The Use of Fuzzy, Neural Network, and Adaptive Neuro-Fuzzy Inference System (ANFIS) to Rank Financial Information

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ABSTRACT

Ranking of a company's financial information is one of the most important tools for identifying strengths and weaknesses and identifying opportunities and threats outside the company. In this study, it is attempted to examine the financial statements of companies to rank and explain the transparency of financial information of 198 companies during 2009-2017 using artificial intelligence and neural, fuzzy and neural-fuzzy network models. Accordingly, the best method to rank financial information transparency is selected. For this purpose, the information about companies in different industries is first sorted using the corporate financial statements in Excel software and then, the ranking of companies in each industry is determined on a scale of 1 to 5 in terms of financial and technical strength in the form of a diagram. In order to rank companies with artificial intelligence, the information obtained has been entered into Matlab software and neural, fuzzy and neural-fuzzy models are then implemented. After reviewing descriptive statistics and Fisher's test, companies are ranked. According to the results of the research, the best method for ranking is the neural method and the neural-fuzzy method. The results of the neuro-fuzzy method with 0.01 distance from the results of the neural method provide the best results after the results of the neural method. But in the fuzzy method, the ranking is far from the intended results and is not suitable for ranking of financial information.

Keywords:

Financial Information Ranking, Neural Model, Fuzzy Model, Neural-Fuzzy Model, Companies Accepted in Tehran Stock Exchange.

1. Introduction

Ranking companies' information is one of the most important tools for identifying strengths and weaknesses and identifying opportunities and threats outside the companies (Rostami & Khatanlu, 2006). Today, various domestic and foreign organizations and magazines are ranking companies. However, the rating process is carried out using different quantitative and qualitative indicators and methods based on the goal of the mentioned institutions. In this regard, some of the most important institutions and magazines include Forbes, Fortune, Bloomberg Businessweek, and IndustryWeek (international), as well as Tehran Stock Exchange and Industrial Management Organization (domestic). They can to a large extent identify internal strengths and weaknesses as well as opportunities and external threats to companies. An important issue in ranking is the appropriate model, criteria and indicators, and mathematical techniques for ranking. Although stock companies' rankings are performed using the usual methods, no comprehensive technique has been developed to identify top stock companiesso far (Ghodratian and Anvari Rostami, 2004). In the present study, it is tried to rank the information of companies using artificial intelligence. Although transparency has been described as a desirable feature of financial reporting, it has not been provided with a comprehensive definition that is generally accepted. Bushman et al. (2004) describe transparency of financial reporting as "broad access to relevant and reliable information about the performance of the firm, financial position, investment opportunities, governance, value and risk of publicly traded companies." From the perspective of Bart & Schipper (2008), financial reporting transparency means that "the financial statements of the business unit present the economic realities in a way that is understandable to users of financial statements."

Effective transfer of funds from savers to companies in the securities market should be done with sound health and economic certainty, requiring methods and models that provide market efficiency for the capital market executives and experts. Designing financial information transparency rating models is a key step to make Tehran's securities more efficient. So far, radar diagrams have not been used for this ranking, which can be achieved using artificial intelligence and fuzzy models. In the past decades, world-class rating agencies, specialized and professional institutions, as well as many researchers in different countries have developed measurement models to rank financial information transparency in order to support investors and other users of information. In Iran, not only has no model been developed to measure this concept, but also Iranian companies have not been included in the sample of international rating agencies and professional bodies to assess the level of information disclosure and transparency (Hajian, 2014).

The purpose of this study is to provide a suitable model for evaluating and ranking the financial information of listed companies in Tehran Stock Exchange. In a way that in addition to considering different aspects of information and qualitative characteristics of information, is in line with the legal and customary structure of Iranian reporting and the reporting requirements and standards and information needs of Iranian information users. In the present study, ratings are based on information transparency and disclosure quality by the financial ratios, financial strength and technical capability of the companies. We use the ratios of liquidity, profit and debt, and the ratio of activity to performance to show the technical capability of companies.

2. Literature Review

2.1. Ranking information transparency

Rankings conducted by various institutions are in different capital markets for greater information transparency to help investors understand the relative status of companies and acceptable transactions. Therefore, various researches on the ranking of companies using different criteria and indices, including criteria derived from financial statements, can be an important step in making information markets more efficient and encouraging companies improve their current situation (Mehrani et al., 2009).

Financial informationis so important that there is a need for clear and specific policies to improve transparency. There should also be a mechanism for measuring and evaluating transparency to identify gaps and shortcomings in the company in order to improve transparency. The degree of transparency, in theory, expresses the degree of access to company's information and the quality of information. Much research has been done by professional institutions and some reputable rating agencies and researchers, with several models of financial information ratings. Stock exchanges of different countries use these models to assess and evaluate the adequacy of information disclosure and transparency. For example, the Disclosure and Transparency Quality Index of the International Center for Financial Research and Analysis can be used for this purpose. In 1955, this center used its own model to investigate the financial information of more than 1,000 companies in 41 countries worldwide. Companies can be evaluated and rated using the model of financial information and disclosure of the Standard & Poor's Institute, which was used to rank 1,500 companies in the US, Latin America, Asia, Southeast Asia, Japan and Europe. Also, some researchers used these models and localized them according to the legal and customary structure and reporting requirements of their country to provide national models for evaluating the financial information of existing companies and rating and calculating the rank of listed companies.

Disclosure is the dissemination of important information affecting market, and transparency can be defined as the simplicity and ease of meaningful analysis of the company's activities and its economic foundations by the outsider. The transparency is the management capability indicator in providing accurate, clear, timely and accessible essential information, specifically audited information that is disseminated both in the form of public reports and through reflection in the mass media and other methods. In other words, transparency reflects whether investors have a realistic view of what is really going on within the company. Therefore, disclosure and transparency are intertwined. Transparent systems require reliable and accurate information that is timely and easily provided to general shareholders, both directly and through reputable agents such as accountants, auditors, rating agencies, securities analysts, journalists and mass media (Hollwood, 2001). Transparency is "increasing the timely and reliable flow of economic, financial, social, and political information available to all stakeholders". Also, Weishwath and Kauffman (1999) refer to lack of transparency as a "deliberate impediment to access information, misrepresentation, or market failure to ensure the relevance and quality of the information provided." One of the investigators defines transparency as canceling confidentiality, and confidentiality is an effort to hide some behaviors and activities for the benefit of certain groups or individuals.

Tajvidi (2007), quoted by Bushman et al. (2003), defines corporate transparency as the availability of relevant and reliable information on the results of periodic performance, financial status, investment opportunities, corporate governance, value and risk of publicly traded corporations. Transparency, on the one hand, assures small shareholders that they will always receive reliable and timely information about the value of the company, and that major shareholders and managers do not seek to undermine their rights, and on the other hand, encourages directors to strive to increase the value of the company instead of pursuing short-term personal interests. It can significantly reduce the scale and severity of financial scandals.

Functions of transparency in financial markets include financial market efficiency, corporate accountability and responsibility, real price discovery, attractiveness for investors and especially foreign investors, information symmetry or the elimination of information rents and nurturing professional managers (Mashayekhi, 2006). Companies that fail to meet transparency standards will face a loss of investor and shareholder confidence, leading to a loss of capital markets and a reduction in their credit standing and market liquidity. It can be said that voluntary disclosure of information and transparent financial reporting by all companies in the long run helps create a competitive market (Madhani, 2009). Disclosure quality is directly related to financial information. Transparent information can be regarded as a tool to carry out the accountability of managers. Increasing the content of financial reports that include complementary information in the form of financial statements notes not only helps accountants to maintain their competitive advantage but also can improve social welfare through decreasing the reverse effects of confidential information (Rahmani and Dad, 2011). According to Lang and Lundholm[12], Wallace et al. [19], Ahmad and Courtis, [1], Cooke and Cofferman [7], and AlSaeed [4], various features of a company are a potential representative for determining the level of information closure. Financial ratios are the most quantitative and recognized criteria and features in companies. Despite being traditional, these ratios are common and strong tools for analyzing financial statements and have been long of interest to enthusiasts of the field, such as financial analysts, creditors, investors, and financial managers. Instead of using general figures of financial statements, combined ratios of these figures are used to get a clear picture of the company [8]. Despite being easily calculated, the ratios are difficult to be interpreted, especially when two or more ratios have contradictory results [3]. Due to weaknesses of linear models, researchers have turned to non-linear models, especially artificial intelligence techniques, in the past few years.

In a study entitled "Identifying and Ranking Factors Affecting the Quality of Online Financial Reporting on the Websites of Companies Listed on the Tehran Stock Exchange" Kamali Ardakani et al. (2017) used fuzzy Delphi methods and found that it is possible to download or print financial information and links to the websites of related institutions and the company's vision document are the most important factors affecting the quality of online financial reporting.

Sepasi and Ghasemi (2017) studied the identification and ranking of factors affecting the implementation of continuous auditing using the decision technique.The results showed that factors, such as staff competence, auditors' independence, the need to use computer-based auditing tools, increased demand from stakeholders to provide ongoing audit reports, increased management accountability, and the establishment of risk management systems have a very strong relationship with the implementation of continuous auditing.

2.2. Affordability

Financial indicators determine the liquidity status, ability to pay financial liabilities, and the amount of profitability that can be calculated by the following ratios:

1) Liquidity ratio that includes instantaneous, current, liquidity, endurance, current assets, cash adequacy and cash flow ratios.
2) Leverage ratios (repayment of long-term debt) that include fixed asset-to-eigenvalue ratios, debt coverage, and operating cash to debt, long-term debt, fixed cost coverage, equity, and cash coverage ratios.
3) Profitability ratios that include net profit ratios, sales returns, asset returns, debt-to-equity, working capital to asset, percentage of profit change, working capital return, loan cash profit index, accumulated earnings to assets, asset profitability earning power, loan cash returns, stock price returns, gross profit margins, earnings per share, price to earnings, cash earnings per share, capital return to marketvalue, cash return on assets, dividend earnings, and cash earnings payable ratios.

2.3. Throughput

Technical indicators, in a specific sense, are indicators that exist in terms of the type of activity of a given and defined industry. These indicators can be calculated for a bank for a number of years and be useful for financial analysis, or they can be calculated for several companies in a year and be useful for comparing performance evaluation of different companies (Schack et al., 2009). The performance indicators are determined by activity ratios and are as follows:

It measures the extent of the institution's activities and performance. These ratios are of interest to management and shareholders because the profitability of the entity in using resources is determined by these ratios. Increase of these ratios indicatesdesirability of activity and performance (Mah Avar, 2007). In general, these ratios can be used to determine the degree of efficiency in terms of efficient use of resources. In this study, the inventory turnover, the period of receivables, the operating period, the creditors' deposit period, the ratio of commodity to working capital, the ratio of current working capital, the asset turnover ratio, and the percentage of sales change are considered (Barth et al., 2004).

Some researchers have studied the ratings and financial information and have been able to obtain indicators for financial information. They also rank companies using different methods and models that are discussed below and their shortcomings are highlighted. It should be noted that in the present study, companies are ranked in terms of financial information on technical and financial capability. Hence, it is a new research. Given the novelty of this research, in which hypotheses have been formulated separately for these two types of information, previous research that has been done on the ranking of financial information so far can be divided into two main groups. One is categorization based on statistical methods and the other is categorization based on artificial intelligence and related techniques. In the context of statistical methods, starting to classify financial information in terms of literature monitoring has made a greater contribution to the field of such data. These methods are less popular in recent years because of the high computational volume and the low accuracy compared to some neural network models.

Namazi and Namazi [14]. performed a study entitled "ranking firms based on the performance evaluation criteria via the multiple attribute TOPSIS technique" and compared the evaluation criteria (evidence from the Tehran Stock Exchange). The results introduced TOPSIS as a suitable technique to rate firms. In addition, there was a significant difference between indicators of economic value, relative proximity, traditional and modern financial criteria. In addition, despite the relationship between new financial ratios and economic value, the mentioned ratios had no significant association with traditional ratios. Moreover, new ratios were closer to ranking all criteria.

Mashayekh and Shahrokhi [13] recognized the corporate credit rating indicators, pointing out that attention must be paid to qualitative and quantitative factors in determining the rating of firms. Therefore, credit rating indices were extracted in two sections of business status (qualitative variables) and financial status (quantitative variables) based on thematic literature. Afterwards, the opinions of experts were asked using a questionnaire and exploratory interviews. By doing so, indicators related to the financial market of Iran were selected for rating of firms. In the mentioned study, binominal and Friedman's tests were considered for testing the assumptions that consider the level of importance of each index in determining the credit rank and for prioritizing the indices, respectively. Ultimately, 12 indicators were recognized as credit rating indices.

In a research entitled "ranking firms based on information transparency", Hajian [10] identified valid global information transparency indexes and selected components to formulate a rating model. In addition, the conceptual matrix was modified, summarized, and assessed for data collection. Ultimately, 129 applicable information components were weighted for rating the transparency of companies considered important by users. In the end, a model was developed for rating firms. A research by Raei [15] was similar to the present research (in terms of data analysis) in that it predicted financial distress of companies using the method of artificial neural networks. In the mentioned study, Raei pointed out that lack of timely or efficient provision of the necessary information to investors will damage the stock exchange market. It was also mentioned that some firms struggle with repaying their debts, lack the necessary return to cover their costs, and are subjected to Article 11 of the business law. In fact, all of these issues show the existence of financial distress in firms, which ultimately leads to bankruptcy and dissolution. The researcher recommends helping investors invest in profitable and value-creating opportunities and preventing the negative impact on macroeconomic indices while adhering to information transparency by predicting the level of distress using artificial neural networks.

Etemadi et al. (2018) conducted a meta-analysis of empirical studies on the effects of acceptance of International Financial Reporting Standards on the value relationship of accounting information. Based on the application of this method on 94 studies with a sample of 72266 companies-years in the period 2000 to 2017, 94 analyzes were performed among different countries. The results showed that, with the exception of voluntary acceptance, the book value of equity decreased in the period following the adoption of International Financial Reporting Standards, but the extent of this reduction depends on the legal and commercial conditions prevailing in the countries.

Tansel et al. [18] rated firms and industries in Turkey using TOPSIS fuzzy method. At first, various industries were rated using industrial macro-economic variables. Afterwards, firms were rated by TOPSIS fuzzy method based on the financial ratios of companies. In the next stage, the rates of industries and their affiliated companies were integrated to form a comprehensive rate for each firm. In the end, experts' opinion was asked about the rating, and the results were compared to rating by TOPSIS fuzzy method, showing an insignificant difference in this regard. In another study, Cheung et al. [6] rated firms in China based on corporate governance. In the end, 56 components were classified into five groups to rate firms:

1) Equity
2) Equitable behavior of stakeholders
3) Role of stakeholders
4) Information transparency

5) Composition and responsibilities of the board of directors

In addition, the rating components of firms were divided into three main classifications, each involving several components:

1) Information transparency (seven components)
2) Financial information disclosure (seven components)
3) Rights of stakeholders (six components)

In an article entitled "transparency and disclosure scores and their determinants in the istanbul stock exchange", Aksu [2] selected 98 criteria from SandP model and modified them based on Turkey's laws. In the end, firms were rated based on 106 criteria fitted to the culture of financial markets in Turkey. In addition, three main criteria were introduced for rating components of firms listed on the Istanbul Stock Exchange: ownership structure and investor relations, financial transparency and information disclosure, and process and structure of board of directors and management.

In a research entitled "disclosure level and the cost of equity capital", Botosan [5] extracted components for information disclosure level from the following documents: business reporting association of American chartered accountants, international SRI questionnaire for investor information needs, study of the annual report of the Canadian institute of chartered accountants, AIMR corporate information committee reports, and AIMR machinery industry subcommittee ranking. In the end, 63 components were used to disclose information and rate firms. Generally, the components were divided into five groups, including company background information, summary of five or ten-year results of firms, key non-financial statistical information of firms, budget information of firms and information related to management analysis.

Recognizing the factors used by former studies in terms of information transparency, level of information disclosure and rating criteria of firms based on information transparency, we aimed to answer the following questions in the present study: is it possible to rate firms listed on the Tehran Stock Exchange based on their financial and technical strength and information transparency using fuzzy and neural network models? Which of the two models yielded better results?

3. Methodology

This research was applied in terms of its objective and descriptive-correlational regarding data collection method. Statistical data were extracted from financial statement of firms using the method of collecting organizational documents. Given the fact that the information is extracted from audited documents, and since the equations applied by the scientific community are used to convert them, it could be expressed that the data measurement tool of the present study was valid. Estimation of evaluated indices requires specific equations known as global standard tools, which are especially established to measure the traits based on documents in the literature and theoretical foundations. According to this view, we can ensure the validity of the measurement tool.

Data were collected using computer databanks and Rahavard Novin Software and by referring to the library of the stock exchange and Codal Website belonging to the stock exchange market. In addition, financial statements of firms, including balance sheets, cash flow statements, and notes attached to financial statements at the end of each financial year (March 19th), were applied as data collection tools.

In this study, fuzzy model, neural network and neural fuzzy model are used to rank information transparency of companies and their financial and technical capabilities. The indices, or indeed the financial ratios of each company, are first calculated using Excell software. Then, they are entered into a radar diagram as a coordinate. After that, the area obtained by the ratios of each company in the radar diagram is compared and each company's rank is obtained. Then, using Matlab software, each of the financial rankings and indices is compared using fuzzy model, neural network and neural fuzzy model. Finally, the best model for ranking information transparency is obtained.

According to what was said, the present research hypotheses are as follows. To answer these questions, we considered the variables of liquidity, profitability, leverage and performance ratios, as defined below

3.1. Main research hypotheses

1) Companies can be ranked using artificial neural network model.
2) Companies can be ranked using fuzzy logic.

3) Companies can be ranked using fuzzy-neural inference system.

3.2. Sub-hypotheses

1.1) Affordability of companies can be ranked using artificial neural network model.
1.2) Throughput of companies can be ranked using artificial neural network model.
2.1) Affordability of companies can be ranked using fuzzy logic.
2.2) Throughput of companies can be ranked using fuzzy logic.
3.1) Affordability of companies can be ranked using adaptive neuro-fuzzy inference system.
3.2) Throughput of companies can be ranked using adaptive neuro-fuzzy inference system.

Research variables:

Input data included financial strength (liquidity ratios, profitability ratios, and leverage ratios) and operational strength (activity ratios), which included the following items.

Liquidity ratios: quick ratio, current ratio, liquidity ratio, endurance period, current asset ratio, cash adequacy ratio, and cash flow ratio.

Profitability ratios: net profit ratio, return on sale, return on asset, profit change percentage, return on working capital, loan cash profit index, stock cash return, stock price return, gross profit margin, earnings per share, dividend per share, return on capital to market value, return on asset, dividend profit ratio, cash profit payout ability, debt-to-capital ratio, ratio of working capital to assets, the ratio of accumulated profits to assets, the power to earn assets, and price to profit ratio.

Leverage ratios: fixed assets to net worth ratio, proprietary ratio, debt coverage ratio, operating cash to debt ratio, long-term debt ratio, fixed charge coverage ratio, and cash interest coverage ratio.

Performance ratios: inventory turnover, inventory to working capital ratio, receivable turnover ratio, operating cycle, payable turnover period, inventory to working capital ratio, current asset turnover ratio, asset turnover ratio, sales percentage change, price-to-sales ratio, and net working capital.

All of the mentioned variables were collected from software information and data registered on the website of stock exchange.

Research population included all companies listed on the Tehran Stock Exchange during a 10-year period (2007-2017). Statistical sample was estimated using systematic elimination method, encompassing companies that met the following criteria:

Table 1. Sample selection based on research limitations

Companies listed on the Tehran Stock Exchange until the end of the Persian year of 96 (March 20th, 2018)	641
Companies with financial statements that do not end on March 20th	42
Companies with missing information or changed the financial year	65
Companies that are among investment companies, holdings, financial institutions and intermediaries	336
The remaining companies in the statistical sample of research	198

In the end, the sample size was estimated at 198 firms based on systematic elimination method. Accountability is directly related to information performance. Performance appraisal can be seen as one of the tools for managers' accountability. By increasing the information content of financial reports, which include supplemental information in the notes to financial statements, not only can accountants maintain their competitive advantage, but also increase social welfare by reducing the adverse effects of confidential information (Rahmani and Dad, 2011). According to Lang and Landholm (2003), Wallace et al. (1994), Ahmad and Kourtz (1999), Cook and Kaufferman (2002), and Al-Saeed (2006), different characteristics of the company are potential representatives for performance evaluation in companies. Financial ratios are the fewest and most well-known internal metrics and characteristics. These ratios are a traditional but still powerful and common tool for analyzing financial statements that have long been of interest to consumers, such as financial analysts, creditors, investors and financial managers. Instead of using general figures of financial statements, the combined ratios of these figures are used to obtain a clear picture of the company (Delan et al., 2013). Although these ratios are easy to calculate, their interpretation is often difficult and controversial, especially when two or more ratios have conflicting results (Ali Mohammadi et al., 2015). The weakness of linear relationship-based models in recent years has led researchers to turn to nonlinear models, specifically artificial intelligence techniques.

There are a number of artificial intelligence methods that can be used to rank companies. This study focuses on the use of artificial neural networks (ANNs), fuzzy logic (FL), and adaptive neuro fuzzy inference system (ANFIS) for modeling corporate rankings. Each of the models is explained below.

We first calculated the rank of liquidity, activity, leverage, and return ratios for each of the companies using the statistical tables as well as the area below the radar chart to obtain the target. The average of three liquidity, return and leverage ratios for the firm was used to evaluate throughput. Operational or activity ratios were also used to assess the technical capability, and then the rankings of each company in the technical capability and affordability were measured using the three models mentioned above and compared with the target. We will explain each of the models below.

An understanding of the artificial intelligence of fuzzy logic systems and artificial neural networks is essential for understanding the structure and work of ANFIS. If the ANFIS system has two inputs X and Y and one output f, the usual set of fuzzy system rules is represented by 2 if – thenrules for the first-order Sogno fuzzy model:

$$Rsule1 = if(xisA1)and(yisB1)then(f1 = p1x + q1y + r1) \tag{1}$$

$$Rsule2 = if(xisA2)and(yisB2)then(f2 = p2x + q2y + r2) \tag{2}$$

Where, r_i, q_i, and p_i are called later parameters that are determined during the training process. F_i is also the output of the fuzzy environment as determined by the fuzzy rules. The governing equations for different layers of the neuro fuzzy model are presented by Nadiri et al. (2014).

4. Results

4.1. First research question

1) Companies can be ranked using artificial neural network model.
   1.1) Affordability of companies can be ranked using artificial neural network model.
   1.2) Throughput of companies can be ranked using artificial neural network model.

For modeling corporate rankings, 198 firm data are available. Each of these companies has several variables and a rating is assigned to each company. In this process, data was divided into three sections: 1) educational data, 2) validation data, and 3) test data.

Generally, 70% of the data encompasses the educational data, divided into two parts: 1) the characteristics and parameters of test and 2) target data, sought to be estimated for each level of parameters using the education of neuro-fuzzy model. After dividing the educational data, it was inserted into the neuro-fuzzy model and the educational process was awaited. Due to the difference in the primary education conditions and its impact on the final result of education, the educational process was repeated several times to achieve the optimal result. After this stage, the validation data was entered into the neuro-fuzzy model, followed by adding the test data to the model in the third stage to ensure the system's accuracy and function.

At this stage, we assessed the level of error in the estimation of parameters.

- Educational data: this data is added to the model during education, and the model gradually adapts itself to the data and reduces its error.
- Validation data: this data is used to measure model generalization, and is applied in the completion and finalization of education.
- Test data: this data is not involved in the model education process and is used to measure the model's function after education.

In order to use the neuro-fuzzy networks in firm rating models, we used 70% of the educational data and 30% of the remaining of the data to test the model.Finally, the remaining 15% of the data will be used to test the model. For this purpose, a neural network with four inputs (parameters) and one output (rank) is considered as follows.

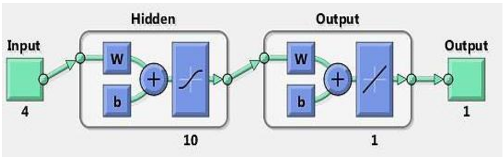


Figure 1: A neural network intended to rank companies

The neural network used here is a two-layer feedforward network. This network uses sigmoid neurons as a hidden layer and uses linear output neurons that are very useful in solving such problems. This network uses the Levenberg-Marquardt backpropagation algorithm. Next, training data and target data are injected into the network. Other definitions for using neural networks are as follows:

Mean Squared Error: The mean squared error is the difference between the output and the target, and the lower the value, the better.Also, zero means that there is no error.

Regression: Regression values are used to express and measure the correlation between outputs and targets. If the regression is one, it means the relationship is completely closed.If the regression is zero, it means there is a random and non-dependent relationship. After performing the neural network training, the error diagram (the difference between the output of the neural network and the actual rank of each company) is as follows:

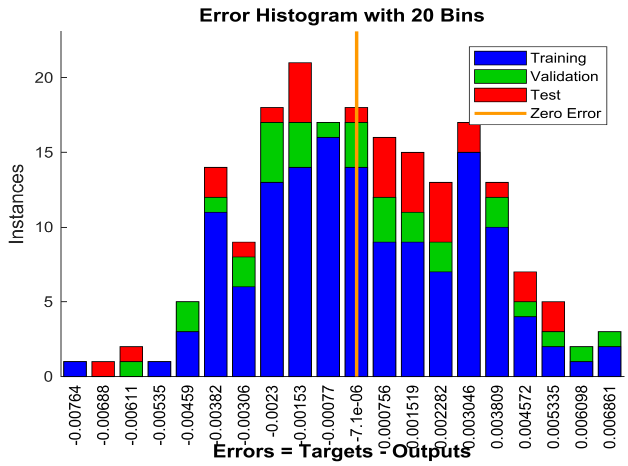


Figure 2: Error curve after neural network training

As can be seen in the figure, the mean squared error is 0.00001, which is a good value.

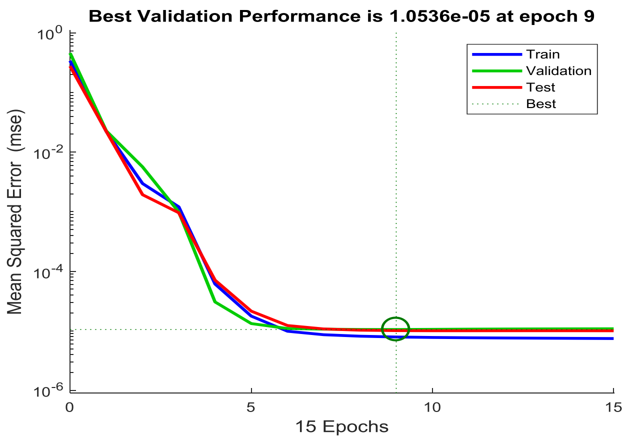


Figure 3: Squared error sum curve

As shown in the regression graph, training and validation are performed well and the test data matched with a 0.003 error, which is a good value. In fact, using this chart, the accuracy of the data in making the data estimates can be realized. As can be seen in the figures, the higher the data, the more accurate the ultimate goal of data estimation can be.Also, the lower the number of data, the higher the error rate. It is also clear from the following diagrams that since the training data is more than the test data, the data matching is also more than the test data.

Adaptive neuro-fuzzy inference system (ANFIS)

An understanding of the artificial intelligence of fuzzy logic systems and artificial neural networks is essential for understanding the structure and work of ANFIS. If the ANFIS system has two inputs X and Y and one output f, the usual set of fuzzy system rules is represented by 2 if - then rules for the first-order Sogno fuzzy model as follows:

(3-2)

$$Rsule1 = if(xisA1)and(yisB1)then(f1 = p1x + q1y + r1)$$

(3-3)

$$Rsule2 = if(xisA2)and(yisB2)then(f2 = p2x + q2y + r2)$$

R_i, q_i, p_i are late parameters that are determined during the training process. F_i is also the output of the fuzzy environment determined by fuzzy rules. The equations governing different layers of the neuro-fuzzy model are presented by Nadiri et al. (2014).

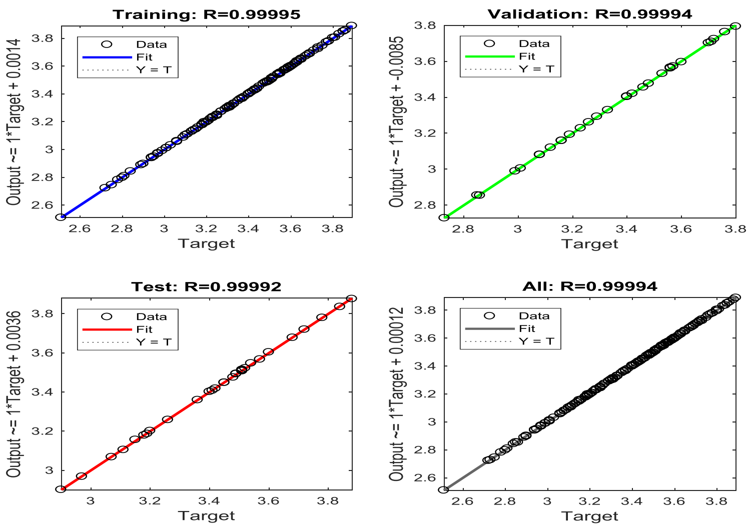


Figure2: Regression curve

Table 2:Resultsof neuralmodel for rankingdifferent industries' companiesbased on financial capability

Company	Industry	Target	Neural
Pegah Azarbaijan	Food and beverages except sugar	2.94	3.02
Abadan Petrochemical	Chemical products	2.95	2.97
Pars Shahab lamp	Electric machines and apparatus	2.78	2.78
Absal	Equipment and machinery	2.83	2.85
Plaskokar Saipa	Rubber and plastic	2.44	2.64
Nilo Tiles	Ceramic and tile	2.78	2.82
Marvdasht sugar	Sugar	3.13	3.15
Iran Ferrosilis	Basic metals	2.67	2.93
Bojnourd cement	Lime, gypsum, and cement	2.90	2.92

Company	Industry	Target	Neural
Azar refractory products	Other non-metallic mineral products	2.84	2.91
Magsal	Agriculture and related services	2.74	2.86
Daroopakhsh	Medicinal	2.86	2.98
Iran Khodro	Automotive and parts manufacturing	2.71	2.75
Bafq mines	Extraction of metal straw	2.90	2.92

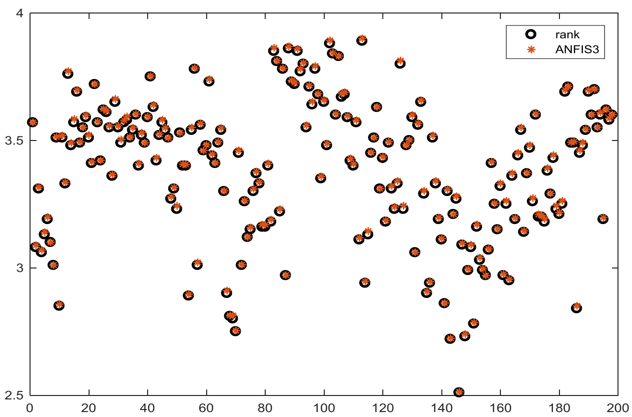


Diagram 1: Evaluation of the neural ranking error with targetin the financial capability

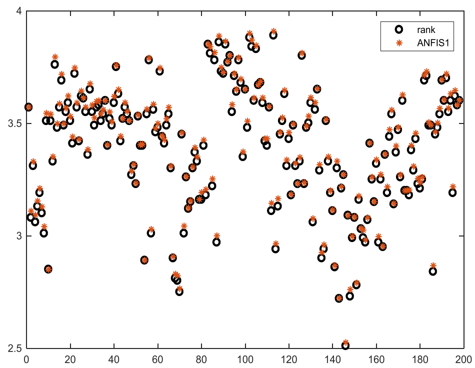
Table 3: Resultsof neuralmodel for rankingdifferent industries' companiesbased on operational capability

Company	Industry	Target	Neural
Pegah Azarbaijan	Food and beverages except sugar	2.84	3.16
Shiraz petrochemical Company	Chemical products	3.20	3.22
Pars switch	Electric machines and apparatus	3.15	3.22
Industrial butane	Equipment and machinery	2.90	2.94
Plaskokar Saipa	Rubber and plastic	2.51	3.16
Takseram Tiles	Ceramic and tile	3.10	3.11
Marvdasht sugar	Sugar	3.06	3.16
Sepahan industrial	Basic metals	3.11	3.09
Ilam cement	Lime, gypsum, and cement	3.13	3.16
Iran glass wool	Other non-metallic mineral products	3.10	3.11
Magsal	Agriculture and related services	3.01	3.16
Abidi pharmaceutical	Medicinal	2.89	2.95
Khodro Shargh electrics	Automotive and parts manufacturing	3.40	3.42
Chadoremlou	Extraction of metal straw	2.98	2.98

Table 4: Examining the relationship between neural network model and the target for operational capability ranking results with Fisher test

	H	p-value	Def
Vartest2 (Fisher test)	1	0.000	197

The results show that h value of 1 confirms the strong relationship between neural network and the target in operational capability ranking, and the p-value equal to 0.000 is confirming this.



The results show that the predictions of the artificial neural network are very close to the target results in terms of both affordability and throughput. Therefore, artificial neural network can be a good way to rank companies in different industries. Therefore, the hypotheses (1.1) and (1.2) can be accepted. Also, diagrams 3 and 4 that show the model error rate in ranking (white points show target and red points show ranking using neural network) indicate slight error rates and many white points are covered by red points. This also confirms the results of this hypothesis.

4.2. Second research question

2) Companies can be ranked using fuzzy logic.
   2.1) Affordability of companies can be ranked using fuzzy logic.
   2.2) Throughput of companies can be ranked using fuzzy logic.

Table 5:Results offuzzymodel forranking different industries'companies based on financial capability

Company	Industry	Target	Neural
Pegah Azarbaijan	Food and beverages except sugar	2.94	3.19
Abadan Petrochemical	Chemical products	2.95	3.08
Pars Shahab lamp	Electric machines and apparatus	2.78	3.40
Absal	Equipment and machinery	2.83	3.35
Plaskokar Saipa	Rubber and plastic	2.44	3.47
Nilo Tiles	Ceramic and tile	2.78	3.28
Marvdasht sugar	Sugar	3.13	3.60
Iran Ferrosilis	Basic metals	2.67	3.13
Bojnourd cement	Lime, gypsum, and cement	2.90	3.78
Azar refractory products	Other non-metallic mineral products	2.84	3.24
Magsal	Agriculture and related services	2.74	3.37
Daroopakhsh	Medicinal	2.86	3.57
Iran Khodro	Automotive and parts manufacturing	2.71	3.16
Bafq mines	Extraction of metal straw	2.90	3.80

Table 7: Examining the relationship between fuzzy model and the target for financial capability ranking results with Fisher test

	H	p-value	Def
Vartest2 (Fisher test)	0	0.1491	197

According to the Fisher test, h value of 0and p-value of 0.1491 confirm the relationship between fuzzy model and target in ranking financial capability.

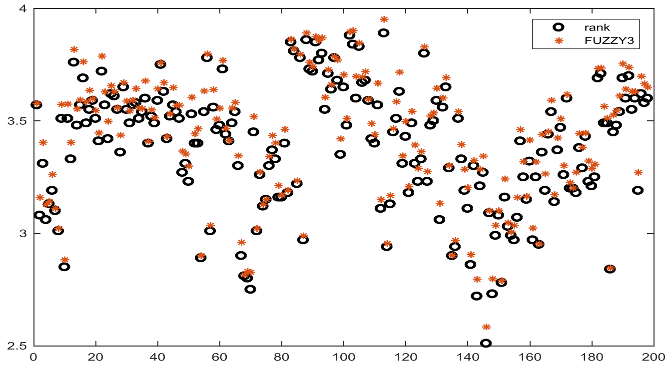


Diagram 3: Evaluation of the fuzzy ranking error with targetin the financial capability

Table 6: Results ofneural model forranking different industries'companies based on operationalcapability

Company	Industry	Target	Neural
Pegah Azarbaijan	Food and beverages except sugar	2.84	3.25
Shiraz petrochemical Company	Chemical products	3.20	4.17
Pars switch	Electric machines and apparatus	3.15	3.79
Industrial butane	Equipment and machinery	2.90	3.07
Plaskokar Saipa	Rubber and plastic	2.51	3.43
Takseram Tiles	Ceramic and tile	3.10	3.70
Marvdasht sugar	Sugar	3.06	3.81
Sepahan industrial	Basic metals	3.11	3.77
Ilam cement	Lime, gypsum, and cement	3.13	3.31
Iran glass wool	Other non-metallic mineral products	3.10	3.38
Magsal	Agriculture and related services	3.01	4.06
Abidi pharmaceutical	Medicinal	2.89	3.54
Khodro Shargh electrics	Automotive and parts manufacturing	3.40	3.82
Chadoremlou	Extraction of metal straw	2.98	3.85

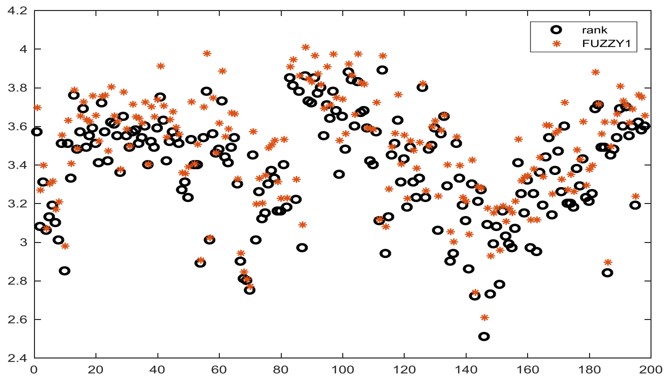


Diagram6: Evaluation of the fuzzy ranking error with target in the operational capability

Table 7: Examining the relationship between fuzzy model and the target for operational capability ranking results with Fisher test

Company	Industry	Target	Neural
Pegah Azarbaijan	Food and beverages except sugar	2.94	3.24
Abadan Petrochemical	Chemical products	2.95	3.52
Pars Shahab lamp	Electric machines and apparatus	2.78	3.66
Absal	Equipment and machinery	2.83	3.69
Plaskokar Saipa	Rubber and plastic	2.44	3.21
Nilo Tiles	Ceramic and tile	2.78	3.23
Marvdasht sugar	Sugar	3.13	3.17
Iran Ferrosilis	Basic metals	2.67	3.35
Bojnourd cement	Lime, gypsum, and cement	2.90	3.53
Azar refractory products	Other non-metallic mineral products	2.84	3.53
Magsal	Agriculture and related services	2.74	3.22
Daroopakhsh	Medicinal	2.86	3.64
Iran Khodro	Automotive and parts manufacturing	2.71	3.50
Bafq mines	Extraction of metal straw	2.90	3.54

Table 8: Examining the relationship between neural-fuzzy model and the target for financial capability ranking results with Fisher test

	H	p-value	Def
Vartest2 (Fisher test)	1	0.000	197

According to the Fisher test, h value of 1and p-value of 0.000 confirm the relationship between neural-fuzzy model and target in ranking financial capability.

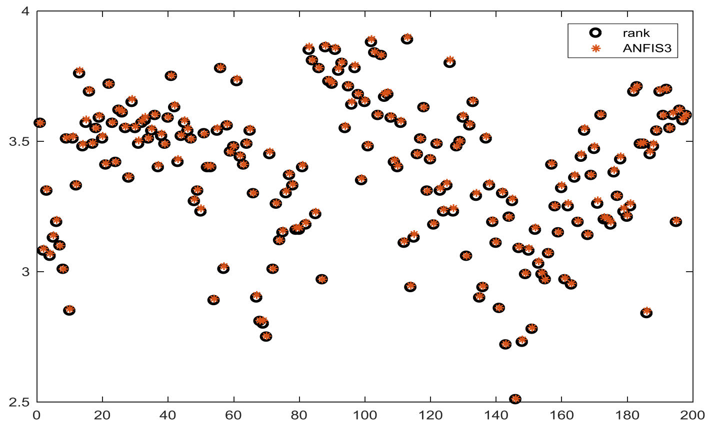


Diagram 5: Evaluation of the neural-fuzzy ranking error with targetin the financial capability

Table 12:Results ofneural-fuzzymodel forranking different industries'companies based on operationalcapability

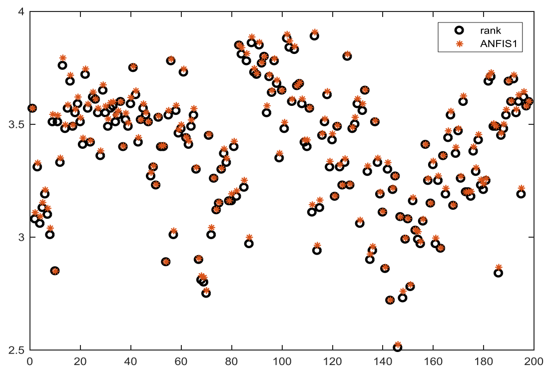
Company	Industry	Target	Neural
Pegah Azarbaijan	Food and beverages except sugar	2.84	3.34
Shiraz petrochemical Company	Chemical products	3.20	3.26
Pars switch	Electric machines and apparatus	3.15	3.38
Industrial butane	Equipment and machinery	2.90	3.00
Plaskokar Saipa	Rubber and plastic	2.51	3.43
Takseram Tiles	Ceramic and tile	3.10	3.23
Marvdasht sugar	Sugar	3.06	3.24
Sepahan industrial	Basic metals	3.11	3.23
Ilam cement	Lime, gypsum, and cement	3.13	3.17
Iran glass wool	Other non-metallic mineral products	3.10	3.36
Magsal	Agriculture and related services	3.01	3.32
Abidi pharmaceutical	Medicinal	2.89	3.03
Khodro Shargh electrics	Automotive and parts manufacturing	3.40	3.63
Chadoremlou	Extraction of metal straw	2.98	3.12

4.3. Third research question

3) Companies can be ranked using fuzzy-neural inference system.
   3.1) Affordability of companies can be ranked using adaptive neuro-fuzzy inference system.
   3.2) Throughput of companies can be ranked using adaptive neuro-fuzzy inference system.

According to the results of the above tables of artificial neural network model with error coefficient of 0.01, it can be said that after neural network, artificial neural network model made the best prediction that was closer both to target and initials prediction data. Therefore, the best prediction among the studied methods after predicting the ranking with artificial neural network method is the adaptive neural-fuzzy inference system. Therefore, hypotheses (3.1) and (3.2) are accepted. Also, diagrams 3 and 4 that show the model error rate in ranking (white points show target and red points show ranking using neural network) indicate slight error rates and many white points are covered by red points. This also confirms the results of this hypothesis.

Based on the results obtained from the research and considering the topics discussed in the previous two sections, it can be concluded that both methods are suitable for corporate ranking. However, comparison of the twoneural and neural-fuzzy methods showed that the neural method gives better results. Of course, the neural-fuzzy method is superior to the neural method in some applications, but in this project, the neural method has a better result. The results also show that the fuzzy model may not be a good approachfor corporate ranking.



5. Discussion and Conclusion

This study was conducted to rank the financial information in listed companies in Tehran Stock Exchange by models of artificial intelligence and among the models of artificial intelligence from fuzzy, neural and neural-fuzzy models. The results indicated that in this study, first the neural model and then the fuzzy neural model can show the closest results to the target. But fuzzy models are not very accurate in ranking, which can be said to be similar to the findings of other researchers. One of the reasons that the fuzzy model cannot give us good results is because the model Fuzzy given the data like neural model - fuzzy model and neural model is not well trained and therefore weakFinally, regarding the third research question on the use of the neural-fuzzy model to rank affordability and throughput of financial information of companies, although in most studies the neural-fuzzy inference system provided better results, it can be said that with an error coefficient of 0.01 of artificial neural network results in this study, it made the best predictions after neural network. Therefore, the best prediction among the studied methods after predicting the ranking with artificial neural network method is the adaptive neural-fuzzy inference system. So, the answer to the third question is yes, and affordability and throughput of financial information can be well ranked using fuzzy-neural model. So far, no research has been done in this regard.

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