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Developing a Hybrid Model for Predicting Financial Performance of Iranian Construction Companies Based on Genetic Algorithm and Adaptive Neuro-Fuzzy Inference System

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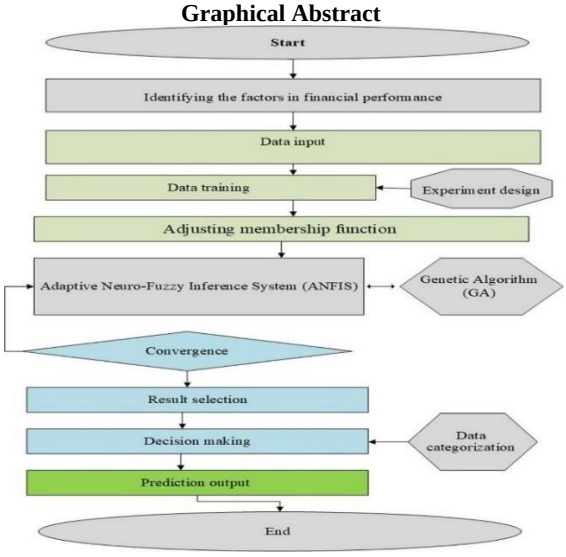
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ABSTRACT

Analyzing financial ratios over consecutive years is beneficial for evaluating the financial performance of construction companies. However, such an analysis can be tedious due to the vast number of the ratios. Therefore, developing an expert system based on artificial intelligence algorithms to identify and predict factors influencing the construction companies' financial performance is essential. To this end, a hybrid model based on Genetic Algorithm (GA) and Adaptive Neuro-Fuzzy Inference System (ANFIS) was introduced in this research to predict the financial performance of construction companies in Iran. This research is applied as descriptive and in terms of methodology well developed; also conducted cross-sectionally. The statistical population included all active construction companies in the construction sector in Tehran. Due to time and resource constraints, a random sampling technique was used. A questionnaire was utilized for data collection and data analysis, factor analysis methods and neuro-fuzzy system combined with GA were employed. The ANFIS combined with GA can evaluate the construction companies' financial performance with the minimum error. The findings ultimately resulted development of a model that forecasts the financial performance of Iranian construction companies, allowing them to concentrate on factors that improve financial performance.

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Graphical Abstract



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1. INTRODUCTION

The construction industry plays a major role in the development of countries. A recession in this industry can lead to a recession in the entire economy of a country. Therefore, many countries have conducted research in recent decades to increase their share in the international arena, with the initial step being the assessment of the current state of the construction industry (1). In Iran, the despite high potential of the construction industry for job creation and increasing the gross national product, it has not been able to fulfill the expectations adequately at the national, regional, and trans-regional levels (2). Currently, Iran's share in the regional and international construction industry is negligible and does not correspond to the existing capabilities, special geographical conditions, and strategic political relationships (3). Therefore, it is necessary to evaluate various aspects of this industry and devise strategies to improve the current situation. Implementing construction projects, given the country's economic conditions and development needs, is of particular importance. Several factors can lead to project cessation, including economic, technical, and managerial issues (4). Economics, specifically the methods of financing construction projects, is a critical factor in the initiation, continuation, and completion of projects, as well as profit calculation post-completion (5). One of the most common economic barriers in project execution relates to the financing method. Currently, financing and securing the necessary budget for infrastructure projects and utilizing the products and services pose one of the major challenges for developing countries (6). In this context, given the specific circumstances of developing countries and their financial crises, securing the necessary capital for large projects is not easy. Therefore, alternative methods such as using internal resources, direct government expenditure, government borrowing, buy-back contracts, build-operate-transfer contracts, civil partnerships, and non-governmental direct investment (including domestic privatization and foreign investment) have been considered as critical steps and prerequisites for project implementation (7). Tripathi et al. (8) stated that the industry in question is recognized as a high-risk business. Furthermore, the construction industry faces a higher proportion of business failures compared to other industries. In today's competitive world, companies that aim to participate in large domestic and global markets need to attract investors by increasing profitability through various means such as cost reduction, quality improvement, subsequently, and increased sales (9). One of the primary objectives of economic enterprises (project-oriented companies) is to maximize short-term profits and increase the owner's economic wealth in the long term. This can be achieved through sound decision-making in the investment process, as rational decisions are directly related to the evaluation and prediction of a company's financial performance. Financial performance evaluation is a fundamental management tool for achieving the goals, strategies, and plans of construction companies. The design and implementation of a financial performance evaluation system, along with its prediction and control, can guide managers toward achieving objectives, enhancing efficiency and effectiveness, and adequately responding to stakeholders (10). This issue has long been a challenge in performance evaluation and neglecting it might lead to incorrect judgments, poor decision-making, resource wastage, and failure. Although the topic is addressed in some cases, the lack of an evaluation model and sometimes the absence of defined indicators necessary for measurement and examination in construction companies has resulted in not considering all aspects of the project or company, leading to an unclear and incomplete evaluation process. Such results lack the required validity and reliability, making it impossible to achieve outcomes that confirm appropriate and expected growth during the specified period and the effective and successful transition of the company or organization to the next phase. In recent years, methods for evaluating financial performance have changed significantly compared to before. Companies must use appropriate methods to determine their financial performance, taking into account the differences that have arisen in their missions. Evaluating a company's position and performance can assist managers in identifying existing conditions, guiding operational-executive matters, and planning to increase the efficiency of the production unit. Therefore, utilizing a targeted management system that can meet managerial needs in line with new changes in short-term and long-term planning has become a necessity. In recent years, various studies have been conducted to evaluate the financial performance of industrial companies. These studies can be broadly categorized into two main groups: 1) The first group of studies focuses on identifying the factors influencing the financial performance of construction companies and, based on their results, analyzes and assesses financial performance; 2) The second group of studies employs statistical techniques and decision-making methods (multi-objective or multi-criteria decision-making) to evaluate financial performance. Although recent research has helped analysts to predict future changes in financial performance assessment in the short term and make better decisions, it has been found that each group has certain deficiencies and limitations in implementation, which will be elaborated upon below. As previously mentioned, the studies of the first group focused on identifying the factors influencing the financial performance of construction companies, and solely relying on identifying these influencing factors can lead to deficiencies and limitations. These include: Lack of comprehensiveness: Identifying factors that influence

financial performance, while important, cannot alone provide a complete picture of a company's financial situatio. Impact of specific conditions: Some influencing factors may operate under specific conditions or during certain periods, which can disrupt the analysis process. Additionally, in the studies of the second group, statistical techniques and decision-making methods were employed to assess the financial performance of industrial companies and the drawbacks of each will be discussed further. The use of statistical techniques has disadvantages such as limitations in data analysis, complexity and high costs, potential errors in modeling, insufficient attention to environmental changes, and an emphasis on short-term results. Given these disadvantages, companies need to employ other analytical approaches alongside statistical techniques to achieve a more accurate assessment of their financial performance. Moreover, the application of decision-making methods in evaluating companies' financial performance can also have specific drawbacks. These drawbacks include inflexibility, failure to consider non-financial indicators, human bias, and the need for significant time and resources. Based on this, considering the examination of the limitations and shortcomings of the methods used to assess and analyze financial performance results in recent studies, there is a need for a method to evaluate the financial performance of construction companies that addresses the limitations and obstacles presented in the evaluation methods and analysis of construction companies' performance. This new approach should provide greater accuracy, high flexibility, and the capability to process large data sets, serving as an effective tool for solving complex issues in various fields. Therefore, this research aims to focus on evaluating financial performance, particularly in construction companies, by employing artificial intelligence methods based on a hybrid approach that combines genetic algorithms and artificial neural fuzzy inference systems. The ANFIS combined with the GA can evaluate the construction companies' financial performance with the minimum error. ANFIS and GA can work together to reduce errors in predictive modeling and decision-making processes. ANFIS is a hybrid intelligence system that combines the learning capabilities of neural networks with the reasoning capabilities of fuzzy logic. It uses a set of fuzzy rules to model complex relationships and can adapt its parameters based on training data. Genetic Algorithms are optimization techniques inspired by the process of natural selection. They are used to search for optimal solutions in large and complex solution spaces. The integration of ANFIS and GA provides a powerful framework for reducing errors in predictive modeling. By leveraging the adaptive learning capabilities of ANFIS and the optimization strengths of GA, practitioners can develop more accurate, robust, and efficient models that perform well in complex and uncertain environments. Also, the use of genetic algorithms and neuro-fuzzy inference systems offers significant advantages over statistical techniques and multi-criteria decision-making methods. These approaches provide effective tools for solving complex problems across various fields by delivering greater accuracy, high flexibility, and the ability to process large datasets. To compare the benefits of employing genetic algorithms and neuro-fuzzy inference systems against statistical techniques and multi-criteria decision-making methods, several aspects can be highlighted: 1) Accuracy and Efficiency: Genetic Algorithms (GA), as a form of metaheuristic optimization, possess a high capability for searching large and complex solution spaces. Inspired by the process of natural selection, this algorithm can enhance the performance of fuzzy inference systems and reduce errors. The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines neural networks and fuzzy logic, enabling it to learn and generalize from nonlinear data. This system can identify complex relationships between inputs and outputs, thereby increasing prediction accuracy. 2) Flexibility: Methods based on genetic algorithms and neuro-fuzzy inference systems generally exhibit greater flexibility compared to statistical techniques. These methods can easily adapt to new data and be optimized accordingly. In contrast, statistical techniques often rely on specific assumptions that may not hold in real-world conditions, potentially leading to inaccurate results. 3) Capability to Process Large Datasets: Genetic algorithms and fuzzy neural systems can effectively work with large volumes of data, utilizing them to learn patterns, whereas statistical techniques may face limitations in this regard. This advantage makes smarter methods like ANFIS much more suitable for complex applications such as financial performance evaluation. 4) Comparison with MCDM Methods: MCDM methods are typically used to evaluate options based on various criteria. While these methods are useful, they may exhibit lower accuracy in situations where data is nonlinear or complex. In contrast, the combination of ANFIS with GA can serve as a hybrid approach that not only enhances accuracy but also provides the capability to process multidimensional information (11). Therefore, the primary objective of this research is to identify the factors influencing financial performance and to develop a hybrid model for predicting the financial performance of construction companies in Iran. The simultaneous use of GA methods and fuzzy neural inference systems combines the strengths of both approaches, resulting in several practical advantages. Here are some key benefits (12-16):

1) Enhanced Optimization:

- GAs: GAs are powerful optimization techniques inspired by the process of natural selection. They can

efficiently search large solution spaces to find optimal or near-optimal solutions.

- Fuzzy Neural Systems: These systems can model complex, nonlinear relationships and handle uncertainty in data. By using GAs to optimize the parameters of fuzzy neural systems, one can achieve better performance and accuracy.

2) Improved Decision-Making:

- Fuzzy Logic: Fuzzy logic allows for reasoning with imprecise and uncertain information, making it suitable for real-world applications where data may not be crisp.
- Neural Networks: Neural networks can learn from data and capture complex patterns. When combined with fuzzy logic, they can provide more interpretable and robust decision-making frameworks.

3) Adaptability and Flexibility:

- Dynamic Environments: The combination of GAs and fuzzy neural systems allows for adaptability in dynamic environments. GAs can continuously optimize the fuzzy neural parameters as new data becomes available, ensuring that the system remains relevant and effective.
- Handling Nonlinearities: This combination can effectively handle nonlinear relationships and interactions between variables, which are common in many practical applications.

4) Robustness to Noise:

- Noise Tolerance: Fuzzy logic is inherently robust to noise and uncertainty, while neural networks can learn to ignore irrelevant features. The integration of these methods can lead to systems that perform well even in the presence of noisy data.

5) Enhanced Learning Capabilities:

- Hybrid Learning: By using GAs to optimize the structure and parameters of fuzzy neural systems, one can enhance the learning capabilities of the system. This hybrid approach can lead to more accurate predictions and classifications.

6) Efficient Feature Selection:

- Feature Optimization: GAs can be used to select the most relevant features for the fuzzy neural system, reducing dimensionality and improving computational efficiency. This can lead to faster training times and better generalization.

7) Interpretability:

- Fuzzy Rules: The use of fuzzy logic provides a level of interpretability to the decision-making process. Users can understand the reasoning behind the system's outputs, which is often a challenge with traditional neural networks.

8) Application Versatility:

- Wide Range of Applications: The combination of GAs and fuzzy neural systems can be applied in various fields, including finance (risk assessment), healthcare (diagnosis), engineering (control systems), and more, making it a versatile approach.

According to above mentioned, the simultaneous use of genetic algorithm methods and fuzzy neural inference systems offers a powerful framework for solving complex problems that involve uncertainty and nonlinear relationships. By leveraging the strengths of both approaches, practitioners can develop robust, adaptable, and interpretable systems that perform well in a variety of practical applications.

The main contributions of this research include:

✓Examining factors influencing the financial performance of construction companies in Iran;

✓Creating an expert system based on artificial intelligence algorithms to identify and predict factors affecting the financial performance of Iranian construction companies;

✓Formulating a hybrid model based on genetic algorithm and fuzzy inference system to identify and predict the financial performance of construction companies;

✓Developing a model for predicting the financial performance of construction companies in Iran.

2. LITERATURE REVIEW

Over the last few decades, construction companies' success has been closely linked to their ability to successfully complete projects within the predetermined parameters of time, cost, and quality. The success of the construction company is not always ensured by the successful completion of projects, as recent observations have demonstrated. Construction companies may still face failure or bankruptcy despite the success of their projects due to high business risks. Therefore, continuous monitoring of the financial performance of construction companies is deemed essential and crucial. The review section is divided into two subsections that provide the background of this research. The first subsection presents an overview of financial performance and examines the factors affecting the financial performance of construction companies. The second subsection addresses the importance of financial performance, utilizing bibliometric software to review existing financial performance evaluation models.

2. 1. Financial Performance and the Factors in Construction Companies

Financial performance refers to the extent to which a company achieves the financial goals of its shareholders to increase their wealth. The company's CEO tries to increase shareholder wealth in terms of profitability (17). A good performance measure for a company covers the amount of additional wealth created, aiding individuals in value-creating decision-making processes. Additionally, measuring the performance and predicting future performance is

important. Financial ratios are employed in the assessment and comparison of firms' financial performance. They are highly effective in quantifying various aspects of a business and are thus indispensable for financial analysis (8, 18). However, some of the ratios hold greater significance compared to others (19). According to Cinca et al. (20), this differs between industries and nations. It is not feasible to take into account every ratio when assessing an industry's financial standing. Additionally, no single ratio can fully describe a company's complete information, while a random combination of ratios might result in redundancy. Conversely, considering only completely independent ratios might omit some crucial information from the analysis. This, in turn, leads to insufficient data to determine the comprehensive financial performance status. To ensure that no information is lost, it is necessary to combine the important ratios into a smaller number of significant factors. Governments and relevant stakeholders need to analyze the critical factors in the financial status of construction companies (21). Traditionally, financial ratios are categorized as liquidity ratios, debt ratios, activity ratios, and profitability ratios (18). However, this classification is based on hypothetical relationships rather than empirical evidence. (22) underlined the necessity of an inductive strategy that incorporates statistically based classification. In order to maximize information retention while utilizing the interrelationships among a large number of variables in terms of common underlying hypothetical variables, factor analysis is utilized. Five significant financial indicators were found by factor analysis applied to the financial ratios of Turkish construction companies over a five years: high activity efficiency, profit margin and growth, asset structure and profitability, and liquidity. Balatbat et al. (23) evaluated more than a hundred financial performance metrics for duration of ten years (1998-2007). With the exception of the years following the implementation of the Goods and Services Tax (GST) in 2000; they concluded that the performance of Australian construction companies that are publicly traded is on par with that of blue-chip companies. Hsu (24) applied factor analysis and computation of decision attribute weights using the concept of entropy. The financial performance rankings of companies before and after the global financial turmoil were compared to demonstrate the minimal impact of the turmoil on their performance. Chen et al. (25) identified four financial indicators: growth index, profitability index, business efficiency index, and debt repayment index based on factor analysis of 13 listed oil companies in China in 2009. Chong et al. (26) looked into the financial ratios' distributional properties for Malaysian companies. They concluded that financial ratios were generally not normally distributed and that corrective actions could be taken to improve the normality of particular ratios. Delen et al. (27) uncovered the fundamental aspects of financial ratios through the application of Exploratory Factor Analysis (EFA) and four widely-used decision tree techniques: Chi-squared Automatic Interaction Detection (CHAID), Quick, Unbiased, Efficient Statistical Tree (QUEST), Classification and Regression Trees (C&RT), and C-5.0. CHAID and C-5.0 demonstrated the highest predictive precision. An examination of sensitivity revealed that earnings before tax to equity and net profit margin were the two most crucial factors. Factor analysis was used by Erdogan (28) to examine the 2010 financial ratios of 500 Turkish industrial companies. Their research validated the debt overflow theory, which postulates that having too much debt may cause businesses to underinvest in lucrative endeavors. Abdel-Basset et al. (29) identified profitability and leverage ratios as the most important and significant criteria affecting financial performance. Vibhakar et al. (18) attempted to use factor analysis to determine the crucial financial performance variables for construction companies. The study identified five indices and determined that the key determinants of Indian construction companies' financial performance were investor return and business efficiency. There are few studies on identifying key financial factors in Iran. Most studies have failed to present a comprehensive model or identifying the influential financial factors. There are limited studies on financial ratios for identifying significant financial performance factors in Iran's construction industry. Additionally, empirical evidence indicates that financial ratio patterns vary from industry to industry. To address this need, an inductive approach emphasizing classification based on statistics has become more popular over time. This study employed Confirmatory Factor Analysis (CFA), which utilizes the interrelationships among a large number of variables based on underlying hypothetical common factors. This method identifies the relationships between latent and observable variables and validates the proposed model using internal and external tests. CFA aims to determine whether the number of factors and the variations measured in these items align with theoretical expectations and the type of process under consideration. additionally, CFA is used to confirm the existing factor structure (18). The goal of this study is to pinpoint important financial performance variables in construction firms. The results provide critical information about the financial performance of construction companies and aid companies and their stakeholders with better planning strategies and policies focused on improving overall company performance.

2. 2. Existing Financial Performance Evaluation Model In Companies Given the importance of financial performance evaluation over time and Iran's position concerning published articles, it is evident that

researchers need to focus more on this subject. A review of the scientific literature reveals that, so far, no research has been conducted to predict the factors affecting the financial performance of construction companies in Iran by presenting a combined model. Most studies have examined financial performance in other industries, with minimal representation of the construction industry. Thus, studies that forecast the variables impacting Iranian construction companies' financial performance through the use of a hybrid model based on Genetic Algorithms (GA) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) are required. The literature review indicated two primary research streams in selecting feature subsets for financial performance prediction models. One research stream relies on domain knowledge based on financial and accounting theories. The main characteristic of features chosen by this stream is their reliance on specific financial and accounting theory-based metrics or ratios for predicting financial status. The other research stream relies on data mining techniques for selecting feature subsets used in predictions. Proponents of the data mining approach believe that the data itself can reveal all necessary insights. This stream has developed approaches using various data mining methods to identify metrics effective in predicting financial performance. Tsai (30) compared five methods for selecting known metrics used in financial indicator predictions and utilized multilayer perceptron neural networks to construct prediction models. His findings indicated that the t-test method was more effective than other methods in identifying predictive metrics. Du Jardin (31) employed a neural network-based model and used the network to select and identify metrics influential in prediction. Drezner et al. (32) demonstrated that the method of exploring metric selection can enhance the accuracy of financial status prediction for large companies by up to 10% compared to the Altman model (1968). There is limited research on metric selection methods, especially those based on data mining. A review of studies related to financial indicator prediction reveals a lack of historical precedence for metric selection based on domain knowledge and data mining, along with an examination of the differences between subsets of metrics identified using expertise and data mining's contribution, and prediction with an optimal combined approach in this area. Vibhakar, et al. (7) indicated in their study that the construction sector plays a significant role in economic activities in a developing country like India. They developed a financial performance evaluation framework for construction companies based on financial factors. They first examined the factors influencing financial performance and then used multi-criteria decision-making methods such as Entropy and Simple Additive Weighting (SAW) to achieve their goal of providing a framework. Consequently, the net financial performance score and performance level of each company were determined, categorizing them into five groups to allocate recommendations for improvement. In another study, Abdel-Basset et al. (29) evaluated the construction companies' performance. using a combined decision-making approach involving AHP and TOPSIS. The results led to the importance-weighting of criteria affecting financial performance evaluation and the ranking of construction companies. Aldalou and Perçin (33) assessed the financial performance of Turkey's construction technology sector using a combined AHP-TOPSIS method. Their findings resulted in identifying the best-performing company financially. Lam et al. (34) combined the Entropy and VIKOR models to assess the performance of Malaysian construction companies. The significant outcome was assessing the financial performance of construction companies and identifying the weight of financial ratios in evaluating the financial performance using the proposed Entropy and VIKOR model. Yen et al. (35) assessed financial performance using the TOPSIS approach, in construction companies from 2016 to 2018. Lam et al. (34) examined financial performance evaluation by integrating the Entropy and TOPSIS methods to identify companies with good financial performance. However, these studies primarily focused on financial performance and identifying influencing factors. To address this knowledge gap, this study developed a model reflecting the unique characteristics of the construction industry by combining factors influencing financial performance. The proposed model is based on integrating the ANFIS-GA to identify and predict the financial performance of construction companies. One of the key innovations of the ANFIS-GA hybrid method is that ANFIS functions as an artificial intelligence system capable of learning and adapting to data, while GA operates as an evolutionary optimization algorithm. Additionally, GA can optimize ANFIS model parameters, seeking the best structure and parameters for specific input data. This combination improves prediction accuracy and the efficiency of the ANFIS model, enabling the model to best fit real-world data. Therefore, the ANFIS-GA combination represents a significant innovation that enhances ANFIS model performance and accuracy in solving complex and real-world problems.

3.METHODOLOGY

The first stage involved a qualitative meta-synthesis method that reviewed the existing literature on construction companies' financial performance, collected and integrated data to derive a comprehensive model of the key criteria affecting financial performance (Key Criteria Affecting Performance). The financial data of construction companies along with its sources are listed

in Table 1). To confirm this, the CFA method of subbranches of structural equations was used with SmartPL software and the model was designed with five dimensions and twelve indicators, as shown in Figure 1.

In the quantitative phase, a survey research method was employed. Data collection tools included a researcher-developed questionnaire containing 12 questions based on a 5-point Likert scale. In the following, to verify the questionnaire outputs and generalize them to other situations, two key concepts of validity and reliability must be carefully examined. To check the validity of the questionnaire, form, content validity, and then to check reliability of the questionnaire, was checked and confirmed by the two criteria of Cronbach's alpha and composite reliability the faculty members of the construction management department. Using both measures of Cronbach's alpha and composite reliability can help researchers be more confident about the validity of their instruments. Then, after checking validity and reliability, the questionnaire was distributed among construction companies active in the field of building and construction in Tehran, which were ranked as Class 1 by the Management and Planning Organization. The Cochran formula was employed to determine the required sample size for the research. The total number of construction companies active in the building sector in Tehran was 214, and according to the Cochran formula, the required sample size was 137. CFA was used to validate the model of the key criteria affecting the financial performance of Iranian construction companies.

TABLE 1. Key criteria affecting performance The financials of construction companie**s**

Dimensions	Indicators	References
Investor return	PBIDT/Net asset	(7, 18)
	ROCE	(7, 18)
	ROE	(7, 18)
	Sales/Net asset	(7, 18)
Business efficiency	PBIDT/Sales	(7, 18)
	CPM	(7, 18)
Operations management	Sales turnover/Expenditure	(7, 18)
	Net profit/Expenditure	(7, 18)
Activity efficiency and coverage	Inventory	(7, 18)
	Interest cover ration	(7, 18)
Asset management	Current ratio	(7, 18)
	Fixed asset	(7, 18)

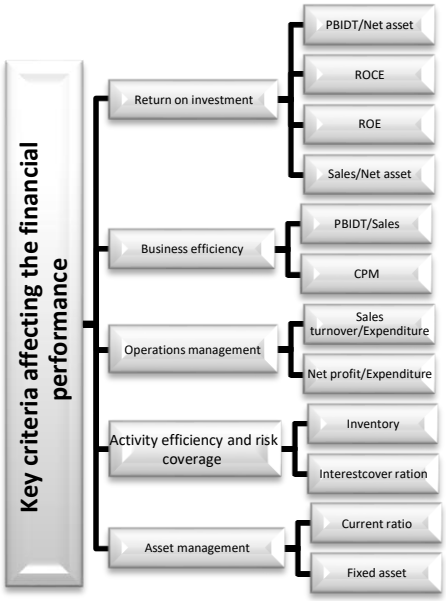


Figure 1. Model of key criteria affecting the construction companies' financial performance companies (7, 18)

In CFA, indicators are grouped to make sure that they ultimately converge into two or more factors, which are sets of variables. Subsequently, the relationships between the factors were determined, and within each factor, the relationships between the indicators were calculated, ultimately achieving the main objective of the research, which was to determine the relationships between the research variables. Before conducting the factor analysis, it is essential to ensure that the number of available data points is adequate for factor analysis. For this purpose, the KMO index and Bartlett's test were used. Based on the significance level, it was concluded that the data were suitable for sampling. To ensure the adequacy of the collected sample, two criteria, the KMO index and Bartlett's test, were utilized (Table 2). The desired threshold for the KMO test is 0.6 or higher. Both tests confirmed the adequacy of the sample for all dimensions of the research.

Additionally, SEM with a Partial Least Squares (PLS) approach was used to evaluate the model fit and analyze the data. Consequently, the model fit was assessed using criteria for reliability, convergent validity, and discriminant validity. Cronbach's alpha and

TABLE 2. Results of sample adequacy assessment using KMO and Bartlett's tests

Dimensions	Index number	KMO test	Bartlett's test
Investor return	4	0.833	Sig=0.000
Business efficiency	2		
Operations management	2		
Activity efficiency and coverage	2		
Asset management	2		

composite reliability were employed to test reliability. Convergent and discriminant validity were used to evaluate the questionnaire's validity. For convergent validity, the Average Variance Extracted (AVE) criterion with an acceptable value equal to or greater than 0.5 was used. Divergent validity was assessed by comparing the differences between the indicators of one variable with those of others in the research model. This was done by comparing the square root of the AVE for each variable with the correlation coefficients between first-order variables. A matrix was formed where the diagonal values represented the square root of each variable's AVE, and the off-diagonal values represented the correlation coefficients between each variable and the others.

The confirmed variables from the confirmatory factor analysis model were used as inputs for a hybrid model to predict the construction companies' financial performance. This was aimed at enhancing accuracy and creating an optimal neural network structure using a genetic algorithm. Identifying and establishing a suitable structure for neuro-fuzzy systems before starting training with the neural network is crucial and significantly impacts the final results. Creating an appropriate structure for a neuro-fuzzy system using a genetic algorithm largely depends on the researcher's judgment and experience. Sometimes, the created structure may not be optimal, and better structures may exist. Therefore, this study employed a combination of GA and neuro-fuzzy systems, illustrated in the flowchart (Figure 2), to optimize the neural network structure through the genetic algorithm. Overall, this hybrid method combines factor analysis for data dimension reduction, genetic algorithms for parameter optimization, and neural networks for learning and prediction.

The process of constructing the fuzzy inference system is as follows: Initially, the independent variables are considered as inputs to the model (36). For each input, the fuzzification process is performed. Then, based on the data, fuzzy rules are designed. In fact, at this stage, the discovery of fuzzy criteria takes place. Fuzzy criteria discovery is a process used in intelligent methods and decision-making that involves identifying and defining criteria based on fuzzy logic principles. Fuzzy logic allows for reasoning that is approximate rather than fixed and exact, which is particularly useful in situations where information is uncertain, imprecise, or subjective. Fuzzy logic extends classical logic to handle the concept of partial truth, where the truth value may range between completely true and completely false. This is particularly useful in real-world scenarios where boundaries are not clear-cut. In fuzzy logic, a fuzzy set is a collection of elements with varying degrees of membership. For example, in a fuzzy set representing "tall people," someone who is 6 feet tall might have a membership degree of 0.8, while someone who is 5.5 feet tall might have a membership degree of 0.4. The process of criteria discovery involves identifying the factors or attributes that influence decision-making in a given context. In fuzzy criteria discovery, these criteria are defined in a way that accommodates uncertainty and vagueness. Fuzzy criteria discovery is a valuable approach to intelligent methods and decision-making, particularly in complex and uncertain environments. Leveraging fuzzy logic principles, allows for a more flexible and nuanced understanding of criteria that influence outcomes, leading to improved decision-making and better insights from data (37). Subsequently, for each rule, a weight is calculated using the Sugeno implication (minimum and Mamdani product) and combining the various parts of that fuzzy rule. This method is used in the ANFIS algorithm to examine the degree of accuracy of the fuzzy rule, a process referred to as implication. In the final model, the input values are known, while the output value is not. In this case, based on the input values and placing them in the membership functions related to the fuzzy rule antecedents, a parameter is calculated. This parameter is then multiplied by the membership function of the output using the Mamdani implication, resulting in a separate membership function for each fuzzy rule. In the next stage, the calculated membership functions for each fuzzy rule are combined using the s-norm maximum, yielding a fuzzy set (aggregation stage). Finally, the defuzzification process is performed, and an

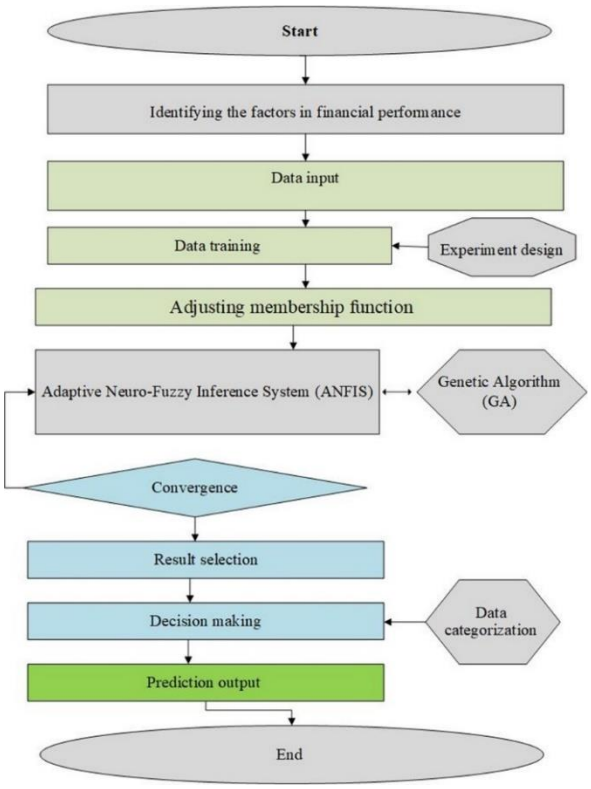


Figure 2. Integration of neuro-fuzzy network with GA

output is calculated. In the overall ANFIS model, a basic FIS is created using the fuzzy c-means clustering method based on the data. Then, during the model design process, the training data and the FIS system are trained, resulting in the final model. An important point is that instead of classical algorithms for the ANFIS training process, intelligent optimization algorithms can be used for potentially better results. In this case, the optimization criterion is the modelling error criterion. In the ANFIS process, the number of fuzzy rules equals the number of clusters calculated in FCM. For optimization with GA in the ANFIS training process, the focus is on changing and determining the optimal parameters related to the model's fuzzy rules. In the fuzzy rules, the membership functions are Gaussian, and the parameters related to the Gaussian functions are adjusted to optimize the modelling error function. To optimize the ANFIS model, the parameters related to the membership functions in the FIS construction process are adjusted to the base fuzzy system parameters according to the modelling error function using the GA optimization algorithm. Ultimately, the fuzzy system with the best parameter values is obtained as the final output (38).

4. FINDINGS

In this section, the primary research question: "How can a hybrid model based on a genetic algorithm and a fuzzy inference system be used to identify and predict factors affecting the financial performance of construction companies in Iran?" is answered. The following steps detail the execution process comprehensively:

Step 1: Identification of factors affecting the financial performance of construction companies in Iran: To identify the factors, a qualitative meta-synthesis method was used. Based on the literature review, data were collected and integrated, resulting in a comprehensive model of key criteria influencing the financial performance of construction companies. This model was designed in five dimensions and twelve indicators, as depicted in Figure 1. To validate the identified factors, factor analysis was utilized. Subsequently, the relationships between the factors were identified, and within each factor, the relationships between the indicators were calculated. Ultimately, the relationships between the research variables were computed. The following steps were sequentially executed and implemented in Step 1:

Evaluation of the reliability and convergent validity of the questionnaire: The completed questionnaires were examined using two criteria, Cronbach's alpha and composite reliability. The acceptable threshold for both criteria is 0.7 or higher. Additionally, the AVE index was also assessed. The results on the reliability of the research tool are presented in Table 3.

As shown in the table above, the reliability and convergent validity of the research model are acceptable. To assess the discriminant validity of the questionnaire, the square root of the AVE for each variable was compared with the first-order correlation coefficients between variables. This was done by forming a matrix in which the main diagonal values were the square roots of the AVE coefficients for each variable and the lower diagonal values were the correlation coefficients between each variable and the others. These values are shown in Table 4.

First-Order Factor Analysis: The first-order factor analysis was done through a series of structural equation modeling (SEM) tests. The initial primary research model is depicted in Figure 1. The factor loadings of each factor or observable variable with its corresponding

TABLE 3. Results of reliability of the research tool

Dimensions	Cronbach's alpha	Combined reliability	AVE
Activity efficiency and coverage factor	0.834	0.900	0.751
Asset management	0.882	0.808	0.691
Business efficiency factor	0.822	0.762	0.654
Investor return factor	0.772	0.870	0.607
Operations management	0.905	0.919	0.507
Significant financial performance factors	0.906	0.825	0.615

TABLE 4. Discriminant validity of the questionnaire

Dimensions	1	2	3	4	5	6
Activity efficiency and coverage factor	0.867					
Asset management	0.371	0.619				
Business efficiency factor	0.700	0.436	0.809			
Investor return factor	0.298	0.355	0.201	0.710		
Operations management	0.660	0.515	0.339	0.383	0.767	
Significant financial performance factors	0.706	0.445	0.203	0.162	0.454	0.784

latent variable were examined. The desired threshold for numerical significance is 1.96 or higher, and the acceptable factor loading value is 0.5 or higher. If any indicator does not meet the significance and factor loading thresholds, it is removed from the model, and the significance and factor loadings are reassessed (See the results in Table 5).

As observed in Table 5, the significance and factor loading values for all model indicators exceed the standard thresholds. Therefore, the first-order factor analysis is confirmed.

Second-Order factor analysis and examination of overall model fit: After performing the first-order factor analysis and removing factors with significance or factor loading values below the standard thresholds, the second-order factor analysis was conducted. In this phase, the model was executed with the new factors, and then the significance and path coefficient of each factor were examined. The desired threshold for significance was 1.96 or higher. If any factor does not meet the significance threshold, it is removed, and the significance and path coefficients are reassessed. The significance values for all model factors exceed the standard threshold, confirming the second-order factor analysis and the final model depicted in Figure 3. Subsequently, the overall model fit of the research was examined. Both the measurement and structural sections constitute the overall research model. The Goodness-Of-Fit (GOF) criterion was used to evaluate the overall model fit, calculated using the square root of the product of the mean AVE and R^2:

$R^2_{Average}$= 0.581

TABLE 5. Examination of significance and factor loadings of factors

Variables	Agent Symbol	Index Number	Indicator Symbol	T-Value	Path Coefficient
Investor Return	IR	4	Q1	6.588	0.806
			Q2	7.064	0.850
			Q3	6.100	0.733
			Q4	3.246	0.874
Business Efficiency	BE	2	Q5	8.250	0.875
			Q6	7.901	0.906
Operation Management	OM	2	Q7	2.807	0.730
			Q8	6.572	0.864
Activity efficiency and risk Coverage	AC	2	Q9	8.172	0.839
			Q10	6.156	0.907
Asset Management	AM	2	Q11	6.859	0.946
			Q12	2.023	0.876

AVE $_{Average}$= 0.637

$R^2_{Average}$ x AVE $_{Average}$= 0.371

$$GOF = \sqrt[2]{R^2_{Average} \text{ x } AVE_{Average}} \approx 0.609097$$

In general, values of 0.01, 0.25, and 0.36 are introduced as weak, moderate, and strong measures of overall model fit or the GOF criterion. Approximately achieving a value of 0.609 for this index confirms a very good fit for the overall model. In the end, it was determined that the measurement model, structural model, and overall research model all fit together.

Hypothesis test results:

H1: Does the investor return factor affect the evaluation of financial performance of construction companies? Data analysis using path coefficient shows that investor return has a significant impact on the evaluation of financial performance of construction companies (P-value = 0.05, t = 18.028, β = 0.848). Therefore, the research hypothesis is confirmed with 95% certainty. Considering the positivity of the correlation coefficient, there is a direct relationship between these two variables, and based on the path coefficient (β), it can be said that for one unit of improvement in the investor's return, the assessment of financial performance is improved by 0.848 standard deviations.

H2: Does the business efficiency factor affect the evaluation of financial performance of construction companies? Data analysis using path coefficient shows that business efficiency factor has a significant impact on the evaluation of financial performance of construction companies (P-value = 0.05, t = 8.552, β = 0.668). Therefore, the research hypothesis is confirmed with 95% certainty. Taking into account the positivity of the correlation coefficient, there is a direct relationship between these two variables, and based on the path coefficient (β), it can be said that for one unit of

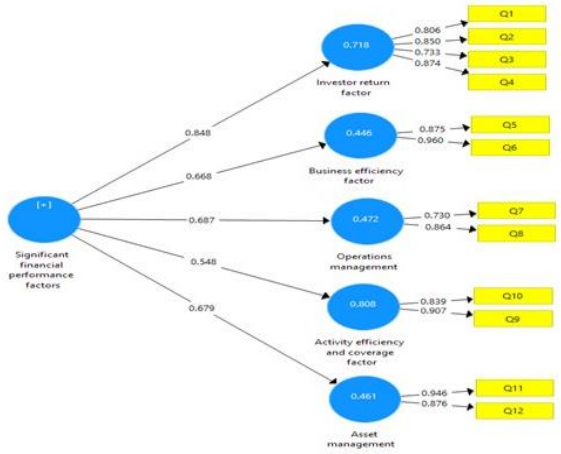


Figure 3. Path coefficient model for research factors

improvement in the business efficiency factor, the assessment of financial performance is improved by 0.668 standard deviations.

H3: Does the operational management factor influence the evaluation of the financial performance of construction companies? Analysis of the data using the path coefficient shows that the operational management factor has a significant impact on the assessment of the financial performance of construction companies (P-value =0.05, t=7.371, β =0.687). Therefore, the research hypothesis is confirmed with 95% certainty. Due to the positive correlation coefficient, there is a direct relationship between these two variables, and based on the path coefficient (β), it can be said that the evaluation of financial performance improves by one unit improvement in the operational management factor by 0.687 standard deviations.

H4: Do activity efficiency and coverage factor into the evaluation of financial performance of construction companies? Data analysis using path coefficient shows that the activity efficiency and coverage factor has a significant impact on the evaluation of financial performance of construction companies (P-value = 0.05, t = 8.152, β = 0.548). Therefore, the research hypothesis is confirmed with 95% certainty. Taking into account the positivity of the correlation coefficient, there is a direct relationship between these two variables, and based on the path coefficient (β), it can be said that for one unit of improvement in the activity efficiency and coverage factor, the assessment of financial performance is improved by 0.548 standard deviations .

H5: Does the asset management factor affect the evaluation of financial performance of construction companies? Data analysis using path coefficient shows that the asset management factor has a significant impact on the evaluation of financial performance of construction companies (P-value = 0.05, t = 9.636, β = 0.679). Therefore, the research hypothesis is confirmed with 95% certainty. Taking into account the positivity of the correlation coefficient, there is a direct relationship between these two variables, and based on the path coefficient (β), it can be said that for one unit of improvement in the asset management factor, the assessment of financial performance is improved by 0.679 standard deviations.

Step 2: Predicting the Financial Performance of Construction Companies with ANFIS-GA: The ANFIS and GA methods were used to enhance the accuracy and speed of the financial performance prediction algorithm. After definition and pre-processing, the target data were entered into the system as input. The output of the system is based on the mean squared error and its square root. In the proposed method, the input data are divided into training and testing sets. In the hybrid network model, six variables (investment rate, business efficiency, operations management, productivity, risk coverage, and asset management) were considered as input variables, and financial performance evaluation was considered as the output variable. The input data are converted into fuzzy numbers (fuzzification phase). To design the base fuzzy inference system (FIS) model for the training data, the corresponding membership functions were established. To adjust the parameters of the base fuzzy system according to the modelling error function, the genetic algorithm (GA) optimization method was employed. Essentially, the input to the fuzzy algorithm consists of the parameters related to the base FIS membership functions. The genetic algorithm was executed using the modelling error cost function and ultimately provided the optimized membership function values for each variable. Then, the optimized membership functions for each variable using the genetic algorithm for the same 10 clusters were illustrated. Initially, several scenarios were designed using an experimental design approach. The Taguchi method was used for the experimental design in the NSGA-II algorithm. Three distinct levels were established for the parameters in this method. This algorithm's pre-planned experiments were then run through every possible combination. Table 6 displays the suggested values for this algorithm's parameters.

Subsequently, the L9 Taguchi design was then used to create a variety of experiments, and Table 7 shows the results of the NSGA-II algorithm running for each experiment. All potential states for the various levels taken into consideration for the NSGA-II algorithm factors are displayed in Table 6. For instance, all factors participate at the lowest possible levels in the first experiment. The PS factor is at its lowest level in the second experiment, while the other factors are at their respective medium levels. The intended response level was estimated using the MID index by carrying out each experiment and figuring out the index value.

The S/N (signal-to-noise) ratio chart was then produced by feeding these outputs into the MINITAB software, as seen in Figure 4. For that factor, the level with the lowest ratio was chosen. The medium level (code 2) of this factor has the lowest signal-to-noise ratio for the CR index; hence, the CR factor in the algorithm

TABLE 6. Parameters of NSGA-II Algorithm

Parameters	Levels		
	Level 1	Level 2	Level 3
Population Size (PS)	75	125	150
Crossover Rate (CR)	0.4	0.6	0.8
Mutation Rate (MR)	0.1	0.4	0.9
Maximum iterations (Max_iter)	250	300	350

TABLE 7. Response variable values in the Taguchi Technique for NSGA-II

Execution number	Algorithm Parameters				MID Index
	PS	CR	MR	Max_iter	
1	1	1	1	1	0.534
2	1	2	2	2	0.612
3	1	3	3	3	0.537
4	2	1	2	3	0.491
5	2	2	3	1	0.576
6	2	3	1	2	0.637
7	3	1	3	2	0.599
8	3	2	1	3	0.973
9	3	3	2	1	0.642

will have a value of 0.7. Furthermore, the MR factor's lowest value occurs at the lowest level of this factor (code 1). As a result, the algorithm will assign this factor a value of 0.2. Last but not least, the Mixite factor will have a value of 200 in the algorithm since, at its highest level (code 3), it has the lowest signal-to-noise ratio.

Now, Table 8 specifies the optimal value for each parameter based on the output as shown in Figure 4. Table 8 lists the ideal value for every parameter.

With the algorithm parameters determined, the membership functions within the optimal ranges for each variable were calculated and formed according to the proposed algorithm. The membership functions for the variables (a) investment return rate, (b) business efficiency, (c) operations management, (d) activity productivity and risk coverage, and (e) asset management related to the optimal FIS were computed and established. Clustering was used to create a structured framework based on the common features of similar patterns and to enhance the model's prediction performance. In ANFIS-GA, clustering is typically performed before applying the ANFIS model and the genetic optimization algorithm. This clustering can help the model identify different patterns in the data and improve prediction performance. By dividing data into different clusters, the ANFIS-GA model can better utilize the patterns in each cluster, thereby increasing prediction accuracy. Clustering was used in ANFIS-GA to improve the accuracy, efficiency, and speed of the model's predictions, providing more precise and reliable results. Following the analyses performed, the membership functions related to the variables in the optimal FIS, along with the fuzzy rules of the optimal model, were determined based on the ten fuzzy rules as described below:

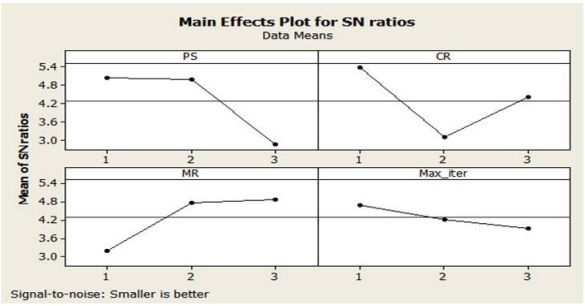


Figure 4. The Taguchi Method's MINITAB output in the NSGA-II algorithm

TABLE 8. Ideal values for the parameters in NSGA-II

Parameter	Optimal value
Population size (PS)	150
Crossover rate (CR)	0.6
Mutation rate (MR)	0.1
Maximum iterations (Max_iter)	350

If the investment return rate is in the i^{th} cluster, business efficiency is in the i^{th} cluster, operations management is in the i^{th} cluster, activity productivity is in the i^{th} cluster, risk coverage is in the i^{th} cluster, and asset management is in the i^{th} cluster, then the financial performance will be in the i^{th} cluster.

Where $1 \leq i \leq 10$.

Therefore, within the aforementioned scenarios, we have a better financial performance. Thus, shifting any of the factors to other clusters disrupts the financial performance. Generally, the difference between clusters in data mining is determined based on a combination of distance metrics, similarity, spatial distribution, cluster center, and feature differences to effectively and logically divide data into different clusters. After defining fuzzy rules, the weights (summation) of the weighted outputs, and the sum of each of the 10 fuzzy rules of the model are aggregated. From left to right, these include: investment return rate, business efficiency, operations management, activity productivity, risk coverage, and asset management (Figure 5).

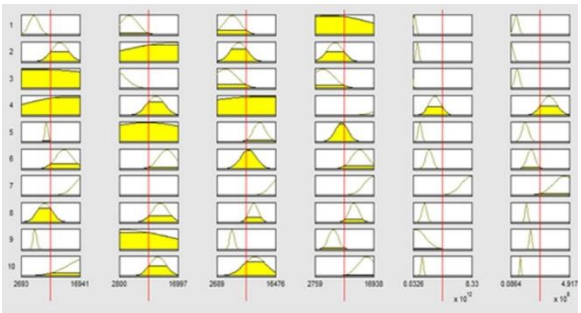


Figure 5. Final Model for Financial Performance Estimation Using ANFIS-GA

Overall, the final ANFIS model of this study with six inputs, performs fuzzification of the inputs, meaning that membership functions for these variables are defined. Following this, implication or the 10 fuzzy rules are formed (Figure 6).

- Normalization of weights (summation)
- Creation of weighted outputs
- Summation
- Output

The alignment graph of the output from the model and the expected output was examined, which indicated how well the obtained output matched the actual output for each sample. The vertical axis of this chart represents normalized actual and predicted financial performance, and the horizontal axis represents the number of samples. Additionally, the error fluctuation chart in Figure 7 was reviewed. This chart shows the error fluctuation for each sample. The vertical axis represents the error amount, and the horizontal axis shows the number of samples. In addition, Figure 7 displays the error histogram, illustrating the range in which errors occur most frequently.

The test data that was not used in the model training process is then applied to test the proposed model. The difference between the actual value and the predicted value within the range is shown in Figure 8. As can be seen, the model has very good predictive accuracy for different samples, with the lines representing actual and predicted performance almost overlapping. Moreover, the financial performance improves over the long term with the continued trend.

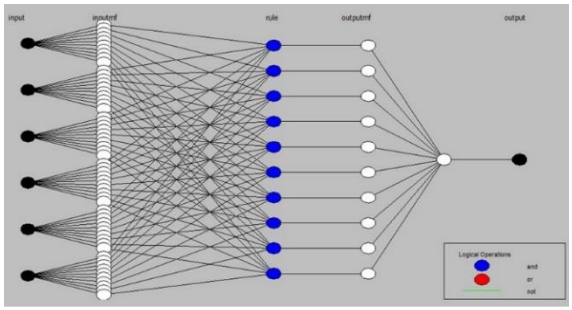


Figure 6. ANFIS-GA Model for financial performance estimation

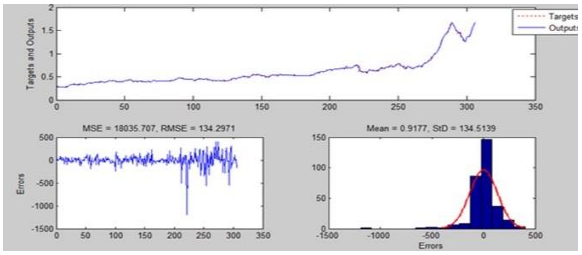


Figure 7. Training process of the hybrid model

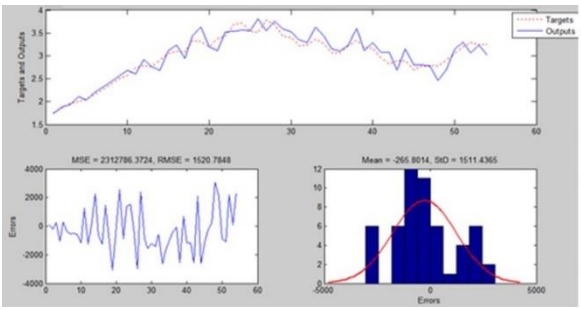


Figure 8. Comparison of training and predicted values in the ANFIS-GA Model

The performance of the hybrid ANFIS method with the GA algorithm for estimating financial performance is summarized in Table 9. Clearly, the hybrid ANFIS method with the GA algorithm performs better.

Based on the computed error rates, the training and prediction data using the ANFIS-GA method had lower computational errors compared to the ANFIS-FCM model, with error rates of 16.25% and 16.94% respectively. To predict the impact of various factors on financial performance in future years using the hybrid ANFIS-GA model, data from past periods were collected and pre-processed, and the model was trained based on these data. The results shown in Figure 9, indicate a significant and logical trend between predicted and actual results. After training the model, it was used to predict the impact of each factor on financial performance in future years.

By following these steps, the hybrid ANFIS-GA model allows for the prediction of the impact of various factors on financial performance in future years, facilitating more rational financial decision-making.

TABLE 9. Summary of performance of various implementation methods

Method	Training data		Prediction data	
	RMSE	Error (%)	RMSE	Error (%)
FCM+ANFIS	0.00351	16.84%	0.00349	17.32%
GA+ANFIS	0.00293	16.25%	0.00288	16.94%

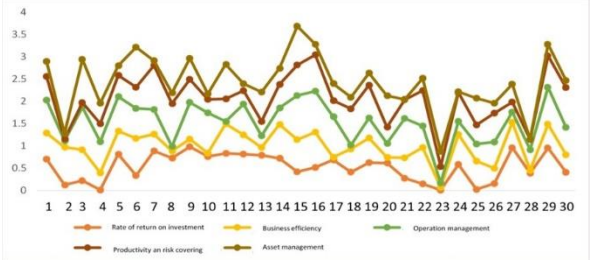


Figure 9. Predicted impact of factors in the ANFIS-GA Model over thirty years

5. CONCLUSION

The factors influencing the financial performance of construction companies in Iran were examined by presenting a hybrid model based on a GA and an ANFIS. Through a qualitative meta-synthesis method and a review of previous literature on the construction companies' financial performance, data were collected and integrated, resulting in a comprehensive model of the key criteria. The factor analysis method was employed to validate the expert opinions, and the model was constructed with five dimensions and twelve indicators. The analysis of results in the first stage, using the factor analysis approach and examining the percentage of variance, revealed that the effectiveness of activity and risk coverage, investment return rate, operations management, asset management, and business efficiency were of higher importance. The extracted factors were named based on qualitative techniques and the nature and extent of variables loaded under each factor. The use of ANFIS and GA models in analyzing and predicting financial performance can significantly enhance the accuracy and efficiency of these models. ANFIS can effectively model complex and nonlinear patterns in financial data. On the other hand, GA can improve the optimization process of ANFIS model parameters or select the best features for financial prediction. Therefore, the integration of ANFIS and GA in financial data analysis can lead to more accurate predictions and improved performance of financial systems. Overall, the results of using ANFIS combined with GA i have been remarkable. Some of the positive outcomes of this combination include:

- **Higher accuracy in financial performance prediction:** The use of ANFIS and GA led to a higher accuracy in predicting financial performance. These results typically show significant improvement compared to traditional models such as linear regression or simple neural networks.
- **Optimal feature selection:** GA has improved the feature selection process, providing the best features for predicting financial performance (14, 39).
- **Parameter optimization:** GA resulted in better parameter tuning for the ANFIS model, enhancing its performance in predicting financial performance (34).
- **High generalizability:** The combination of ANFIS and GA, due to its high generalizability, is capable of predicting financial performance in various dynamic conditions, demonstrating considerable stability.

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Persian Abstract

چکیده

تجزیه و تحلیل نسبت‌های مالی در طول سال‌های متوالی برای ارزیابی عملکرد مالی شرکت‌های ساختمانی مفید بوده است. با این حال، چنین تحلیلی به دلیل تعداد زیاد نسبت‌ها می‌تواند خسته کننده باشد. بنابراین، توسعه یک سیستم خبره مبتنی بر الگوریتم‌های هوش مصنوعی برای شناسایی و پیش‌بینی عوامل مؤثر بر عملکرد مالی شرکت‌های ساختمانی ضروری است. برای این منظور، مدل ترکیبی مبتنی بر الگوریتم ژنتیک (GA) و سیستم استنتاج عصبی فازی تطبیقی (ANFIS) در این تحقیق برای پیش‌بینی عملکرد مالی شرکت‌های ساختمانی در ایران معرفی شد. این پژوهش از نظر ماهیت کاربردی- توسعه ای و از نظر روش توصیفی به صورت مقطعی انجام شده است. جامعه آماری شامل کلیه شرکت های ساختمانی فعال در بخش ساختمانی شهر تهران می‌باشد. با توجه به محدودیت زمانی و منابع، از روش نمونه گیری تصادفی استفاده شد. برای جمع‌آوری داده‌ها از پرسشنامه و برای تجزیه و تحلیل داده‌ها از روش‌های تحلیل عاملی و سیستم عصبی فازی همراه با GA استفاده شد. ANFIS همراه با GA می‌تواند عملکرد مالی شرکت‌های ساختمانی را با حداقل خطا ارزیابی کند. یافته‌ها در نهایت منجر به توسعه مدلی می‌شود که عملکرد مالی شرکت‌های ساختمانی ایرانی را پیش‌بینی می‌کند و به آن‌ها اجازه می‌دهد بر روی عواملی که عملکرد مالی را بهبود می‌بخشند تمرکز کنند.