is repeated ten times for different divisions of the original dataset into K subsets. In addition, in order to minimize the bias associated with the starting of the method, each of the mentioned k-fcv experiments is repeated ten times for randomly selected initial values of the parameter in our applied method. Thus, a total of 100 single fcv experiments are performed for each K. Besides, in order to increase the reliability of the performance evaluation and to provide a comparative approach with alternative methods reported in the literature, four values of K are taken into consideration: k = 10 (i.e., learning to testing ratio of 1:9), k = 5 (ratio of 1:4), k = 3 (a ratio of 2:1), and k = 2 (a ratio of 1:1). A non-pattern ratio of 1:2.6 is considered for the dataset. In all experiments, the genetic learning process is performed using 1000 generations (during 1000 generations), the initial population has 10000 individuals, the tournament selection is equal to 2, and the mutation and crossover probabilities are equal to 0.7 and 0.5, respectively. The performance of fuzzy rule classification is evaluated in terms of its accuracy and interpretability. The main accuracy measurement criterion is $Q_{ACC}^{(lrn)}$ for the training data and $(Q_{ACC}^{(tst)})$ is the mathematically defined for the test data. The accuracy of fuzzy rule classification can also be expressed as the percentage of correct decisions: $ACC^{(lrn)} = Q_{ACC}^{(lrn)}.100\%$and $ACC^{(tst)} = Q_{ACC}^{(tst)}.100\%$.Some other measures of accuracy on training and test data can be used in two-class classification tasks. These include the true positive ratio (TPR) or sensitivity and the true negative ratio (TNR) or specificity, which are defined as follows (Baser, 2023):

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}\ , \mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{20}$$

Where TP (true positive) is the number of correctly classified positives, TN (true negative) is the number of correctly classified negatives, and FP (false positive) and FN (false negative) are the number of incorrectly classified negatives and positives, respectively. Indeed, the accuracy (precision) of the above sum is $Q_{ACC} = (TP + TN)/(TP + FN + TN + FP)$.

The main measure of interpretability isQ_{INT}. In addition, several other interpretability indices such as the number of rules (R) in the rule base, the number of indices (n_{ATR}) used by the classifier, the number of Persian sets (linguistic terms) that represent the classifier indices (n_{FS}) and the number of indices per rule ($n_{ATR/R}$)) are applied (Gorzałczany et al., 2016).

During genetic learning, the evaluation of special individuals (fuzzy knowledge bases) in the framework of a Pittsburgh-type approach should be performed in each generation. For this reason: 1) a fuzzy set theory representation of the linguistic rule set should be formulated and 2) a fuzzy estimation inference model should be used. Generally, there are two different interpretations of if-then rules. First, it refers to the composition-based approach, deals specific rules as independent local forms and hence is collected separately. In the second case, which is called the logical or application-based approach, these rules are called fuzzy constraint rules; thus, they are based on the principle of minimum features that are collected separately. Fuzzy models are learned from a set of data-based pairs that are independent local examples of system behavior. Thus, the relation-based model is more compatible with the nature of the learning data compared to the logical model and is used exclusively (e.g., the MAMDANI model with t-norms to combine large records and records with results related to the rules, as well as the max-type norms for rule collection). To the extent related to fuzzy estimation inference scheme, two schemes are used in the literature (Mamdani, 1977).

Table 1- A summary of the models used in the research

Formula	Criterion
$\mu_{B'}(y) = \max_{r=1,2,\ldots,R} \mu_{B'^{(r)}}(y) = \max_{r=1,2,\ldots,R} \min\left[\alpha^{(r)},\ \mu_{B_{(sin\,gl.)j^{(r)}}}(y)\right]$, $\alpha^{(r)} = \min_{\substack{i=1,2,\ldots,n,\\ sw_i^{(r)} \neq 0}} \alpha_i^{(r)}$, $\alpha_i^{(r)} = \begin{cases} \mu_{A_{i,sw_i^{(r)}}}(x_i'), & for\ \ sw_i^{(r)} > 0, \\ \mu_{\bar{A}_{i,sw_i^{(r)}l}}(x_i'), & for\ \ sw_i^{(r)} < 0. \end{cases}$	Fuzzy estimation inference based on fuzzy rules
$Q_{ACC}^{(lrn)} = \frac{1}{K}\sum_{k=1}^{K} \delta(y_k', y_k^{(lrn)})$, $\delta(y_k',\ y_k^{(lrn)}) = \begin{cases} 1,\ for\ y_k' = y_k^{(lrn)}, \\ 0,\ otherwise, \end{cases}$	Classification accuracy based on fuzzy rules
$Q_{ACC} = (TP + TN)/(TP + FN + TN + FP)$	Accuracy
$Q_{INT} = 1 - Q_{CPLX}$, $Q_{CPLX} = \frac{Q_{RATR} + Q_{ATR} + Q_{FS}}{3}$ $Q_{RATR} = \frac{1}{R}\sum_{r=1}^{R} \frac{n_{ATR}^{(r)} - 1}{n - 1}\ ,\ n > 1\ ,$ $Q_{ATR} = \frac{n_{ATR} - 1}{n - 1}\ ,\ n > 1\ ,$ $Q_{FS} = \frac{n_{FS} - 1}{\sum_{i=1}^{n}\ a_i - 1}\ ,\ n > 1.$	Interpretability related to complexity

Formula	Criterion
$\sigma_{ik_i} = \rho_{i,k_i-1} = d_{ik_i} - e_{i,k_i-1}, \quad k_i = 2,3,\dots,a_i$	Interpretability related to sematic
$d^{(1)}_{ik_{i\,new}} = \gamma d^{(1)}_{ik_i} + (1-\gamma) d^{(2)}_{ik_i},$	Database processing (genetic algorithm)
$d_{new} = d + rand(-0.2,\ 0.2)\ [xi, min_{i,max}$	Mutation operator of database (Genetic algorithm)
f (s)= $\frac{1}{1+e^{-s}}$	Neural network

Research Results

1-The Form of Model behavior

First, the graph output of the prediction models applied in this study is shown. Figure 3 depicts the output of neural network training data, the output of neural network performance, and the output of genetic algorithm performance. In the neural network model composition, 70% of the data is used as training, 15% as testing, and 15% as validation. Based on each epoch, the error of validation data is calculated and finally training is stopped. According to the figure on the right, the green Chart shows the efficiency and performance of the network and after intersecting with the network error based on the hidden layer neurons (blue graph), it is increasing. Also, based on the behavior of the genetic algorithm, the best behavior of the model is increasing generation production for predicting the best behavior of the model regarding selection, mutation, and crossover. The output of training data of the adaptive neural-fuzzy system is demonstrated in Figure 4. The figure on the right indicates all the fuzzy logic rules in the training data. The more the number of rules, the less is the model error in this figure.

The speed of the neuro-fuzzy network is shown in Figure 4. In this figure, if the speed is higher, the network behavior is descending. This means that the model error has been considerably reduced and the accuracy of the model has been correctly realized. The figure on the left indicates the combination of the genetic algorithm and the neuro-fuzzy model for all four ANFISs. Here, the training data accuracy which has been recognized by the model is almost close to 100 % and is quite normal. But the important result, which is the accuracy of the test data, was more than 95 %, which is a very good result.

Figure 5 depicts the three-dimensional behavior of the four ANFISs. According to the rule of neuro-fuzzy network, if the speed is increased, the acceleration should have a descending behavior, but if the distance is increased, the acceleration behavior is ascending. The three-dimensional figure is the continuous (smoothed) structure of rules. We can have them for any value of any combination of speed or distance. Figure (5) shows the ANFIS levels and the ANFIS function after training. This figure is the same level created between the input variables (company management features, financial variables of the capital market, internal control quality, industry factors, competitive situation and credit and economic situation) and the output variables (ranking) as being obtained using the ANFIS model.

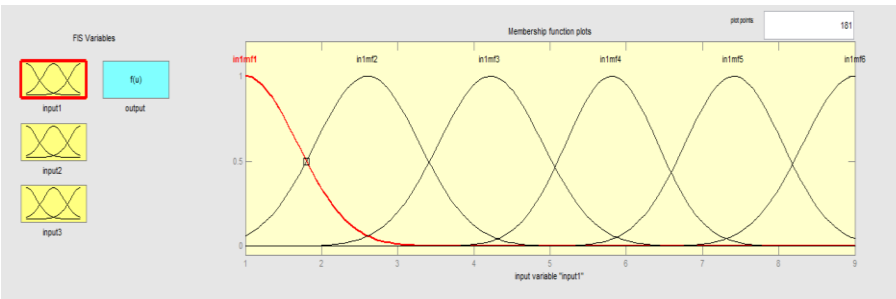


Figure 3 - Output of training data of adaptive neuro-fuzzy network

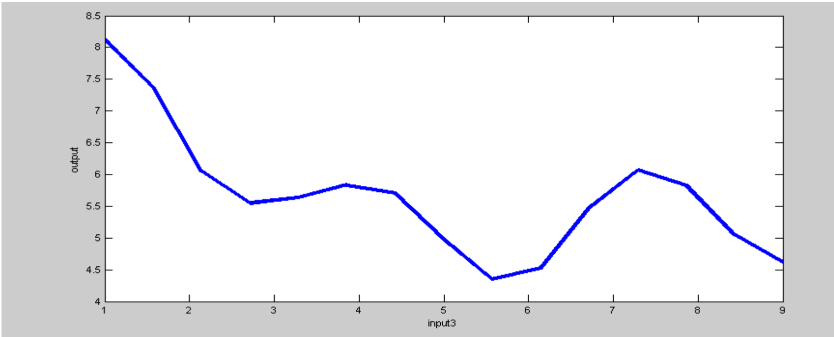


Figure 4- Output of adaptive neural-fuzzy system training data

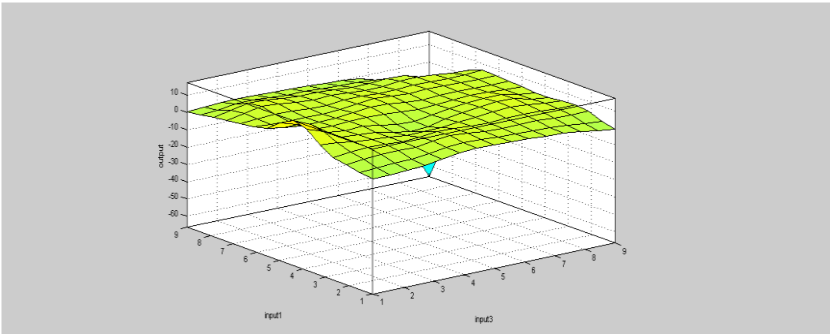


Figure 5- Levels created between input and output variables in different ANFISs (1 to 4 from right to left, respectively)

2- Comparing prediction models

According to the data and the proposed GA-ANFIS model, the output of the bi-objective expert scoring function is presented in Table 3. This function is the balance between the interpretability and accuracy based on the complexity of fuzzy rules (QCPLX) and the complexity of model learning accuracy (Q_{ACC}^{lrn}). All fuzzy rules, the number of fuzzy sets and the number of fuzzy active features are considered in the interpretability criterion, and in the accuracy criterion, learning accuracy and testing accuracy are considered as inputs. As shown in Table 3, financial variables of the capital market showed the highest balance and credit and economic status have the least balance of the objective function between the interpretability and accuracy criteria.

As shown in Table 4, the average interpretability of the model based on the ANFIS number should tend towards the value 6. In other words, any model closer to the number 6 has higher interpretability. In the over-mentioned table, the combination of the genetic algorithm with the neuro-fuzzy model with 3/28 has higher interpretability compared to other models. Also, the model accuracy in the combination of the genetic algorithm with the neuro-fuzzy model is 87%, which shows the high accuracy of the model in predicting the credit ranking of firms.

The ANFIS-GA model is the best model in terms of accuracy, interpretability and computational efficiency in Rating Investment firms. As shown in Table 4, this shows that the above model has high accuracy and comprehensiveness based on the weighting of criteria and also the low percentage of error of the model in calculations. Also, the existence of uncertainty in risk and crisis, this model could solve this problem in investment firms by using fuzzy logic.

Table 3 - Classification of effective factors on investment firms based on accuracy and interpretability criteria

-----------	Objective function		Interpretability criteria				Accuracy criteria	
Effective factors	**1-Q_{INT}=Q_{CPLX}**	$1 - Q_{ACC}^{lrn}$	**R**	**n_{ATR}**	**n_{FS}**	**$n_{ATR/R}$**	**$ACC^{(lrn)}$**	**$ACC^{(tst)}$**
Corporate managerial characteristics	0.1621	0.1609	4	4	4	1.	85.5%	85.6%
Financial variables of capital market of Iran	0.256	0.211	4	4	4	1.7	89.6%	91.1%
Internal control quality of company	0.1821	0.1711	4	3	2	1.6	86.5%	87.4%
Industrial factors	0.1824	0.1804	4	3	3	1.6	87.5%	89.9%
Competitive condition	0.1123	0.1108	4	4	3	1.2	82.5%	83.2%
Credit and economic condition	0.1299	0.1251	4	4	3	1.2	82.3%	82.9%

Table 4 - Comparison of the behavior of the models used in the research based on accuracy and interpretability criteria

Model	Symbol	Interpretability average of model	Accuracy percent of model
Genetic algorithm	GA	5.22	0.71
Fuzzy logic	FIS	5.45	0.74
Artificial Neural Network	ANN	5.81	0.77
Adaptive Neuro-Fuzzy network	ANFIS	5.95	0.84
Neuro-Fuzzy Genetic Network	ANFIS-GA	5.96	0.86

5-Rating of firms in different Crises

After predicting different behaviors and having access to a final model in the form of a combination of genetic algorithm and Neuro-Fuzzy model and also the high accuracy of the aforementioned model, we can rank investment firms, as the risk score of each crisis and each ANFIS or factor is shown in Table 5. This table indicates how much risk each factor has in each Crisis. Given the risk classification from one to 10 (because each factor has risk, zero is not used in the classification and the risk range is defined between 1 and 10). Also, the financial crisis has the highest sensitivity in the industry factor. Also, in the credit and economic situation, the credit and economic crisis has the highest sensitivity.

Table 6 shows the risk classification of investment company factors. Based on this Table and Table 5 which shows the scoring range of these factors based on risk, according to the experts; management features and internal control quality are regarded to have low risk for firms. Also, financial variables of the capital market, industrial factors and competitive situation have high risk and credit and economic situation showed very high risk.

Table 5 - Investment firms ranking

Factors	Financial crisis	Credit crisis	Economic crisis
Managerial features of company	3.77	3.68	4.5
Financial variables of capital market of company	6.83	6.5	5.25
Internal control quality of company	3.44	3.62	4.83
Industry factors	6.22	5.25	6.16
Competitive condition	6.18	5.93	5.83
Credit and economic condition	6.125	8.68	8.73

Table 6 - ANFIS score classification

Impact intensity	Score
Very low	1-2
Low	2.1 to 3.9
Average	4 to 4.9
Much	5.7
Very much	Above 7.1

Table 7- Classification of investment firms factors in terms of crisis risk

Ranking companies	Factors	Crisis score	Crisis classification
1	Managerial features of company	3.85	Low
2	Financial variables of capital market of company	6.12	Much
3	Internal control quality of company	3.95	Low
4	Industry factors	5.77	Much
5	Competitive condition	6.05	Much
6	Credit and economic condition	7.92	Very much

Conclusion, Discussion and Recommendation

The current study is aimed to design a Rating model for investment firms based on risk criteria under crisis conditions. Given the importance of the topic, the present study has identified all risks and crises related to investment firms. In the results, the combination of genetic algorithm with neural-fuzzy model with the value 5.28 has more interpretability than other models. Also, the accuracy of the model in the combination of genetic algorithm with neural-fuzzy model is 87%, which shows the high accuracy of the model in prediction. In the Rating of factors with crisis, financial crisis has the highest sensitivity in the industry factor. Also, in the credit and economic situation, credit and economic crisis has the highest sensitivity.

According to the experts, management features and internal control quality are considered to have low risk for firms. Also, financial variables of the capital market, industrial and competitive situation factors have high risk and credit and economic situation have very high risk.

To have access to financial markets to transfer money and trade different types of investment instruments, investors and businesses mostly challenge with future cash flows and risk. While investors are expected to make their investment decisions individually, such tasks are given to professional fund managers and investment firms. As a result, the majority of investment assets are managed professionally. These include pension funds, insurance funds, endowments, portfolio management services, hedge funds, and mutual funds. Mutual fund is a combined investment tool designed specifically for individual investors. The advent of mutual funds as a preferred investment tool for individual investors is verified in the Investment Company Institute Fact Book, 2020 (Investment Company Institute, 2020), which indicates that the average assets managed by mutual funds around the world are 53 % of the world's GDP.

The results of the risk-based firm rankings show that investment firms can better adapt to the crisis conditions that occur in the market than other listed firms. So, investment in investment firms, with some features such as: professional management, securities diversification and risk reduction, high liquidity, economies of scale and cost reduction, and presenting diverse services to owners of investment units and shareholders, can be introduced as two safe and profitable investment methods instead of savings and direct investment to all classes of society, especially the households who are the main owners of actual savings and potential capital. On the other hand, it can be used as a tool to guide the liquidity and savings of the society to a dynamic and useful market for Iran's economy.

Unfortunately, unlike Western countries, investment funds do not have high diversity, and there is no interest in investing in investment funds, although they have a simpler structure and function and investing in this financial institution is easier and less risky, and this is also true for investment firms. It seems that the most important reason for this is the lack of confidence of individuals in Iran's capital market. Unfortunately, the capital market in Iran has not been able to absorb people and entities after several decades of its establishment.

The purpose of investment for every investor is to increase or at least protect financial capital; therefore, evaluating investment performance is of great importance for all investors. However, after a correct and integrated evaluation, the performance of a company is not satisfactory, and investors have no choice to continue investing and may react by selling the shares of that company and acquire shares of another company or generally exit the financial industry and the investment firms sector in the market. This has undesirable outcomes such as a decline in stock prices, which is neither the taste of the shareholder nor in the taste of the company. For this reason, it is expected that correct evaluation of the performance of investment firms is of great importance for investors and even the company itself.

The findings of this research indicate that the intelligent hybrid algorithm based on accuracy and interpretability can effectively optimize the parameters of the adaptive neuro-fuzzy system for the appropriate evaluation of training and test data with minimal prediction errors. It is inferred that the proposed approach can enhance the initial population's performance based on the genetic algorithm by minimizing the number of evaluation and prediction errors. The studies mentioned above, highlights the importance of optimizing the parameters of the adaptive neuro-fuzzy system to improve forecasting models for factors influencing investment companies. Moreover, very few researchers have utilized parameter-tuned adaptive neuro-fuzzy system approaches for modeling the prediction of advanced manufacturing processes such as additive manufacturing and non-traditional machining processes.

The significance and great importance of the stock investment branch based on both performance criteria is something that has been mentioned and predicted in all researches in this field, because the information on this branch of investment is completely available as the main activity of investment firms and is always of the main debate. However, the main novelty of this study is to examine and investigate the other two branches of investment. In the non-stock market investment branch, statistical significance was supported at a 95% confidence level. This indicates that the information on this branch of investment is not processed and neglected when evaluating the financial performance of firms from the market's view. Indeed, when the market can not collect data on this branch, it does not analyze it. This result can make Investment Company managers think that despite having a high percent of the total investments of these firms, the market can not consider the proper performance of this branch. The fact that the non-stock market investment branch has no significant effect on the performance of these firms requires a detailed examination and scientific analysis of the reasons. In fact, the information of this branch of activity is not transferred to the market and naturally cannot be considered in the analysis of the company's performance. Thus, if this investment branch is unimportant that neither in the statement of the portfolio of appropriate information nor anywhere else, information from it is not transferred to the market to be analyzed, why does a lot of capital flow from the company to this investment branch? This problem should be resolved by the managers of these firms. The same is true about the third branch of activity, because the money importance of this branch indicates that we should provide much information to the market, while its statistical significance was verified. Therefore, despite the large amount of information we have about investment firms, it is worth to mention that most of this information is related to the stock market investment branch and there is still a lack of useful information sources regarding the non-stock market investment branch and projects. In order to obtain minimum information about these activities, it is required to make much more information about the activities of these firms to enable more exact analysis and evaluation of financial performance. Finally, it is worth noting that since some investment firms active in the Iranian market are based on quasi-governmental system, as they are forced to buy less profitable shares in case of crisis in the market due to various political, financial, social reasons, etc. This can affect their performance during that period and subsequently the results of the research.

1. The Tehran Stock Exchange, as the main organization to manage capital market, has introduced investment in mutual funds and investment firms as two alternative methods of saving and direct investment to all individuals and different sectors of society, and provides a suitable platform for the participation of many members of society in the capital market.
2. Regarding investment firms, it is recommended that the law maker provides a definition of this financial institution, because the securities market law of the Islamic Republic of Iran, approved on November 22, 2005, recognized the concept of an investment company as one of the financial institutions being listed in the stock market, without providing a comprehensive and complete definition of an investment company. This legislation weakness becomes more evident when we see that the legislator has defined the holding company and the parent, although with some corrections, but has not referred to non-holding investment company. This causes that we mistake non-holding investment company for holding firms. Although legal experts and capital market activists perceive the difference between these two financial institutions, it causes many problems for the individuals who do not know much about financial institutions listed in the capital market and intend to invest in holding investment firms or non-holding investment firms. Thus, the main purpose of establishing the capital market is to absorb the wandering capital of these ordinary people.
3. 3.. The creation of investment firms with a broader scope of activity in diverse assets such as stocks, gold, currency and construction can mitigate the risk resulting from lack of diversification in investment and neutralize the adverse impacts of inflation on capital.

1. **B- Recommendations for future research:**
2. It is recommended that other nonlinear methods and hybrid intelligent models such as: modern artificial neural network, fuzzy expert system, etc. be used to design models to measure and predict the ranking of investment firms. It is also recommended that these indicators be applied quantitatively as a complete model and model of investment firms in the TSE.
3. In future studies, researchers can compare the proposed model with other optimization models and hybrid models for risk prediction and analyze the results to detect the most optimal responses.
4. It is suggested that researchers should help stock exchange firms improve their financial constraints by developing the presented model based on new parameters and indicators of customers and stakeholders, so that the output of the model provides some recommendations in this regard.

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