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Comparison of the Ability of Modern and Conventional Metaheuristic and Regression Models to Predict Stock Returns by Accounting Variables and Presenting an Effective Model

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ABSTRACT

Investment in the stock market requires decision-making and access to information on the future of the stock market. Given the importance of predicting stock returns, the present study aimed to discover the variables and indices that could predict stock returns. The prediction of stock returns has long been a 'hot topic' in Development countries. While effective steps have been taken in this regard, the accurate prediction of stock returns remains a problem due to numerous issues. In this study, an accurate, applicable, and effective model was proposed for the prediction of stock returns. The statistical sample included 138 active companies listed in Tehran Stock Exchange (TSE) during 2008-2017. In total, 1,380 data years were selected for the research to evaluate the questions. Data analysis was performed using an adaptive neuro-fuzzy inference system (ANFIS), multi-gene genetic programming, and regression analysis. In addition, statistical tests were applied to evaluate the accuracy of the model, implemented by MATLAB and Gene X Pro Tools. According to the results, the hybrid metaheuristic method had a lower error rate compared to artificial neural network and regression analysis in terms of stock return prediction. Therefore, the proposed model could provide more accurate data within a shorter time to predict the stock market status since it makes predictions after selecting the most optimal input variables through ANFIS.

1 Introduction

Accounting is primarily based on the provision of useful information in line with the goals of managers and investors in decision-making. Predictive ability is an important criterion of accounting information, and the prediction of stock returns is an indicator of the effectiveness of this ability. Therefore, the recognition of the factors associated with stock returns plays a key role in the improvement of accounting. The importance of predicting stock returns has persuaded researchers to seek the indicators and variables that could properly explain stock returns. Stock returns are among the hottest scientific debates in developed countries. Nonetheless, the accurate prediction of stock returns remains an issue despite the effective steps that have been taken in this regard [32]. To date, traditional methods (e.g., regression) have been relatively successful, while their outcomes have failed to meet researchers' needs due to the

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nonlinear and chaotic behavior of stock market indices. In general, a regression could evaluate phenomena in a nonlinear manner through the ability to present nonlinear prediction models. However, the nonlinear mathematical functions in regression (e.g., logarithms) are limited and cannot properly evaluate these behaviors. On the other hand, research is required using the existing presumptions (i.e., nonlinear functions) in order to work with nonlinear regression functions as researchers cannot properly recognize the actual correlations of independent and dependent variables. Today, metaheuristic models are widely used for the prediction of stock returns as the accurate tools to track nonlinear behaviors and make predictions in chaotic spaces [12] The neural network is a techniques used to resolve this issue with its unique features, which render it a powerful tool to predict and analyze stock market data. The artificial neural network (ANN) has been used for stock market predictions for several years. While the method is considered superior to other techniques, it has some limitations. For instance, determining an optimal set of input variables is a major issue in the ANN structure, mainly due to the fact that the selection of input variables directly affects the prediction accuracy. In addition, no unique method is available to determine the number of the neurons in the latent layer, and researchers mostly determine this number experimentally and based on trial-and-error. Another limitation of the ANN is its 'black box', which deems the technique unable to present a mathematical model for a dependent variable based on independent variables. Therefore, the ANN cannot separately evaluate the effects of independent variable on the dependent variable [11].

The ANN only presents a number as a prediction and cannot determine correlations, even those with an accuracy as low as regression. Today, researchers use genetic programming (GP) to overcome this issue. GP eliminates the limitations of the ANN to propose a mathematical model and provide an accurate nonlinear mathematical model for stock return prediction. In addition, GP provides investors, analysts, managers, and other users with a proper perspective regarding the effect of each independent variable on the dependent variable [16]. Determining the most appropriate independent variables with the highest impact on the dependent variable (stock returns) is another issue that requires accurate analysis, mainly due to the fact that modeling with the variables that have an insignificant impact on the dependent variable increases both the accuracy of the model and its preparation time. Therefore, presenting a method to recognize the independent variables with the highest impact on stock returns is paramount [33-40]. According to the research regarding the capital market aiming to compare the predictions based on the genetic algorithm with the ANN-based predictions, hybrid methods based on the genetic algorithm are associated with fewer errors, thereby providing more accurate information to the investors in order to predict the capital market status. In addition, predictions occur within a shorter time since the most optimal input variables are selected before making a prediction [10].

According to the literature of stock return prediction, artificial intelligence (metaheuristic) methods such as the adaptive neuro-fuzzy inference system (ANFIS) have never been used in the accounting field to determine the independent variables with the highest impact on stock returns. Furthermore, genetic methods such as multi-gene genetic programming (MGGP), which are applied to predict stock returns and eliminate the 'black box' limitation in traditional artificial intelligence methods (e.g., neural networks),is an innovation of this studies in this regard. The present study aimed to evaluate the effects of ANFIS on the modeling speed and accuracy in the prediction of stock returns not only as a predictive tool, but also a smart tool for determining the input independent variables. Therefore, we integrated ANFIS and MGGP to propose a model for predicting stock returns in a faster and more accurate manner. This was the first research to only use accounting and financial variables as the independent variables of stock return predictions (dependent variable) without applying economic variables.

2 Theoretical Foundations and Research Background

Research on stock prices and returns has led to the emergence of two contrary views, which are known as competing hypotheses (Watts and Zimmerman, 1986). One of these hypotheses is the random walk hypothesis, which emphasizes the unpredictability of stock returns. The other hypothesis is that stock prices and returns could be predicted based on a set of information. Efficient-market hypothesis, capital asset pricing model, multi-factor models, arbitrage pricing theory, technical analysis, and fundamental analysis are classified as the two hypotheses of prediction [6]. The conventional techniques used for prediction include statistical methods such as multivariate regression, time-series models (e.g., moving average), exponential smoothing, and the Box-Jenkins method, which have been applied in previous studies. While the efficiency of the models used for data with simple processes has been proven in these methods, the correlations between the variables that affect stock returns and the trends in stock time series are invariably nonlinear and have a chaotic trend. Therefore, one of the most important issues in the development and use of a prediction model is the accuracy in the modeling of the chaotic and non-linear trends in most systems. Today, artificial intelligence models such as ANN, fuzzy logic, and genetic algorithms have been assessed in various fields given their remarkable ability to model complicated engineering issues and nonlinear systems. Currently, various models have been presented with the development of artificial intelligence techniques with a better performance compared to conventional techniques. Neural network models are among the most conventional models in this regard. After training, a neural network model could be used for the prediction of stock returns in the future. Recently, the dominant approach to the problem of prediction has been the use of hybrid artificial intelligence models, mainly due to the higher flexibility of these models and their greater ability to discover nonlinear patterns in data compared to other models [28].

In a research in this regard, Ince and Trafalis [17] aimed to predict the stock prices of Dow-Jones, Nasdaq, and S&P 500 by integrating independent component analysis and support vector machine (SVM), which were applied to determine the independent variable and predict stock prices, respectively. In another study, Wu and Ting [7] used the multilayer perceptron (MLP) method to predict stock prices and were able to predict the stock prices using the data of the Shanghai Stock Exchange, as well as the back-propagation neural network. According to the results of the mentioned study, the neural network could efficiently predict the stock prices of Shanghai Stock Exchange. In another research, Sheta et al. [33] compared the accuracy of multiple regression, neural network, and SVM regarding stock price prediction. In addition, they used the S&P 500 data for prediction, and the results indicated the higher accuracy of the SVM compared to the other two techniques. The neural network method also yielded more accurate results compared to multiple regression. On the same note, Chauhan et al. [6] exploited MLP to predict stock prices, and the findings indicated no linear correlations between the independent and dependent variables. Therefore, the conventional regression methods were considered to be proper solutions for future predictions. The researchers also aimed to use ANNs to predict stock prices, and the obtained results indicated the extremely higher accuracy of these techniques compared to the conventional methods. In another study, Melek Acar [15] predicted the stock returns of Istanbul Stock Exchange using ANFIS, with the primary goal of determining whether fuzzy-nervous systems could accurately predict stock returns. The researcher attempted to design an optimized network by using macroeconomic variables, such as gold price, deposit interest rates, US dollar exchange rate, inflation (consumer price index), and industrial production index as the independent variables during January 1990-December 2008 based on the performance evaluation criteria of the root-mean-square error, coefficient of determination (R^2), and covariance. According to the results of the mentioned study, the designed model had 98% accuracy and was recognized as a useful tool for the prediction of the monthly stock returns of Istanbul Stock Exchange. The short-term prediction of stock returns by artificial neural networks was carried out in a research by Renu [31], who considered 10 technical parameters, such as 482 observations during 2008-2009 as the variables. According to the obtained results, MLP with (1-4-10) structure under the back-propagation training algorithm had the mean error of ¾. Furthermore, Asalakis [4] evaluated the stock market prediction techniques published in more than 100 articles, focusing on neural and fuzzy neural networks in terms of the input data to design effective networks, prediction methods, and performance measurement criteria. According to the obtained results, soft computing techniques (especially artificial neural and fuzzy neural networks) were widely accepted for assessing the behavior of the stock market behavior, and their proper accuracy was confirmed. In the mentioned research, the prediction of the stock returns was reported to be complicated due to market fluctuations, which necessitated the use of accurate models. In this respect, one solution was the use of artificial intelligence systems, which are useful tools for predicting the nonlinear behavior of complex and chaotic environments, such as the stock market.

In a research, Karil et al. [18] compared the linear and nonlinear models of stock returns, while also comparing and evaluating the linear models of stock return prediction (Fama and French, 1992) and nonlinear models of stock return prediction (neural network and genetic algorithm). In brief, their results were indicative of a significant difference between the linear and nonlinear models and the number of the variables in each model. Overall, the nonlinear models were more observed to be more efficient compared to the linear models. On the other hand, Beigi and Abdulvand [2] developed a hybrid artificial neural network and imperialist competitive algorithm (ICA) to predict the stock price of Iran Khodro during 2010-2016 on a daily basis and predicted the company's stock price. The results of the proposed model were also compared to conventional methods (e.g., regression) to determine the accuracy, which showed the high accuracy of the presented model. In another study, Gholamnejad et al. [9] evaluated the ability to estimate and predict the desired samples using two multivariate regression and intelligent neural network models. In the mentioned study, the criteria of the mean error and root-mean-square deviation of the regression model and artificial neural network model, reporting that the intelligent neural network model had a higher predictive accuracy compared to the multivariate regression model. Using a neural network, Rajabpour et al. [30] predicted the stock prices of the companies listed on the Tehran Stock Exchange (TSE) based on endogenous and exogenous data.

The present study aimed to demonstrate the accepTable ability of ANNs (especially back-propagation networks with developed algorithms) to predict the stock prices of the TSE companies. In addition, we were able to present more reliable results compared to the similar studies by using macroeconomic data, such as inflation rate, exchange rate, the macroeconomic indicators of the stock market, and the price of gold along with endogenous data of the companies (financial ratios and stock information) in the proposed model. According to the obtained results, a three-layer architecture with eight neurons in the first layer, four neurons in the second layer, and two outputs, and a two-layer architecture with 12 neurons in the first layer and two outputs were considered as the most appropriate models. In another research, Ahmadifar [1] predicted stock returns using a hybrid model based on ANFIS, and two ANNs and ANFIS models were applied based on the data of oil prices, gold prices, open market exchange rates, and stock price indices during 2010-2015 as the independent variables.

MLP is applied in the modeling of artificial neural networks under the Levenberg-Marquardt algorithm with a four-layer structure (4-10-10-1). The optimal model was designed in the neural-fuzzy systems using a hybrid training algorithm and Takagi-Sugeno fuzzy inference system after 35 iterations.

Finally, the results of the two models were compared based on error measurement indicators, including the mean absolute percentage error, median absolute percentage error, normalized root-mean-square error, and mean-square error (MSE). Studies have been indicative of the more proper performance of neural-fuzzy systems compared to ANNs. For instance, Monajemi et al. [25] predicted stock prices using a neural-fuzzy system and genetic algorithm in comparison with ANNs. According to the obtained results, the hybrid model of the fuzzy neural networks and genetic algorithm reduced the stock price estimation error compared to the ANN technique after assessing the criteria of R^2 and RME of stock price prediction of the next day.

3 Research Methodology

According to the literature, the following Research Questions are raised:

1. *What is the most appropriate set of independent variables to predict stock returns? Does the ANFIS method work properly in selecting the most appropriate variables affecting stock returns?*
2. *Could the MGGP technique provide a mathematical model for the prediction of the stock returns of the listed companies?*
3. *Does the proposed ANFIS-MGGP model have high accuracy in terms of statistical tests?*
4. *Is the ANFIS-MGGP model more efficient than the MGGP model in terms of the modeling time and accuracy in stock return predictions?*
5. *Is the prediction accuracy of the ANFIS-MGGP model higher than conventional artificial intelligence methods (e.g., neural networks)?*
6. *Does the ANFIS-MGGP method provide a more accurate prediction compared to the multivariate regression method?*

This was an applied research in terms of the objective and a descriptive-correlational study in terms of the design. One of the main features of this study was the use of various techniques to assist the prediction of stock returns and improvement of accuracy in the estimation of stock returns. In fact, we exploited the two artificial intelligence techniques of ANFIS and MGGP to predict stock returns within the shortest time with the highest accuracy, which is a first in the field of accounting, and no evidence have not been found in this regard so far. The sample population included all the companies listed on the TSE during 2008-2017.

Table 1. Sampling Stages

Number of the companies listed on TSE at the end of the Persian year (2017)	512
Number of the companies not listed on TSE before Farvardin (April 2008) and/or experienced symbol halt until the end of (2017)	122
Number of companies with different fiscal year-end from the calendar year-end (March)	83
Number of the companies that were part of financial institutions, investments, banks, and insurance companies	106
Number of companies with more than three months of trading halts	31
Number of companies with unavailable required data to calculate the operational research variables	32
Number of sample companies	138

According to the information in Table 1, 138 companies were selected, and 1,380 data years were used for each research variable to address the research questions. Data were collected using the library method and by referring to related archives. The required data were also collected from the information published by the TSE, and Rahavard Novin software was employed as well. Initially, a list of the independent variables applied in the literature regarding the prediction of stock returns was prepared and completed based on expert opinions. At the next stage, the required data for the independent variables (listed companies on TSE) were collected, followed by the Kolmogorov-Smirnov test to assess the normal distribution of the data. In addition, parametric methods were used in the case of data normality; otherwise, non-parametric techniques were applied for the statistical evaluations. The significance level of below 0.05 showed the non-normal distribution of the data, for which the Mann-Whitney U test was used as a non-parametric test to assess the difference between the significance and applicability of the samples. After preparing the primary list, a questionnaire was distributed among the experts, the items of which were scored based on the scale of 1-5 (extremely poor to extremely good) to measure the significance and applicability of the variables. Notably, the reliability of the test was assessed based on the Cronbach's alpha, and the value of higher than 0.7 was considered acceptable. The P (parameter) coefficient of the significance and applicability of each input was also determined after collecting the questionnaires and performing the Mann-Whitney U test. In some cases, this parameter was lower than 0.05, which indicated a significant difference between the significance and applicability of the variable. Therefore, we only selected the inputs with the P-value of more than 0.05.

After determining the important and applicable criteria, the important and applicable variables were also determined, followed by selecting the most appropriate set of variables for the prediction of the dependent variable using ANFIS. Initially, the accounting and financial variables were assessed to predict the stock returns using ANFIS, and their error rate was also determined in modeling. In fact, the variables were tested in sets of two, three, and n-1 to use the most effective variables (lowest error rate) in the MGGP modeling. Afterwards, a mathematical model was proposed for the prediction of the stock returns based on the selected independent variables using the MGGP technique. At this stage, a mathematical model was proposed based on the MGGP method and Gene X pro Tools. To propose an accurate mathematical model, data were divided into the training and experimental sections. The accuracy of the answers had to be checked in the experimental section if the most appropriate mathematical equation with the highest accuracy was to be obtained in the training section. In addition, a proper mathematical equation was achieved when the two sections yielded the correct answer.

A) Training Section

In this section, we used 75% of the entire data for the training and finding of the most suiTable structure; notably, this process was implemented in all the predictive artificial intelligence methods, including neural network, neural-fuzzy network, and SVM.

B) Experimental Section

After obtaining the most appropriate mathematical equation for the prediction of the stock returns based on the independent variables, the accuracy of the model was evaluated in the experimental section using the remaining data (25%). The accuracy and applicability of the mathematical model could be confirmed if the results of the experimental section had a low error rate and high accuracy. In addition, the results obtained from the novel intelligent genetic methods were compared to the conventional intelligent method (e.g., neural network and regression) to properly demonstrate the accuracy and speed of the model in stock return prediction.

Data analysis was carried out using ANFIS-MGGP, neural networks, and regression, which were implemented using MATLAB, Gene X pro Tools, and SPSS. Different statistical tests were also used to evaluate the accuracy of the model, and the accuracy of the model was determined based on correlation-coefficients and MSE, which have been used in the previous studies on artificial intelligence.

$$R = \frac{(\sum_{i=1}^{n}(h_i - \overline{h_\iota})\ (t_i - \overline{t_\iota}))}{\sqrt{\sum_{1=1}^{n}(h_i - \overline{h_\iota})^2\ \sum_{i=1}^{n}(t_i - \overline{t_\iota})^2}} \quad (1)$$

$$MSE = \frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n} \quad (2)$$

In the present study, the Smith test (1986) was used to evaluate the predictive accuracy of the model.
A: If R>0.8, the model had high accuracy;
B: If 0.3<R<0.8, the model had accepTable accuracy;
C: If R<0.3, the model had extremely low accuracy.
Notably, the mentioned conditions were applicable when the MSE was below its limit.

3.1 Research Variables

In order to assess the research hypotheses, the variables were classified as independent and dependent and selected in accordance with the research literature [6] and the expert opinions.

Table 2: Independent Variable (independent variables: accounting and financial)

Column	Variable	Column	Variable	Column	Variable
1	Net profit to sale	12	Current ratio	23	Ratio of operating cash flow to capital employed
2	Gross profit to sale	13	Quick ratio	24	Asset turnover
3	Operating profit to sale	14	Current asset ratio	25	Receivables collection period
4	Ratio of price to earnings per share	15	Ratio of working capital to total assets	26	Cycle of operations
5	Ratio of Dividend per share to price	16	Turnover ratio	27	Asset turnover
6	Dividend per share (DPS)	17	Debt-to-asset ratio	28	Return on assets (ROA)
7	Earnings per share (EPS)	18	Ownership ratio	29	Return on equity (ROE)
8	Book-to-market ratio	19	Debt-to-equity ratio	30	Return on sales (ROS)
9	Return on capital employed	20	Times interest earned	31	Working capital turnover ratio
10	Ratio of operating cash flow to operating profit	21	Inventory turnover	32	Return on net worth ratio
11	Total shareholder return	22	Current capital turnover		

In this study, we determined the most appropriate independent variables with the highest impact on stock returns using the U Mann-Whitney test and the neuronal artificial intelligence method known as ANFIS.

Dependent Variable

Stock Returns

In the current research, the stock returns were considered as the dependent variable and selected as the output variable of the selected network. We predicted and measured the stock returns using the following equation:

$$R = \frac{(1 + \alpha_1 + \alpha_2)(P_1 + D) - P_0 - \alpha_1(1000)}{P_0 + \alpha_1(1000)} \quad (3)$$

α_1: Percentage of capital increase from receivables and cash contributions;
α_2: Percentage of capital increase from savings;
P_0: Share price at the beginning of the period;

P_1: Share price at the end of the period
The nominal price of each share in Iran is 1,000Rials.

3.2 Research Implementation Stages

The following steps were taken in the present study to implement the ANFIS-MGGP model.
Step one: Careful assessment of the research literature and providing a complete list of the accounting and financial variables (in terms of stock return estimations) based on the research literature and expert opinions.
Step two: Designing a questionnaire (Appendix 2) to determine the significance and applicability of the listed input variables based on experts' opinions (professors of accounting, auditors as members of certified public accountants, stock market analysts, and financial managers).
Step three: Collection of relevant data for the primary variables (second step).
Step four: Using ANFIS to determine the most effective final variables with the highest impact on the stock market altogether.
Step five: Presenting a mathematical model for the stock returns using the most effective variables and the MGGP technique.
Step six: Using the MGGP model based on the variables determined in step three and comparison of the results of the step with the outcomes of the ANFIS-MGGP model.
Step seven: Assessing the accuracy of the AFNIS-MGGP model using different statistical tests, which indicated the accuracy of the prediction model.
Step eight: Comparison of the proposed model with the MLP.
Step nine: Comparison of the proposed model with multilayer linear regression.

4 Results and Data Analysis

Here we provide the responses to the research questions as follows:

1. ***What is the most appropriate set of independent variables to predict stock returns? Does the ANFIS method work properly in selecting the most appropriate variables affecting the stock returns?***

After determining 32 independent accounting and financial variables based on the literature and experts' opinions in the present study, the required data were collected on the independent variables (companies listed on the TSE), followed by the Kolmogorov-Smirnov test to evaluate the normality of the data. The significance level of the Kolmogorov-Smirnov test was below 0.05, indicating the non-normal distribution of the data; therefore, non-parametric methods were used for statistical assessments. In fact, the Mann-Whitney U test was employed as a non-parametric test to determine the difference between the significance and applicability of the samples. To this end, questionnaires were distributed among the experts after preparing the primary list to measure the significance and applicability of the variables. In the questionnaire, score one showed extremely poor accuracy, and scores two, three, four, and five demonstrated poor, moderate, acceptable, and extremely good accuracy, respectively.
Notably, the reliability of the applied tool was assessed using the Cronbach's alpha, which was estimated to be higher than 0.7, indicating the acceptable reliability of the questionnaire. According to the information in Table 2, the values of the items of the Cronbach's alpha were all above 0.7, confirming the reliability of the tool.

Table 3: Cronbach's Alpha Values

Variable		Variable		Variable	
Current Ratio		Current Capital Turnover		Net Profit to Sale	
Significance	Applicability	Significance	Applicability	Significance	Applicability
78%	81%	73%	84%	91%	90%
Quick Ratio		Asset Turnover		Gross Profit to Sale	
Significance	Applicability	Significance	Applicability	Significance	Applicability
78%	92%	95%	73%	98%	91%
Current Asset Ratio		Receivables Collection Period		Operating Profit to Sale	
Significance	Applicability	Significance	Applicability	Significance	Applicability
73%	75%	86%	89%	97%	91%
Ratio of Working Capital to Total Assets		Cycle of Operations		Dividend per share to price	
Significance	Applicability	Significance	Applicability	Significance	Applicability
77%	86%	79%	79%	83%	79%
Liquidity Turnover Ratio		Total Assets Turnover		Earnings per Share Ratio	
Significance	Applicability	Significance	Applicability	Significance	Applicability
88%	83%	89%	74%	76%	77%
Debt-to-Asset Ratio		Return on Assets Ratio		Dividend per Share Ratio	
Significance	Applicability	Significance	Applicability	Significance	Applicability
78%	81%	73%	84%	91%	90%
Ownership Ratio		Return on Equity		Price-To-Earnings per share Ratio	
Significance	Applicability	Significance	Applicability	Significance	Applicability
73%	75%	86%	89%	97%	91%
Debt-to-equity Ratio		Return on Sales		Book-to-market Ratio	
Significance	Applicability	Significance	Applicability	Significance	Applicability
8%	81%	73%	84%	78%	81%
Times Interest Earned		Working Capital Turnover Ratio		Return on Capital Employed	
Significance	Applicability	Significance	Applicability	Significance	Applicability
73%	80%	90%	84%	76%	77%
Inventory Turnover		Return on Net Worth Ratio		Ratio of Operating Cash Flow to Operating Profit	
Significance	Applicability	Significance	Applicability	Significance	Applicability
91%	90%	73%	84%	73%	97%
Ratio of Operating Cash Flow to Capital Employed		Total Stock Returns			
Significance	Applicability	Significance	Applicability		
77%	82%	73%	97%		

The P (parameter) coefficient for the significance and applicability of each input was determined after collecting the questionnaires and performing the Mann-Whitney U test. In some cases, the parameter was below 0.05, indicating a significant difference between the significance and applicability of the variables; therefore, we only selected the inputs with a higher P than 0.05. According to the obtained results, 22 out of 23 primary variables (Table 3) were the most appropriate independent variables (most significant and applicable). After determining the significant and applicable criteria, the most appropriate set of the variables was also selected by ANFIS to predict the dependent variable.

Table 4: Selected Variables at Questionnaire Stage

Column	Variable	ρ	No.
1	Ratio of operating cash flow to capital employed	0.32	A1
2	Gross profit to sale	0.11	A10
3	Operating profit to sale	0.56	A11
4	Dividend per share	0.98	A14
5	Debt-to-asset ratio	0.31	A34
6	Return on equity	0.21	A25
7	Ratio of price to earnings per share	0.40	A15
8	Working capital turnover ratio	0.71	A17
9	Ratio of operating cash flow to operating profit	0.12	A18
10	Net profit to sale	0.11	A9
11	Debt-to-equity ratio	0.27	A36
12	Profit ratio before tax deduction	0.57	A26
13	Liquidity turnover ratio	0.09	A33
14	Current capital turnover	0.21	A19
15	Inflation	0.32	A7
16	Receivables collection period	0.79	A21
17	Ownership ratio	0.31	A35
18	Asset turnover	0.90	A23
19	Current ratio	0.10	A29
20	Book-to-market ratio	0.60	A16
21	Inventory turnover	0.32	A38
22	Return on assets	0.31	A24

Table 5: Independent Variables with Highest Impact (lowest error rate) on Dependent Variable

Column	Variables	Column	Variables
1	Net profit ratio	7	Ratio of price to earnings per share
2	Gross profit ratio	8	Return on capital employed
3	Operating profit margin	9	Ratio of operating cash flow to operating profit
4	Dividend per share	10	Profit ratio before tax deduction
5	Ratio of stock returns from net profit to mean assets	11	Ratio of operating cash flow to capital employed
6	Return on equity	12	

4.1 ANFIS Implementation

The Exhsrch command was used to implement ANFIS. This command has a parameter known as 'S', which indicates the number of the variables. For instance, if S=1, ANFIS calculates the effect of each variable on the dependent variable (i.e., stock returns). If S=2, ANFIS evaluates the effect of two variables on the stock returns simultaneously, and if S=3, ANFIS assesses the effect of three independent variables on the dependent variable simultaneously. In the current research, this process was performed for all the variables (n=22), and the variables with the lowest error rate were selected as the set of variables with the highest impact on the stock returns altogether. After ANFIS implementation, 11 variables with the highest impact on the dependent variable were presented in Table 4.

2. ***Can the MGGP-ANFIS technique provide a mathematical model for the prediction of the stock returns of the listed companies?***

After determining the most effective independent variables using ANFIS, which had the highest impact on the dependent variable, the related data were collected, and a mathematical model was proposed using the MGGP method (Gene X pro Tools). Table 5 shows the data related to this section based on the 11 main variables. Notably and as mentioned in Chapter 3, the data were classified into the training and experimental sections. When the most appropriate mathematical equation with the highest accuracy in the training section was obtained with 75% of the total data, the correctness of the answer in the experimental section would be checked with the remaining 25% of the data. The suitability of the mathematical equation would be confirmed when a correct answer was obtained in the two sections.

Table 6. MGGP Structure for Prediction of Stock Returns by Mathematical Model

	Parameters	**Value**
General	Chromosomes	40
	Function set	×,/,+,-, power (x, y*) ,e^r,Cos, Sin, Atan
	Number of genes	4
	Head size	10
	Linking function	+
Fitness Function	RMAE	
Genetic Operators	Mutation rate	0.033
	One-point recombination rate	0.3
	Two-point recombination rate	0.4
	Gene recombination rate	0.5
	Gene transportation rate	0.5
Numerical Constant	Constants per gene	3
	Data type	Floating Point
	Lower bound	-5
	Upper bound	+5
Number of Run		126

According to the findings of the current research, the most suiTable mathematical model for the prediction of stock returns using the MGGP method was as follows:

$$Y = \left[x_9 + \frac{Cos(x_8+x_6)^3}{(x_6+x_1)-Sin(x_8)}\right] + \left[Cos(x_{10}) - (x_{11})^2 + x_1 + x_4 + \frac{x_4}{x_9}\right] + [e^{x_9} - x_2 + x_1] + \left[x_8 - Cos\left(x_7 + (x_7 + x_9)^2 + Atan\big((x_5) \times (x_{11})\big)\right)\right] + [e^{x_9}] + \left[Cos(x_{10}) - (x_{11})^2 + x_1 + x_4 + \frac{x_4}{x_9}\right]$$

X_1=Net profit ratio;

X_2=Gross profit ratio;

X_3=Operating profit ratio;

X_4=Dividend per share;

X_5=Stock returns obtained from the net profit to the mean assets ratio;

X_6=Equity ratio;

X_7=Ratio of price to earnings per share;

X_8=Return on capital employed;
X_9=Ratio of operating cash flow to operating profit
X_{10}=Profit before tax deduction to sales ratio
X_{11}=Ratio of operating cash flow to capital employed
After obtaining the most appropriate mathematical equation for the prediction of the stock returns based on 11 independent variables, the accuracy of the model was examined in the experimental section. Figures 1 and 2 show the accuracy of the model in the training and experimental sections, respectively.

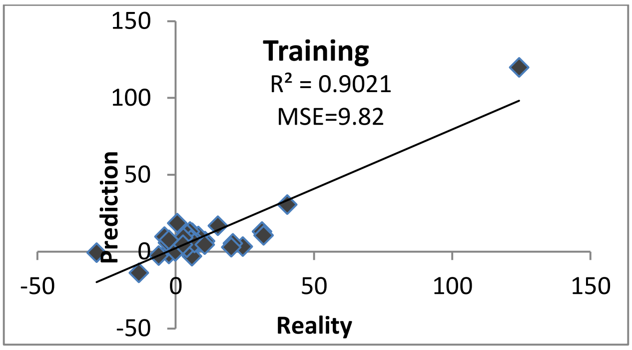

Fig. 1: Accuracy of Model in Training Section

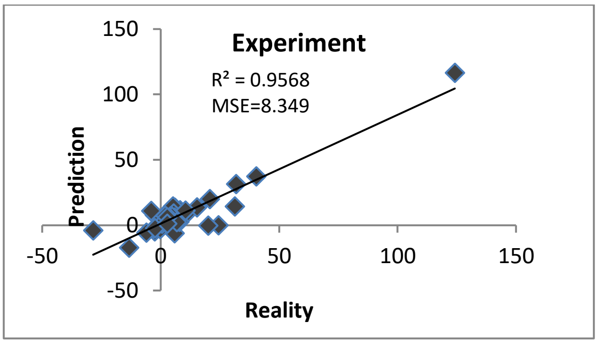

Fig. 2: Accuracy of Model in Experimental Section

As is observed, the MGGP method provided the most appropriate model after 126 different implementations and had accepTable accuracy in the training and experimental sections as well.

3. ***Does the presented ANFIS-MGGP model have a high accuracy in terms of statistical tests?***

In this section, we aimed to evaluate the accuracy of the model based on the statistical tests of the behavioral modeling (prediction). At this stage, the Smith test (1986) was applied to evaluate the predictive accuracy of the model.
A: If R>0.8, the model had high accuracy;
B: If 0.3<R<0.8, the model had proper accuracy;
C: If R<0.3, the model had extremely low accuracy.
Notably, these conditions were applicable when the error rate (MSE) was below its limit.
As is observed in Fig. 1 and 2, the training and experimental correlation-coefficients were higher than 0.8, indicating the high predictive accuracy of the proposed ANFIS-MGGP model.

4. ***Is the ANFIS-MGGP model more efficient than the MGGP model in terms of modeling time and accuracy for stock return prediction?***

In this section, we evaluated the effects of ANFIS as a tool to determine the most effective independent variables in the modeling process. In fact, the goal of this section was to assess the effects of ANFIS on the time and accuracy of modeling. To this end, we applied the MGGP technique and 22 variables. As is shown in Fig. 3 and 4, the pure MGGP model could present a model after 968 implementations with lower accuracy in the training and experimental sections.

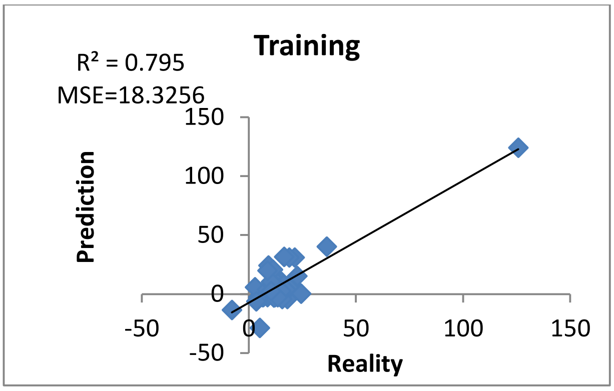

Fig. 3: Accuracy of Model in Training Section

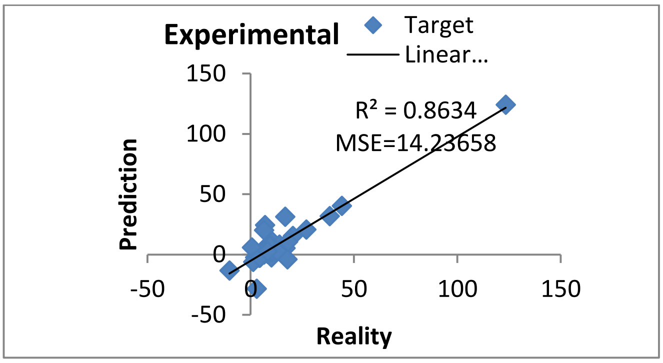

Fig. 4: Accuracy of Model in Experimental Section

The comparison of Figures 1 and 2 with Figures 3 and 4 also indicated that the R^2 value was higher in the training and experimental sections of the ANFIS-MGGP model compared to the pure MGGP model. However, the MSE was lower in the training and experimental sections of the ANFIS-MGGP model compared to the pure MGGP model. Notably, the ANFIS-MGGP and pure MGGP models were implemented 126 and 968 times, respectively, and the higher prediction speed of the ANFIS-MGGP model was observed compared to the pure MGGP model.

Table 7: Neural Network Parameters

Multilayer Perceptron (MLP)	Output
Latent Layers	1
Number of Neurons in Each Latent Layer	3
Stimulus Function	Tanh X
Law of Learning in First Latent Layer	Momentum
Output Stimulus Function	Linear Sig. (X)
Number of Turnovers	1,000

5. Is the predictive accuracy of the ANFIS-MGGP model higher than conventional artificial intelligence methods (e.g., neural networks)?

To answer this question, we applied the MLP method and used the data similar to the ANFIS-MGGP model for the training and testing of the model. Afterwards, the obtained results were evaluated in terms of R^2 and MSE in the training and experimental sections. Notably, 289 implementations with various structures were carried out to achieve the most appropriate MLP structure for the prediction of stock returns. Table 6 shows the optimal parameters of the MLP structure used in the current research.

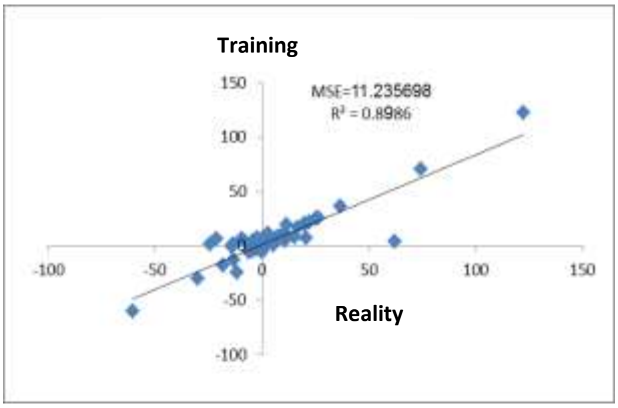

Fig. 5: Accuracy of Model in Training Section

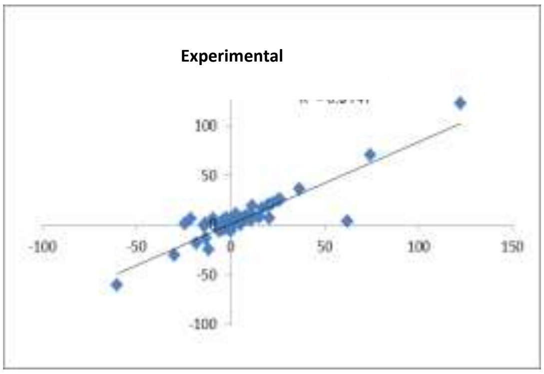

Fig. 6: Accuracy of Model in Experimental Section

As is observed in Fig. 5 and 6, the MLP method had an extremely accepTable performance regarding the prediction of stock returns in the training and experimental sections. In this respect, R^2 and MSE were estimated at 0.8935 and 11.235689 in the training section and 0.9147 and 10.57951 in the experimental section, respectively.

Therefore, it could be concluded that the MLP method had a high performance in the prediction of stock returns. From a practical perspective, the following questions should also be considered:

- *How are managers going to use this neural structure (neurons, latent layer, and stimulus function) in the real world?*
- *How can we understand the correlations between independent variables and stock returns based on the obtained neural structure?*

Neuron methods (e.g., neural network and neural-fuzzy network) have extremely low applicability in the real world due to the fundamental issues in the structure of ANNs, such as:

A) Determining an optimal set of input variables since the direct selection of the input variables affects the predictive accuracy;
B) Lack of a unique method to determine the number of the neurons in the latent layer, so that researchers would have to determine this number experimentally and by trial-and-error;
C) A neural network cannot present a mathematical model for the dependent variable based on the

independent variables, thereby failing to separately assess the effects of the independent variables on the dependent variable.

A neural network could only provide a number as a prediction and is unable to show a correlation, even when the accuracy is as low as regression. In addition, prediction in this method is rather time-consuming since the input variables should be determined by trial-and-error. As such, the implementations must be repeated multiple times.

Table 8. Results of Multivariate Regression in SPSS

Mode	**Sum of Squares**	**Degree of Freedom**	**Mean Squares**	**Significance Level (p)**	**Coefficient of Determination**	**Mean Square Error**
Regression	34.533	1	8.633	0.000	0.627	26.32489
Residual	53.333	30	0.141			
Total	87.866	29				

Predictive Variables	**Estimated Coefficients**	**Significance Level**
Constant	2.562	0.000
X_1=Net profit ratio	0.578	0.000
X_2=Gross profit ratio	0.148	0.000
X_3=Operating profit ratio	0.336	0.000
X_4=Dividend per share	0.489	0.000
X_5=Ratio of stock returns from net profit to mean assets	0.356	0.000
X_6=Equity ratio	0.204	0.000
X_7=Ratio of price to earnings per share	0.035	0.000
X_8=Return on capital employed	0.158	0.000
X_9=Ratio of operating cash flow to operating profit	0.114	0.000
X_{10}=Profit before tax deduction to sales ratio	0.337	0.000
X_{11}=Ratio of operating cash flow to capital employed	0.501	0.000

6. ***Does the ANFIS-MGGP method provide a more accurate prediction compared to the multivariate regression method?***

To answer this question, we applied multivariate regression using the data similar to those used for the ANFIS-MGGP model without classification into the training and experimental sections. The data were thoroughly evaluated since the regression model was not an artificial intelligence method. Afterwards, the obtained results were assessed in terms of R^2 and MSE, which were estimated at 0.627 and 26.32489, respectively. The comparison of these values to the values obtained from the ANFIS-MGGP method demonstrated a significant difference between the multivariate linear regression and ANFIS-MGGP method. In other words, the accuracy of the proposed model was extremely higher than multivariate regression.

According to the information in Table 7, the ANFIS-MGGP model had higher accuracy and speed in the training and experimental sections compared to other modern and conventional metaheuristic models. In addition, the model was considered to be a more applicable technique as it presented a mathematical model for prediction and had extremely higher accuracy compared to conventional predictive models (e.g., regression).

$Y=2.562+0.578\,X1+0.148\,X2+0.336\,X3+0.498\,X4+0.356\,X5+0.204\,X6+0.035\,X7+0.158\,X8+0.114\,X9+0.337\,X10+0.501\,X11$

Table 9: Comparison of Results Obtained from Metaheuristic and Regression Models in Terms of Predictive Accuracy and Speed

Model	Coefficient of Determination		Mean Square Error		Number of Implementations (model speed)
	Training	Experimental	Training	Experimental	
ANFIS-MGGP	0.9021	0.9568	9.82	8.349	126
Pure MGP method	0.795	0.8634	18.3256	14.2366	968
MLP	0.8935	0.9147	11.2356	10.580	289
Multivariate Regression	0.627		26.3249		-

Table 10: Variables with Highest Impact

Column	Variable	Column	Variable
1	Net profit ratio	7	Ratio of price to earnings per share
2	Gross profit ratio	8	Return on capital employed
3	Operating profit ratio	9	Ratio of operating cash flow to operating profit
4	Dividend per share	10	Ratio of profit before tax deduction to sales
5	Ratio of stock returns from net profit to mean assets	11	Ratio of operating cash flow to capital employed
6	Equity ratio	12	

5 Discussion and Conclusion

Given the nonlinear correlations between variables in the real world, the use of conventional methods may not yield accurate and reliable outcomes, and metaheuristic techniques could be a proper alternative for determining the most appropriate independent variables in this regard. As a metaheuristic method used in the present study, ANFIS was able to select the variables with the lowest error rate as the set of the independent variables, which had the highest impact on the dependent variable (stock returns). In the current research, 11 variables were considered most appropriate among the independent accounting variables, which had the highest impact on the stock returns. These variables are shown in Table 10. This was the first study to use ANFIS to determine the most proper influential criteria in the assessment of stock return behavior, and no previous studies have been focused on the selection of the most appropriate independent variables using ANFIS or other artificial intelligence methods. In addition, the number of the independent variables has been significantly low in the previous studies, and the variables have mostly been economic. In the present study, several articles were initially reviewed [6], and experts' opinions were collected on numerous highly applicable accounting and financial variables. For instance, Ince and Trafalis used five independent variables (operating profit ratio, dividend per share, equity ratio, ratio of the operating cash flow to the operating profit, and net profit to sales) to predict stock returns. In another study, Yaon and Soo used the four variables of the ratio of price to profit per share, return on the capital employed, ratio of the operating cash flow to the operating profit, and net profit to sales to estimate stock returns. The literature search revealed that this was the first research to evaluate the prediction of stock returns using a large number of variables (n=32). In addition, the issue of selecting the input factors was discussed for the first time.

In the current research, the ANFIS-MGGP method was able to present a mathematical model with high predictive accuracy. To further elaborate, it could be stated that the related data were collected after determining the independent variables (n=11). At the next stage, the data were classified as the training and experimental sections, with the latter used for the optimization of the MGGP structure. After obtaining the most appropriate mathematical equation with the highest accuracy, the experimental data were also used as an unseen dataset to evaluate the accuracy and power of the model in the prediction of stock returns. Finally, the results were indicative of the high accuracy of the ANFIS-MGGP model in the training and experimental sections. Although several studies have been performed to predict stock returns based on independent variables, an accurate evaluation revealed that the present study was a progressive project due to using the MGGP artificial intelligence in the field of accounting.

A review of the literature revealed that many domestic and foreign researchers have used outdated artificial intelligence methods (e.g., neural network, neural-fuzzy network, and SVM) to estimate stock returns without mentioning the limitations of these techniques in terms of presenting an accurate mathematical model and only focusing on the fact that neural structure encompass several latent layers and a number of neurons in each layer for the prediction of the output variable with a high accuracy. Nonetheless, the issue of the applicability of such research to the stock market in the real world has not been addressed so far. For instance, Sheta et al. applied the SVM to predict stock returns. Notably, SVM is recognized as a 'black box' as it is unable to present a mathematical equation between independent and dependent variables or assist managers and investors in the real world. In this regard, Sheta et al. [33] and other researchers (Chauhan et al. [9], Fallahpour et al. [12], Melek [24], and Renu [31]) have not evaluated applicability in the real world. In the present study, the proposed ANFIS-MGGP model had a high accuracy in terms of the statistical tests since the correlation-coefficient of the training and experimental sections were estimated to be higher than 0.8 based on the Smith model. Therefore, the ANFIS-MGGP model was considered to have a high predictive accuracy. In fact, we proved the high ability of ANFIS to increase the accuracy of the model and decrease the modeling time. As mentioned earlier, ANFIS is used as a tool to select the most appropriate input variables. According to the literature, when ANFIS is removed as the input variable selector, the time to obtain the most appropriate MGGP structure greatly increases, while the accuracy of the model extremely decreases in terms of the R^2 and MSE values. In this respect, our findings were indicative of the effectiveness of ANFIS in decreasing the modeling time (prediction) and increasing the estimation power (estimation). In addition, the proposed model had higher accuracy compared to traditional predictive artificial intel ligence methods (e.g., neural network).

In this regard, our findings confirmed that the genetic predictive models had an extremely higher ability compared to neuron predictive models. In fact, not only do the genetic predictive models have high accuracy, but they can also eliminate neuron predictive methods, such as MLP and other models in the field, which are recognized as a 'black box'. In other words, genetic prediction models enable researchers, managers, and investors in the stock market to analyze the effects of each variable in the real world by providing a highly accurate mathematical equation for the output variable (stock return) based on the input variables, while also helping with the better understanding of the reality and future. In the current research, the ANFIS-MGGP method was compared to conventional predictive methods (e.g., multivariate regression), and the results demonstrated the extremely higher power of the genetic predictive methods. Furthermore, the review of the literature indicated that a small number of domestic and foreign researchers have used only an extremely outdated method (e.g., regression) to estimate stock returns. Researchers usually compare the regression method with other methods, such as SVM and neural networks. In all cases, the regression method has not had a favorable power compared to artificial intelligence methods. Similar to the findings of Sheta et al. [22], Chauhan et al. [9], Fallahpour et al. [11], Melek [24], and Renu [31], many other researchers have only used such techniques in their research. Our findings could be used by stock exchange analysts in an applicable manner, so that more valuable counseling services could be provided to the investors who intend to invest in the stock exchange market. In addition, our findings are applicable for institutional and individual investors since they enable these individuals to analyze the stock market behavior in an optimized manner in order to more accurately predict stock returns and make proper decisions regarding investment in the stock exchange market and achieve the maximum benefits from the least resources. For the future study we provide the following suggestions:

1. It is recommended that multi-criteria decision-making methods (e.g., analytical hierarchy process) be used to measure the significance of each input variable determined in the research and compare the results with those obtained from ANFIS to select proper input factors.
2. It is recommended that the SVM be used and compared to genetic methods rather than a neural network.
3. It is recommended that other genetic programming models (e.g., gene expression programming or linear genetic programming) be used rather than multi-gene genetic programming applied in the present research for comparison with the SVM regarding the prediction of stock returns.
4. It is recommended that methods other than AFNIS (e.g., Delphi method) be used to select inputs.
5. It is suggested that economic variables be considered in addition to accounting variables.
6. It is proposed that the time-series method be employed by other researchers to estimate stock returns and the results be compared to our findings.

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