Journal of Industrial and Systems Engineering
Vol. 17, No. 3, pp. 1-21
Summer (July) 2025

Providing an Intelligent Model Based on an Adaptive Fuzzy Artificial Neural Network for Stock Price Prediction

Davood Katal[1], Khosro Faghani Makrani[2*], Ali Zabihi[1]

[1]*Department of Accounting, Sar.C., Islamic Azad University, Sari, Iran*

[2]*Department of Accounting, Se.C., Islamic Azad University, Semnan, Iran*

Abstract

Investment is one of the most important topics in the economies of all countries, with significant importance for individuals and high-level officials. In this research, we estimate the stock returns of sample companies using an adaptive fuzzy neural network model. In this method, fuzzy logic is used to improve neural network performance by incorporating uncertainty. In the present study, the initial price, highest and lowest prices, closing price, and trading volume variables were used as input data for the model. By defining and preprocessing data related to listed companies, the data were divided into two categories: training and testing, and in the design of the hybrid network model, 6 input variables and 1 output variable were used. Then, by converting the input data into fuzzy numbers, the basic fuzzy inference system model was designed, and a mathematical model for selecting the optimal stock portfolio was introduced. The results showed that Bank Mellat's stock was placed as the best recommended stock in the trading market. The proposed intelligent method can replace current methods in existing stock price prediction software in the stock exchange to help brokers, and investors can also benefit from the model presented in the present study to improve their decision-making power.

Keywords: Stock return, Fuzzy logic, Stock price, Prediction

1-Introduction

The initial investigation into profit prediction has been conducted using models that can be effective in predicting profit. Profit prediction and other related variables are important indicators for financial analysts and investors, and can be particularly significant in decision-making for stock pricing in buying and selling, dividend distribution, profit smoothing, asset valuation, investment risk assessment, profitability evaluation, stock valuation models, and more (Aghamohammadi et al., 2022). Therefore, to achieve these goals, it is necessary to design a profit prediction model so that current and future investors and other users can act with greater confidence in meeting their expectations. So far, various models have been

* Corresponding Author
ISSN: 1735-8272,

presented for predicting stock portfolios and forming stock portfolios, mostly based on time series analysis and mathematical relationships between factors affecting stock returns. Such analyses yield different results with the inclusion or exclusion of variables from the model and offer varying accuracy over various time periods (Keihani 2021; Yang et al., 2024). However, in recent years, with the emergence of data mining and the extraction of hidden knowledge in data, many data-driven models have been proposed. One such model is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which extracts relationships between existing data based on time series data and interactions among them, and presents the final model (Akbay et al., 2020; Ghasemi et al. 2023). For this purpose, in the present study, the ANFIS model is used to optimize the stock portfolio, and the question of how accurately the ANFIS model performs in providing an optimal stock portfolio is answered.

Financial markets are the pulse of every country's economy, interacting with other sectors of the economy. The capital market is considered a subset of financial markets, as a portion of the financial resources needed by manufacturing companies is supplied from this sector (Faridi et al., 2022; Roudaki et al. 2025). The most important role of the capital market is to facilitate the conversion of individuals' and commercial units' savings into investments in other economic units. Capital plays a significant role in the economic growth process. In recent decades, the expansion of financial markets, especially the capital market, has played a crucial role in the economic growth of countries such as the United States, Japan, England, South Korea, Singapore, and others (Chan and Linda, 2017). The stock exchange is the most important component of the capital market, serving as an official reference for investing the stagnant savings of holders. Various indicators are considered for analyzing the performance of stock exchanges, and one of these indicators is the stock price of different companies (Mousavi, 2022; Samieifard et al. 2024).

Investment can be considered one of the fundamental pillars of any country's economy. No doubt increasing production, as one of the first steps in the development process, will require increased investment. For this reason, theories in economics suggest that the underdevelopment of some countries is due to a lack of capital and investment, and they attribute the vicious cycle of low production to the absence of investment (Haratizadeh et al., 2023; Delshad et al. 2024). In addition to the macroeconomic consequences of investment, this issue is also considered desirable from the investors' perspective, because, in addition to preserving the purchasing power of money against inflation, it also ensures that the time value of money and the reward from delayed consumption are taken into account. For this reason, investment, from both the supply and demand sides of capital, is considered an essential prerequisite for progress. In our country, with the expansion and development of the capital market, at the head of which is the stock exchange, a significant portion of investors' assets is in the form of shares of companies listed on the exchange. The nature of commercial and investment activities is such that earning returns requires risk. Risk plays a key role in financial markets, so it must be identified, measured, and predicted (Nozari, 2023).

Increasing profit and reducing investment risk in the stock market has always been the main concern of investors, and they are mostly looking for a way to have the best stock purchase recommendations, such that they have the highest return and the lowest investment risk. High and stable profit through profitable investments is the ultimate goal for investors. In financial literature, to reduce the risk arising from the stock itself, investment in a stock portfolio has been suggested. A stock portfolio is a suitable combination of risky securities that an investor purchases. If the securities are risky, the main problem for every investor is to determine the securities whose utility is maximized. This problem is equivalent to selecting the optimal stock portfolio from the set of possible portfolios, which is called the portfolio selection problem (Chan and Linda, 2017; Yordanova et al., 2025). Therefore, in this research, using an adaptive neuro-fuzzy inference system model, we estimate the stock returns of sample companies and seek to answer the question of which stock portfolio has the highest return, or, in other words, is optimal?

The remainder of the article is organized as specified. Section 2 provides a literature review of the research topic. Section 3 presents the mathematical modeling method and its solution approach. Section 4 presents the results obtained from applying the research model, and finally, a general conclusion along with suggestions for future research is provided.

2- Literature Review

Sutiene et al. (2024) reviewed portfolio management improvement policies in their study. This study reviewed current modern approaches by answering the main question of how artificial intelligence changes the stages of portfolio management. Furthermore, since the use of AI in finance is challenged by transparency, fairness, and explainability requirements, a case study of post-asset allocation explanations is presented. Finally, they discussed recent regulatory developments in European investment trading and highlighted specific aspects of this business where explainable AI can enhance the transparency of the investment process. Yang et al. (2024) presented a synergistic multi-objective evolutionary algorithm with diffusion population generation for portfolio problems in their study. This is because the use of multi-objective evolutionary algorithms (MOEAs) provides an effective approach to dealing with complex data involved in multi-objective optimization problems. However, current MOEAs often rely on a single strategy to achieve optimal solutions, leading to premature convergence and insufficient population diversity. In this study, a new MOEA called synergistic MOEA with diffusion population generation is proposed to address the limitations of existing MOEAs. Cui et al. (2023) presented an intelligent deep learning-based approach for CVAR in cryptocurrency markets. For this purpose, a new cryptocurrency portfolio model framework based on the CVaR risk measure and a deep reinforcement learning optimization framework has been developed. Cryptocurrency market data from 2015 to 2021 was used, and it was shown that the CVaR measure with deep learning performs better than the traditional portfolio construction technique. Zhang et al. (2023) presented a knowledge-based constructive estimator of the distribution algorithm for bi-objective portfolio optimization with cardinal constraints. For this purpose, a hybrid scheme of Ant Colony Optimization (ACO) and Estimation of Distribution Algorithm (EDA) has been proposed. Mendonça et al. (2020) in their study used a multi-objective integer Conditional Value-at-Risk (CVaR) portfolio optimization model with cardinal constraints and two different decision-making methods to guide and select a non-dominated portfolio solution generated by the proposed evolutionary algorithm to approximate investor behavior (conservative, moderate, and aggressive).

According to the results, the maximum monthly drawdown and cumulative return over the entire study period were considered, and the optimization model was made robust considering three simulated profiles. The methods always show higher cumulative returns than safe investments for the analyzed period, and aggressive profiles achieve higher profits with higher risk. Akbay et al. (2020) investigated the portfolio optimization problem with cardinal constraints in their study. Cardinality constraints transform the quadratic optimization model into a mixed-integer quadratic programming problem, which has been proven to be NP-hard, making it very difficult to achieve an optimal solution in a reasonable time using exact methods. To develop an efficient solution method for optimal portfolio optimization with cardinality constraints, this study presents a parallel variable neighborhood search algorithm combined with quadratic programming. The variable neighborhood search algorithm calculates the combination of portfolio assets, and quadratic programming calculates the asset ratios. The performance of the proposed algorithm was tested on five datasets and compared with other solution methods in the literature. The obtained results confirm that the presented solution approach is highly efficient.

Given the above and due to the complexity of the stock market and the high volume of information to be processed, using a simple system often does not yield good results. For this reason, researchers have tried to provide a system with less complexity and higher efficiency and accuracy by presenting hybrid models. Today, various patterns such as statistical techniques (discriminant analysis, logit, and factor analysis) and artificial intelligence techniques (neural networks, decision trees, case-based reasoning, genetic algorithms, and fuzzy logic) or a combination of these two techniques are used to predict stock prices. The multiplicity of artificial intelligence methods used, as well as the diversity of these methods, and also considering that in most of the reviewed studies, artificial intelligence methods have been compared with linear methods and have shown better results compared to them, it can be concluded that artificial intelligence methods have a high capability in the prediction process. In this research, the aim is to investigate the capability of two artificial intelligence methods in the field of prediction. One of the most important and efficient artificial intelligence-based methods used is the Adaptive Neuro-Fuzzy Inference System (ANFIS). This method is a combination of rules related to neural networks and fuzzy logic. In this method, fuzzy logic is used to improve the performance of neural networks by adding the concept of uncertainty. This method has been frequently used in various articles, so using this method can lead to increased prediction accuracy. In addition, to increase the speed and accuracy of the algorithm, it was combined with a genetic algorithm.

3- Research Method

The current research model is based on the ANFIS model. This model is a small artificial intelligence model that combines fuzzy logic and neural network functionalities. Introduced by Jang in the 1990s, it is recognized as a powerful method for modeling and controlling complex systems. The ANFIS model consists of two main stages:

First stage: Fuzzification of data. In this stage, the ANFIS system uses input data and relevant fuzzy information in the form of IF-THEN rules. In fact, ANFIS learns how to create these fuzzy rules based on the input data.

Second stage: Optimization and adaptation of weights. In this stage, ANFIS automatically optimizes the weights related to its predictions. This optimization and adaptation allow for improving the accuracy of the ANFIS model.

The ANFIS method can be used for prediction, control, optimization, and decision-making problems in various fields, including finance, neuroscience, engineering, and more. For this reason, in the current research, which focuses on designing a model for optimal portfolio formation and trading strategies, using the ANFIS model can help analyze complex patterns in the financial market and design optimal trading strategies. This model, with its ability to combine fuzzy precision and neural power, can assist in making intelligent decisions and increasing returns.

Generally, in the ANFIS model, the process of constructing the fuzzy inference system proceeds as follows:

First, independent variables (which in this research are 6 variables: opening price, highest price, lowest price, closing price, trading volume, and final price) are considered as model inputs. For each input, the fuzzification process is performed; in other words, membership functions are first defined for each variable. Then, fuzzy rules are designed based on the data. Next, for each rule, a weight is calculated using Sugeno implication (minimum and Mamdani product) and combining its different parts. It is worth noting that due to the ease and acceptable accuracy of Mamdani implication, this method is used in the ANFIS algorithm to check the degree of correctness of the fuzzy rule, and the mentioned stage is called the implication process. In fact, in the final model, the input values are known, and the output value is not. In this case, considering the input values and placing them in the membership functions corresponding to the preconditions of the fuzzy rules, a parameter is calculated, and this parameter is multiplied by the output membership function (the exact output value is not known) using Mamdani implication, and finally, a separate membership function is determined for each fuzzy rule. In the next stage, the calculated membership functions for each fuzzy rule are combined using the s-norm maximum, the output of which is a fuzzy set (aggregation stage). Finally, the defuzzification process is performed, providing us with an output.

4- Findings

In this section of the research, the proposed method for stock price prediction is implemented. In this regard, a stock price prediction model based on the data of selected companies (statistical sample) in the stock exchange is designed and executed using a hybrid ANFIS and genetic algorithm approach.

4-1- Stock Price Prediction Process

Investment is one of the most important topics in the economy of all countries, which is of high importance for individuals and national authorities. For this reason, in the last two decades, the development of financial markets and the provision of new tools have been one of the appropriate solutions at the international level to attract more capital (Bertini, 2009). Portfolio management is an important issue in economics, and its main subject is the scientific management and selection of a combination of assets that meet specific investment goals. Maximizing value and minimizing portfolio risk are among the most important goals of the portfolio management problem. Given the importance of the topic, this research investigated the optimization model of a stock portfolio using a fuzzy neural network. To this end, first, by reviewing the research literature and library studies, the independent variables effective in stock price prediction were identified. Subsequently, data corresponding to the independent and dependent variables for the selected companies were collected as a statistical sample. To design the stock price prediction model, the data from 1/7/1398 to 1/7/1399 were prepared, normalized, and finally divided into two categories: training and test data. Then, a hybrid method of fuzzy neural network and genetic algorithm was used to estimate stock prices.

4-2- Introduction to Numerical Datasets

According to the public relations of the Tehran Stock Exchange and the Department of Statistics and Information, the list of the top 10 companies on the Tehran Stock Exchange for the third quarter of 98 was as follows: Mobarakeh Steel Company of Isfahan, Persian Gulf Petrochemical Industries, National Iranian Copper Industries, Bank Mellat, Gol Gohar, Pars Petrochemical, Oil, Gas and Petrochemical Investment Company, Isfahan Oil Refinery, MAPNA Group, Bandar Abbas Oil Refinery, and Tehran Oil Refinery, which ranked from sixth to fifteenth in the table of the most active listed companies in the third quarter of 98. Also, for the fourth quarter of 98, Persian Gulf Petrochemical Industries, Mobarakeh Steel Company of Isfahan, National Iranian Copper Industries, Bank Mellat, Oil, Gas and Petrochemical Investment Company, Gol Gohar, Iran Khodro, MAPNA Group, and Tehran Oil Refinery ranked from first to tenth in the table of the top listed companies in the fourth quarter of 98. Based on the mentioned points, the case study sample was selected from the existing stocks in the stock exchange by choosing the top 10 companies (Table 1).

Table 1. Symbols of the top 10 selected stock exchange companies for implementing the proposed algorithm

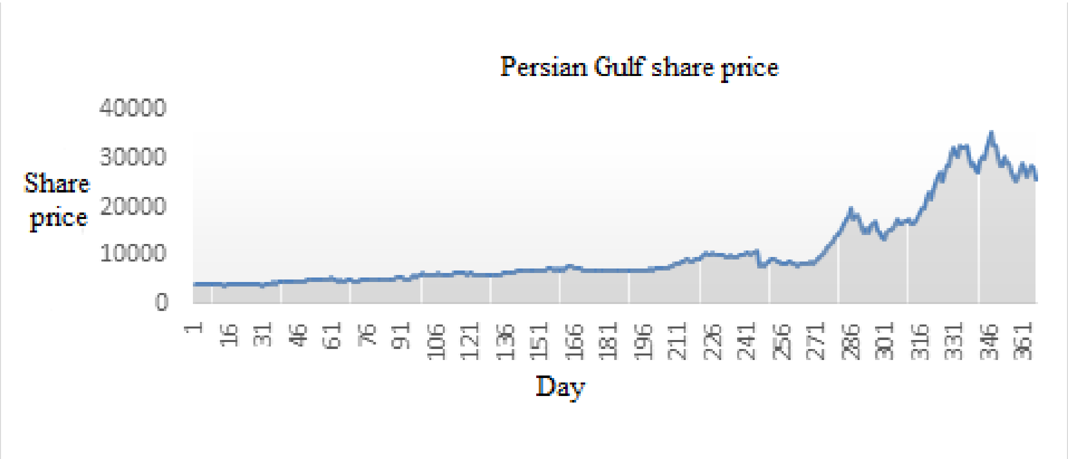
Row	Company Name	Stock Symbol	Symbol in this study
1	Persian Gulf Petrochemical Industries	Fars	Khalij
2	Mobarakeh Steel Company	Foolad	SM
3	National Iranian Copper Industries Company	Fmeli	SIN
4	Bank Mellat	Webmelat	Mellat
5	Tamin Oil, Gas and Petrochemical Investment Company	Tapico	TP
6	Gol Gohar	Kaggle	GG
7	MAPNA Group	Rampna	Mapna
8	Tehran Oil Refining Company	Shatran	PT
9	Esfahan Oil Refining Company	Shapna	SI
10	Bandar Abbas Oil Refining Company	Shabandar	BA

In this study, daily data, as well as the closing price and trading volume of the companies participating in the research, have been used to predict stock prices.

Table 2. Mean and standard deviation of the top 10 sample stock exchange companies

Row	Company Name	Average	Standard Deviation
1	Fars (Khalij)	10643.6	7982.7
2	Foulad (SM)	6750.3	5057.1
3	Fmeli (SIN)	9530.3	9057.6
4	Webmelat (Mellat)	7191	6608.2
5	Tapico (TP)	5351.8	5340.2
6	Kaggle (GG)	9468	4386.1
7	Rampna (Mapna)	14503.3	11737.6
8	Shatran (PT)	10206.6	9929.3
9	Shapna (SI)	12061	9845.9
10	Shabandar (BA)	17421.1	9863.3

In the present study, 6 variables (opening price, highest price, lowest price, closing price, and also closing price and trading volume) of the companies participating in the research were used as input data, and their daily values over a one-year period for the top 10 stock exchange companies were extracted from the Tehran Stock Exchange website. For example, the distribution of variables for the Persian Gulf Petrochemical Industry and Bank Mellat is shown in Figures (1) and (2).



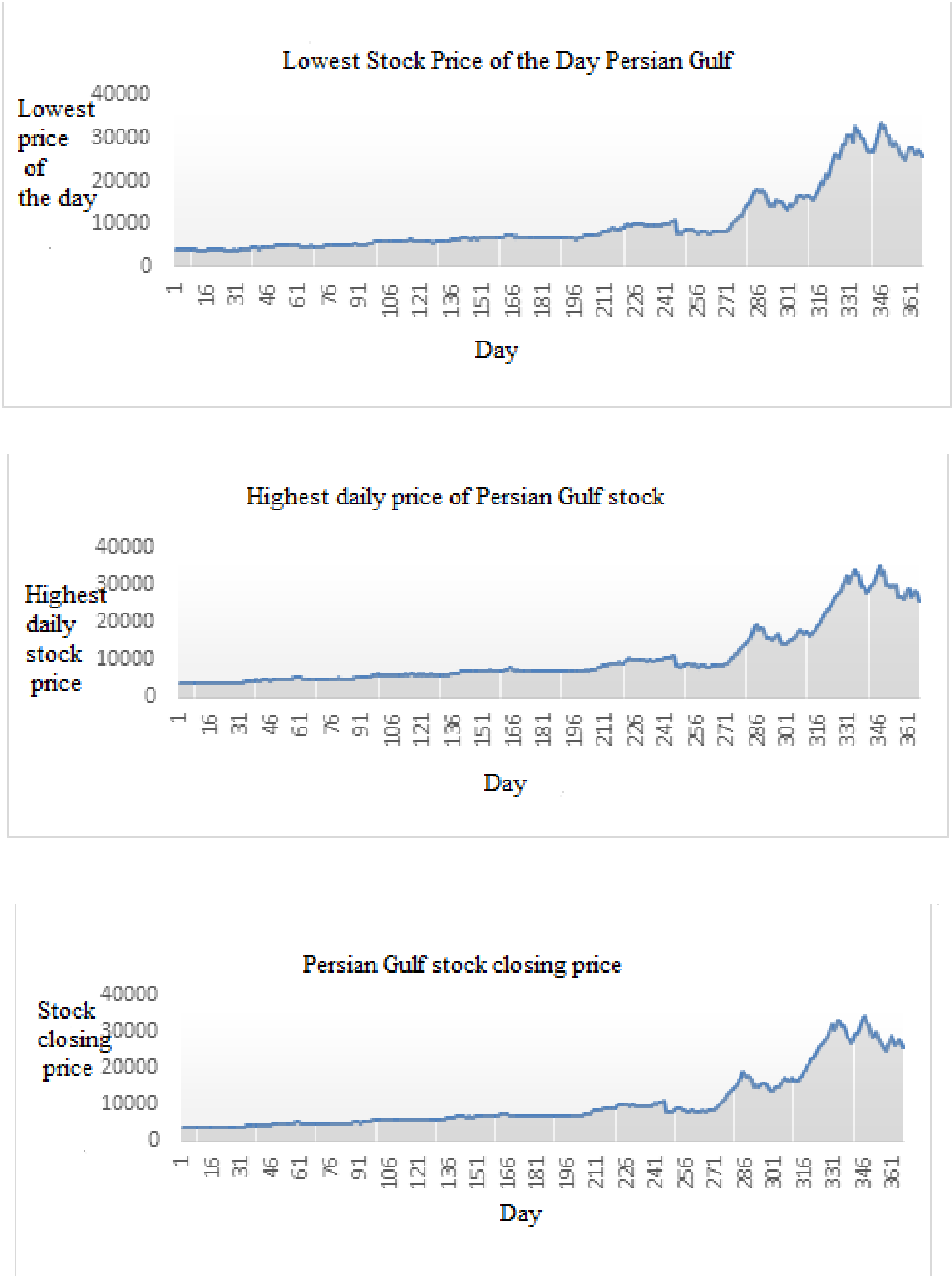


Figure 1. Distribution of research variables for the Persian Gulf share

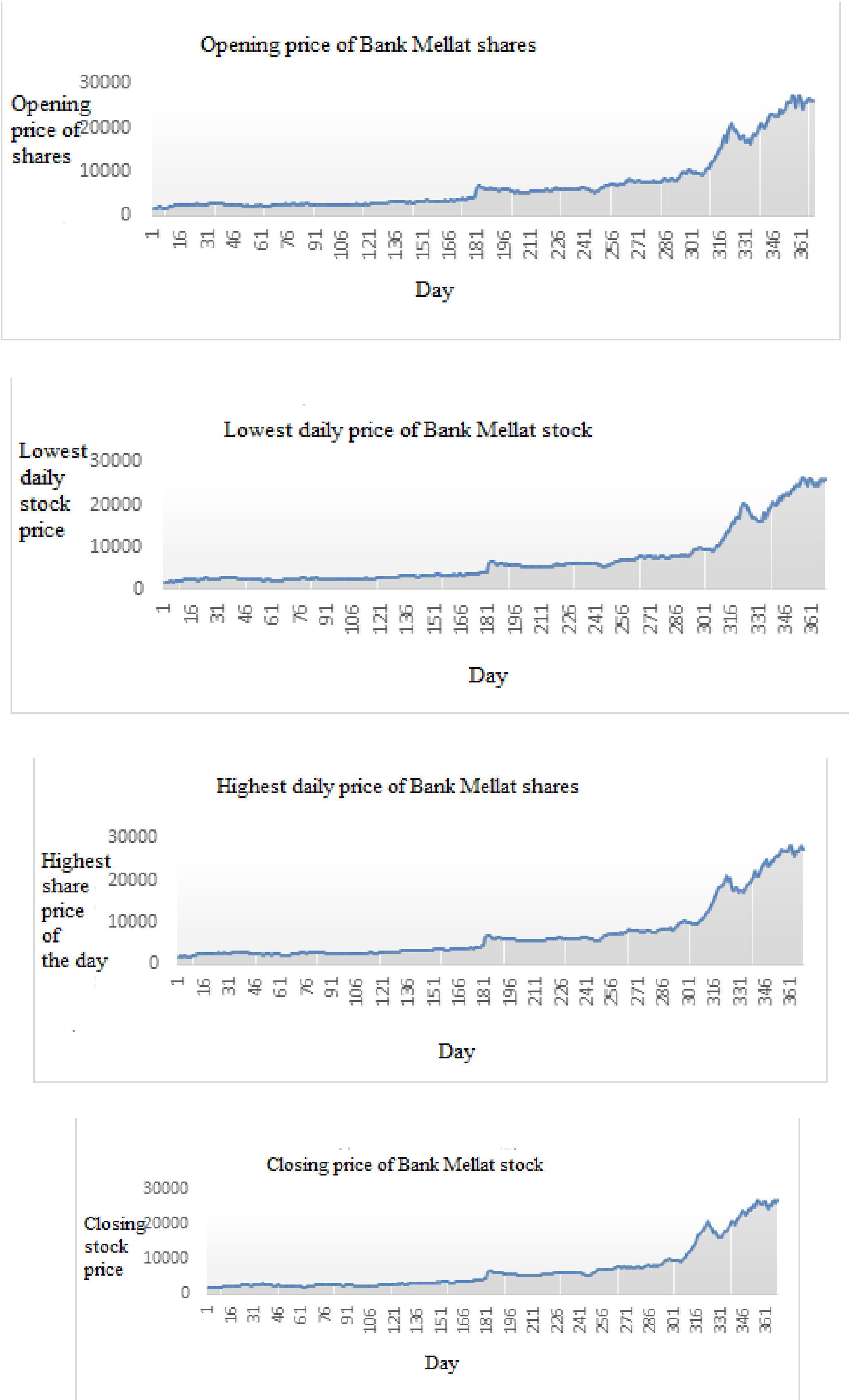


Figure 2. Distribution of research variables for Bank Mellat's share

Descriptive statistics for the variables of the two sample companies were calculated using SPSS software, and the results are shown in Table 3.

Table 3. Descriptive statistics for two sample stocks over one year

	Variable	Count	Maximum	Minimum	Mean	Median	Standard Deviation
Persian Gulf Petrochemical Share	Opening price	360	35450	3769	10656.5	19609	8005.3
	Highest price	360	35450	3800	10847.9	19625	8167.9
	Lowest price	360	33770	3740	10422.9	18755	7783.6
	Closing price	360	34250	3766	10646.9	19008	7984.1
Bank Mellat Shares	Opening price	360	27350	1810	7186.7	14580	6599.1
	Highest price	360	28330	1881	7358.4	15105	6808.6
	Lowest price	360	26500	1810	7020.6	14155	6418.2
	Closing price	360	27160	1873	7198.3	14516	6613.7

4-3- Stock Price Prediction with the Proposed Method

In this section, the proposed method is used to improve the accuracy and speed of the stock price prediction algorithm. For this purpose, after definition and preprocessing, the data of the target stock exchange companies are fed into the system. The system's output is based on the mean squared error and its root. The output is presented in the form of three charts and the average percentage error. In the proposed method, the input data were divided into two categories: training and testing. In the design of the hybrid network model, 6 variables (opening price, highest price, lowest price, closing price, trading volume, and final price) are considered as input variables, and the stock price is the output variable of the model. The input data are converted into fuzzy numbers (fuzzification stage).

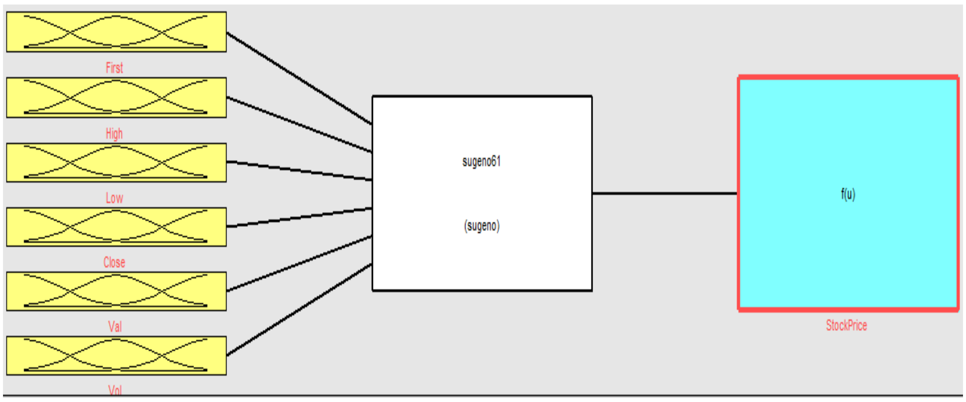


Figure 3. Proposed stock price estimation model using 6 input variables in MATLAB environment

To design the basic fuzzy inference system model, it is designed for training data, and then the membership functions related to the basic fuzzy inference system were formed. In this regard, the membership functions related to the initial price variable in the range of 0 to 17000 Rials were formed with Gaussian functions and using the FCM clustering method based on the data of this variable in 10 clusters in different ranges within ten clusters.

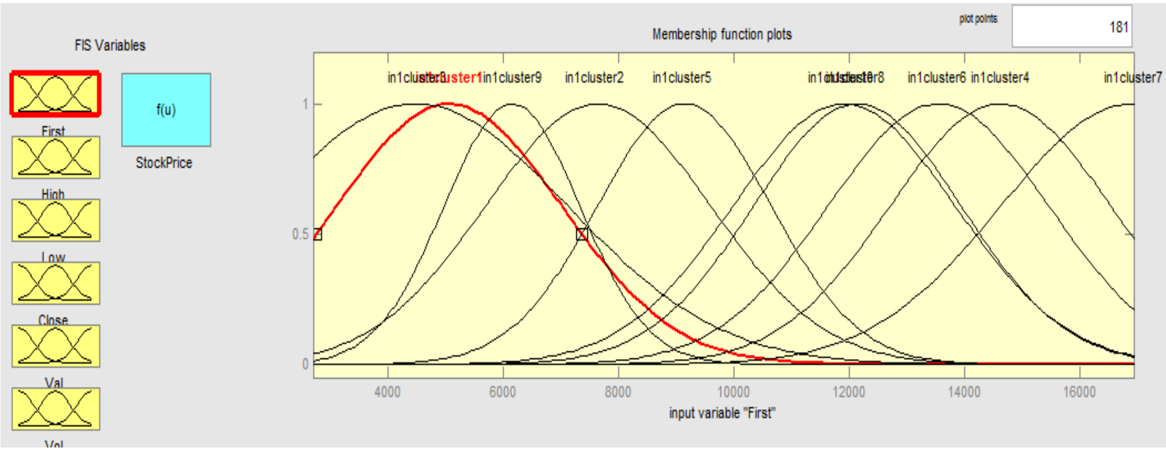


Figure 4. Membership functions related to the initial price variable for the basic fuzzy inference system.

Similarly, membership functions related to the highest price variable in the range of 0 to 17000 Rials were formed using Gaussian functions and in 10 clusters across different ranges.

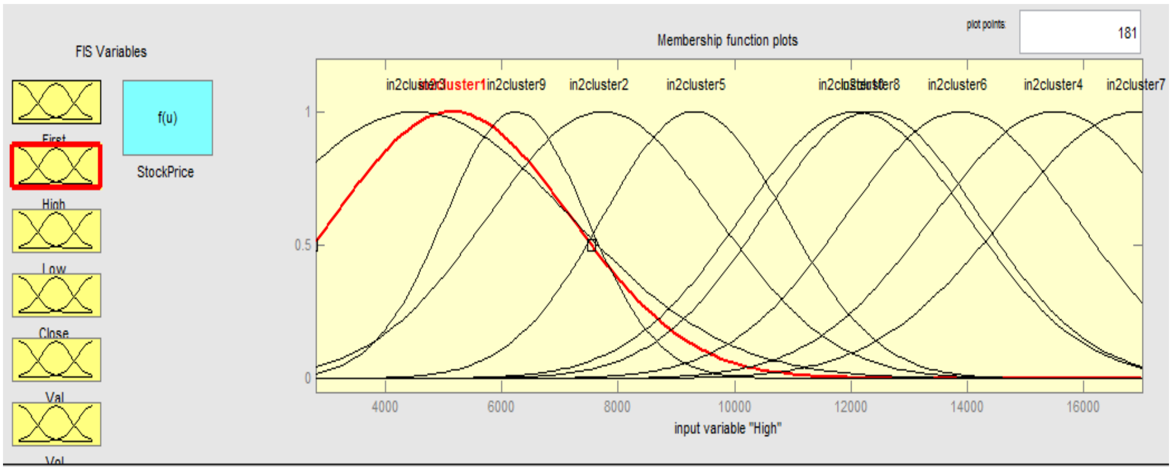


Figure 5. Membership functions related to the highest price variable for the basic fuzzy inference system

The membership functions related to the initial price variable in the range of 0 to 17000 Rials with Gaussian functions and the FCM method. This variable was formed into 10 clusters in different ranges within ten clusters.

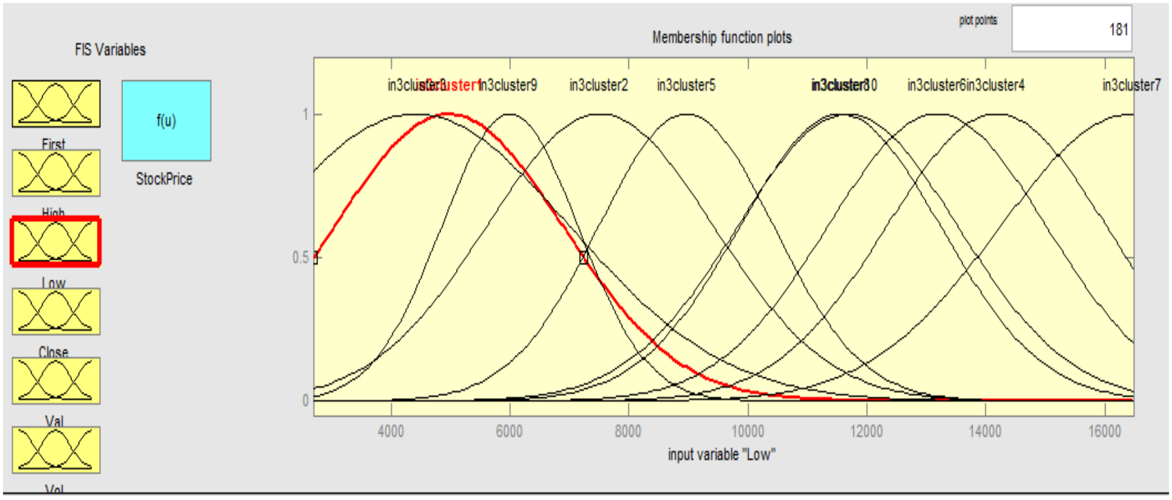


Figure 6. Membership functions related to the lowest price variable for the basic fuzzy inference system

The membership functions related to the closing price variable in the range of 0 to 17000 Rials with Gaussian functions and the FCM method. This variable was formed in 10 clusters in different ranges within ten clusters.

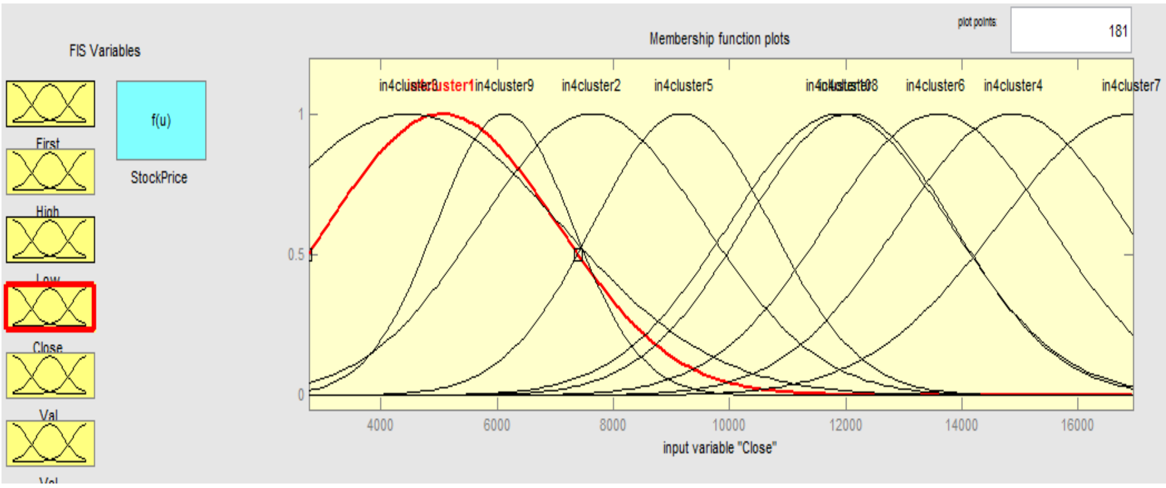


Figure 7. Membership functions related to the initial price variable of the basic fuzzy inference system

The membership functions related to the transaction value variable in the range of 0 to 8×10^{12} were formed using Gaussian functions and the FCM method based on the data of this variable in 10 clusters in different ranges within ten clusters.

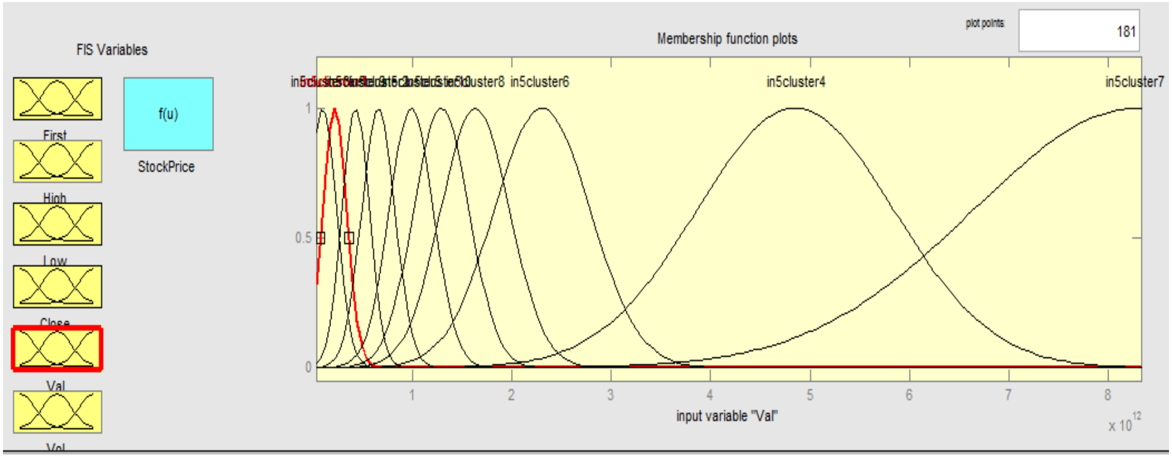


Figure 8. Membership functions related to the initial price variable for the basic fuzzy inference system.

The membership functions related to the trading volume variable in the range of 0 to 5×10^5 were formed using Gaussian functions and the FCM method based on the data of this variable in 10 clusters across different ranges.

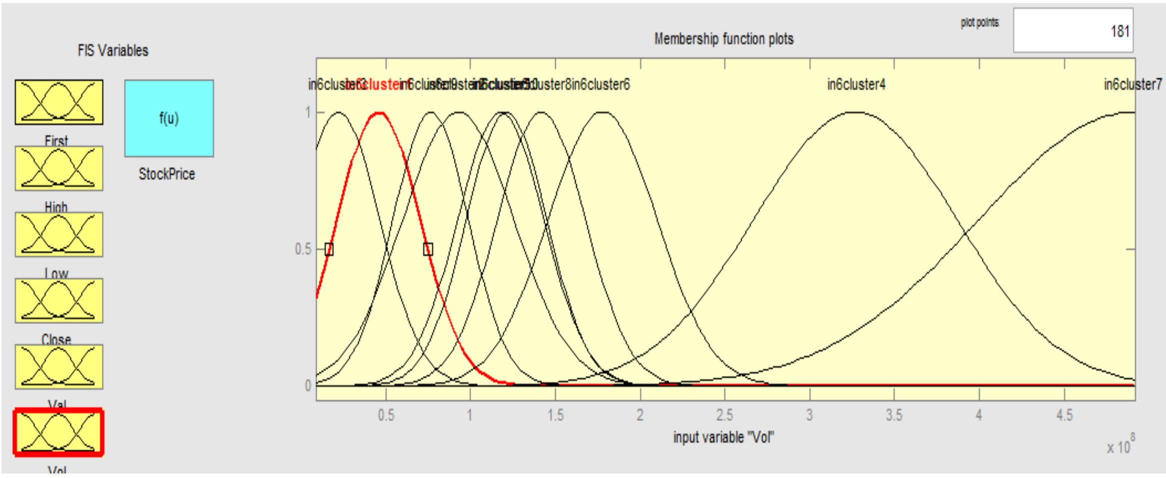


Figure 9. Membership functions related to the trading volume variable of the basic fuzzy inference system.

Next, in order to adjust the parameters of the basic fuzzy system, the genetic algorithm optimization algorithm was used based on the modeling error function. In fact, the input of the fuzzy algorithm is the parameters related to the membership functions of the basic fuzzy inference system. Finally, the membership functions in the optimal ranges related to the initial price variable of the optimal fuzzy inference system were calculated and formed for six variables.

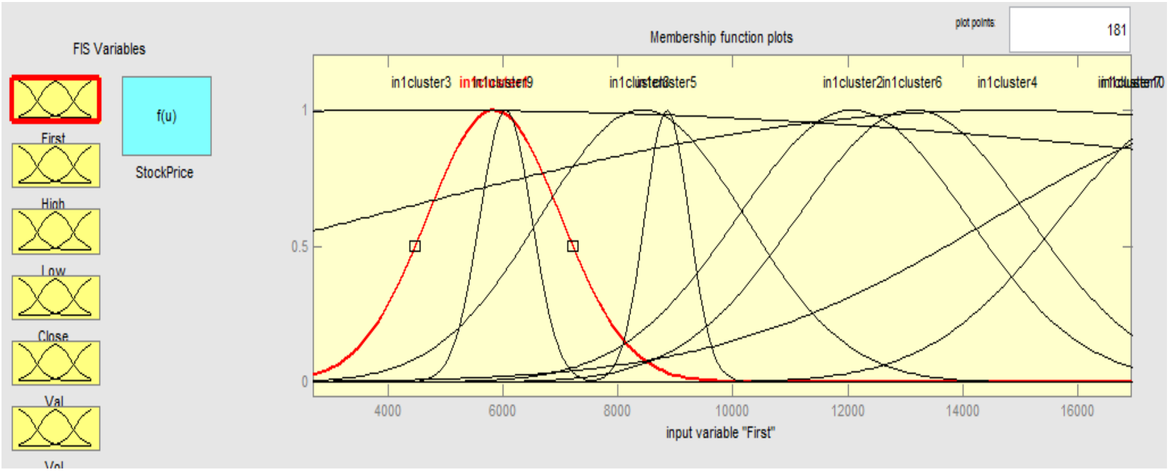
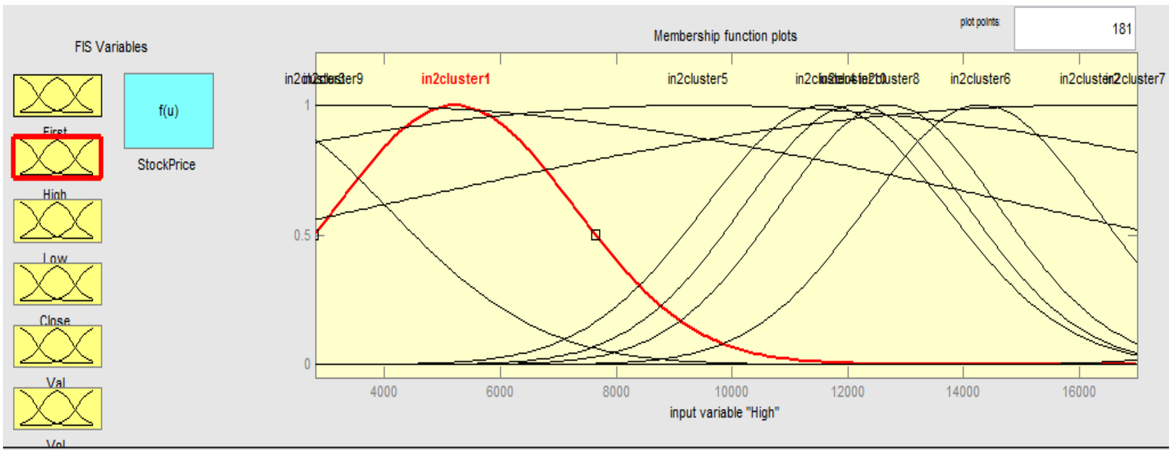
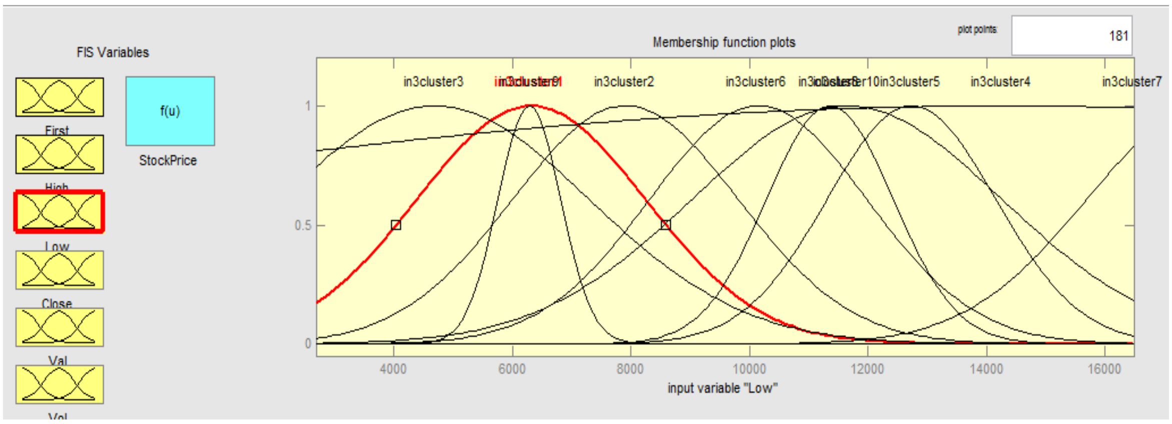


Figure 10. Membership functions related to the initial price variable for the optimal fuzzy inference system

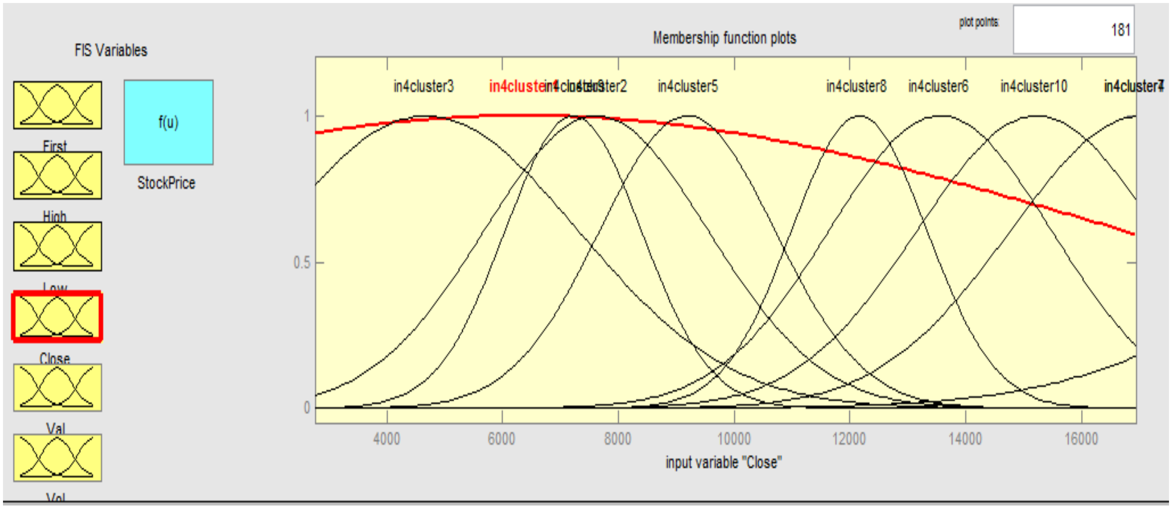
The optimal range membership functions related to the membership functions for the variables (a) highest price, (b) lowest price, (c) closing price, (d) transaction value, corresponding to the optimal fuzzy inference system, were calculated and formed.



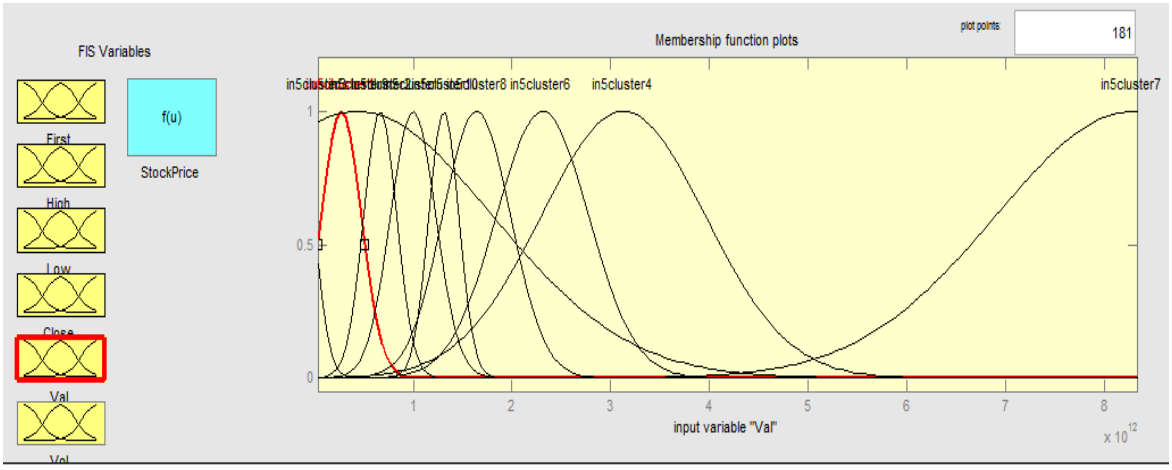
(a)



(b)



(c)



(d)

Figure 11. Membership functions related to the variables (a) highest price, (b) lowest price, (c) closing price, (d) transaction value, for the optimal fuzzy inference system.

Similarly, membership functions in the optimal ranges related to the initial price variable for the optimal fuzzy inference system were calculated and formed for six variables.

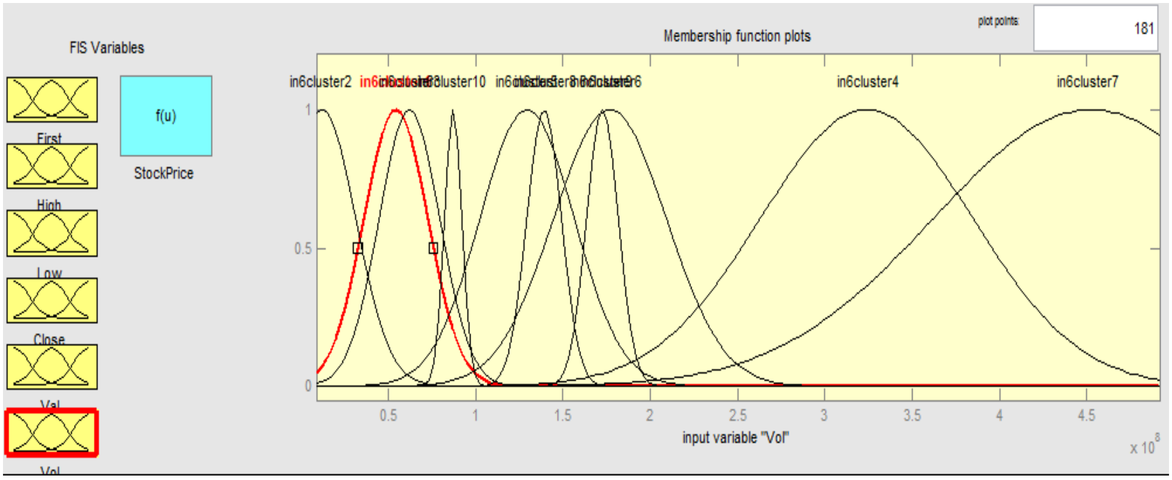


Figure 12. Membership functions related to the highest price variable for the optimal fuzzy inference system.

Then, the fuzzy rules of the optimal model were determined in 10 fuzzy rules.

- If the opening price is in the first cluster, the highest price in the first cluster, the lowest price in the first cluster, the closing price in the first cluster, the value of transactions in the first cluster, and the volume of transactions in the first cluster, then the stock price will be in the first cluster.
- If the opening price is in the second cluster, the highest price in the second cluster, the lowest price in the second cluster, the closing price in the second cluster, the value of transactions in the second cluster, and the volume of transactions in the second cluster, then the stock price will be in the second cluster.
- If the opening price is in the third cluster, the highest price in the third cluster, the lowest price in the third cluster, the closing price in the third cluster, the value of transactions in the third cluster, and the volume of transactions in the third cluster, then the stock price will be in the third cluster.
- If the opening price is in the fourth cluster, the highest price in the fourth cluster, the lowest price in the fourth cluster, the closing price in the fourth cluster, the value of transactions in the fourth cluster, and the volume of transactions in the fourth cluster, then the stock price will be in the fourth cluster.
- If the opening price is in the fifth cluster, the highest price in the fifth cluster, the lowest price in the fifth cluster, the closing price in the fifth cluster, the value of transactions in the fifth cluster, and the volume of transactions in the fifth cluster, then the stock price will be in the fifth cluster.
- If the opening price is in the sixth cluster, the highest price in the sixth cluster, the lowest price in the sixth cluster, the closing price in the sixth cluster, the value of transactions in the sixth cluster, and the volume of transactions in the sixth cluster, then the stock price will be in the sixth cluster.
- If the opening price is in the seventh cluster, the highest price in the seventh cluster, the lowest price in the seventh cluster, the closing price in the seventh cluster, the value of

transactions in the seventh cluster, and the volume of transactions in the seventh cluster, then the stock price will be in the seventh cluster.

- If the opening price is in the eighth cluster, the highest price in the eighth cluster, the lowest price in the eighth cluster, the closing price in the eighth cluster, the value of transactions in the eighth cluster, and the volume of transactions in the eighth cluster, then the stock price will be in the eighth cluster.
- If the opening price is in the ninth cluster, the highest price in the ninth cluster, the lowest price in the ninth cluster, the closing price in the ninth cluster, the value of transactions in the ninth cluster, and the volume of transactions in the ninth cluster, then the stock price will be in the ninth cluster.
- If the opening price is in the tenth cluster, the highest price in the tenth cluster, the lowest price in the tenth cluster, the closing price in the tenth cluster, the value of transactions in the tenth cluster, and the volume of transactions in the tenth cluster, then the stock price will be in the tenth cluster.

After defining the fuzzy rules, the weights (summation) of the weighted outputs, the sum of each of the 10 fuzzy rules of the model is added together.

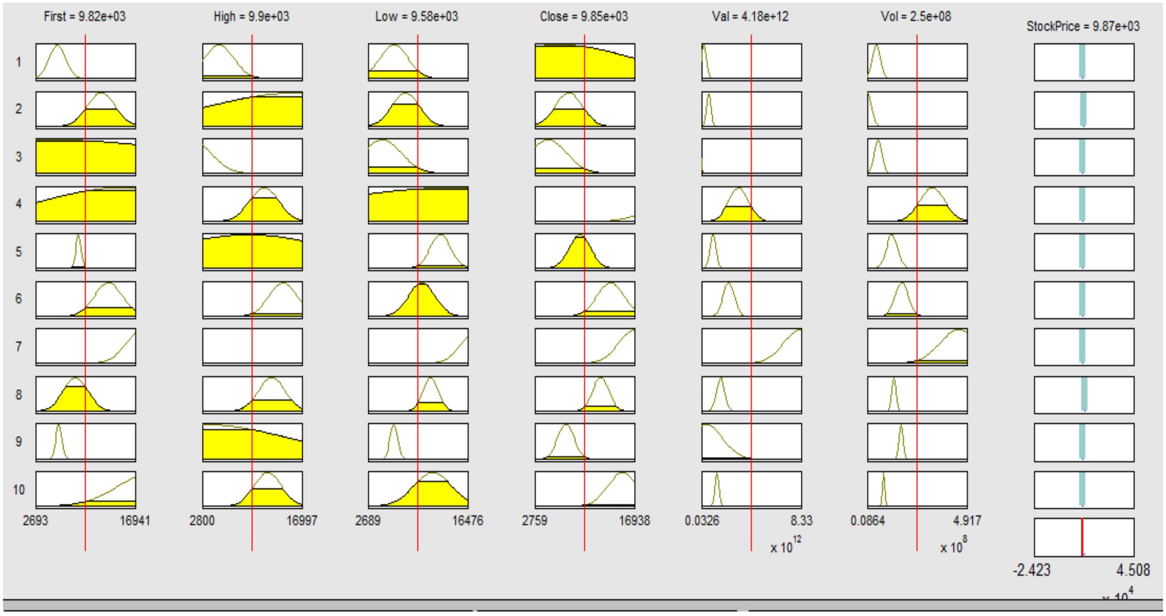


Figure 13. Final stock price estimation model with the proposed method

5 -Conclusion

The ANFIS method is one of the most important and effective artificial intelligence-based methods. This method is a combination of rules related to neural networks and fuzzy logic. In this method, fuzzy logic is used to improve the performance of neural networks by adding the concept of uncertainty to them. This method has been widely used in various articles, so using it can lead to increased prediction accuracy. In addition, to increase the speed and accuracy of the algorithm, it was combined with the genetic algorithm. In fact, identifying and creating a suitable structure for neuro-fuzzy systems before starting their training by the neural network is essential and highly effective in achieving final results. Creating a suitable structure for a neuro-fuzzy system largely depends on the researcher's taste and experience. In some cases, the created structure may not be optimal, and better structures might be available. For this purpose, after definition and preprocessing, data related to listed companies were entered into the system, and the output was generated based on the mean squared error method and its square root. The output is displayed in the form of three charts and the average percentage error. In the proposed method, input data are divided into two categories: training and testing. In the design of the hybrid network model, 6 variables (opening price, highest price, lowest price, closing price, trading volume, and final price) are used as input variables, and the stock price is used as the output variable. And the input data are converted into fuzzy numbers. Then, to design the basic fuzzy inference system model for training data, first, membership functions related to the basic fuzzy inference system are defined, and then the membership functions of the initial price variable for the range of 0 to 17000 Rials are performed using Gaussian functions and the clustering method in ten clusters based on the data. By examining various optimal states, Bank Mellat's share was placed on the efficient frontier and was determined as the best proposed share in the mentioned range. This research has advantages compared to other research. For example, this research is based on the result that Sutiene et al. (2024) used artificial intelligence methods for portfolio management. The use of artificial intelligence in finance can optimally demonstrate the requirements of transparency, fairness, and explainability. Unlike the study by Yang et al. (2024), who presented a synergistic multi-objective evolutionary algorithm with diffusion population generation for portfolio problems in their study, this research uses a novel intelligent hybrid model based on ANFIS. This study, while using computational tools as recommended by Sutiene et al. (2024), differs from the studies by Cui et al. (2023) and Zhang et al. (2023), which used traditional CVAR methods, contrary to the recommendations of the current research and Sutiene et al. (2024). This is because using ANFIS as an intelligent hybrid method for portfolio management can provide improved performance, flexibility, and accuracy. It is a combination of neural networks and fuzzy processing systems that has the ability to combine the power of both methods. This combination allows for the use of different artificial intelligence features to improve performance and accuracy in portfolio management. It has the ability to learn and adapt to different environments and conditions. This flexibility allows for improved efficiency and adaptation to current conditions and developments for portfolio management. As a hybrid system, it can benefit from parallel processing, which can increase the speed of operations related to portfolio management. It can combine high accuracy and the ability to interpret models. This feature can help portfolio managers make better decisions and achieve better strategies. Finally, comparing the performance and efficiency of artificial intelligence-based methods such as neural networks, evolutionary algorithms, reinforcement learning, and clustering in designing optimal portfolios and trading strategies is proposed as an approach for future research.

References

Aghamohammadi, R. , Tehrani, R. and Khademi, M. (2022). Investigating the Effect of Study Period Selection on Solving Portfolio Optimization Based on Different Risk Criteria Using Meta-Heuristic Algorithms. *Financial Management Perspective*, 12(37), 95-122. (In persian). doi: 10.52547/JFMP.12.37.95

Akbay, M. A., Kalayci, C. B., & Polat, O. (2020). A parallel variable neighborhood search algorithm with quadratic programming for cardinality constrained portfolio optimization. *Knowledge-Based Systems*, *198*, 105944.

Bertini, T. C. (2009, August). New model for cost of equity evaluation in emerging markets: The telecommunication sector in Brazil. In *2009 ITU-T Kaleidoscope: Innovations for Digital Inclusions* (pp. 1-5). IEEE.

Chan, M., & Linda, D. (2017). Income uncertainty, stock returns and cost of equity. A dissertation for the degree of doctor of philosophy, *The University of Arizona*.

Cui, T., Ding, S., Jin, H., & Zhang, Y. (2023). Portfolio constructions in cryptocurrency market: A CVaR-based deep reinforcement learning approach. *Economic Modelling*, *119*, 106078.

Delshad, M. M., Chobar, A. P., Ghasemi, P., & Jafari, D. (2024). Efficient humanitarian logistics: multi-commodity location–inventory model incorporating demand probability and consumption coefficients. *Logistics*, *8*(1), 9.

Faridi, S., MADANCHI, Z. M., Daneshvar, A., Shahverdiani, S., & Rahnama, R. F. (2022). Stock portfolio optimization based on the combined model of omega ratio and mean-variance Markowitz based on two-level ensemble machine learning. *FINANCIAL KNOWLEDGE OF SECURITY ANALYSIS (FINANCIAL STUDIES)*, 15(55), 33-54. (In persian). SID. https://sid.ir/paper/1063401/en

Ghasemi, F., Khadem, M., & Chobar, A. P. (2023). Supplier Selection for Supply Chain by Risk-Averse Decision Maker with Multi-Criteria Decision Making. *International journal of industrial engineering and operational research*, *5*(3), 50-62.

Haratizadeh, S. and Rezaee, F. (2023). A novel machine learning approach for portfolio optimization. *Journal of Decisions and Operations Research*, 8(2), 527-539. (In persian). doi: 10.22105/dmor.2022.307005.1488

Keihani, H. (2021). Macro Economic Factors Influencing the Indian Stock Market with Special Reference to Bombay Stock Market. *Shodh Sarita*, *8*(29), 263-268.

Keihani, H. (2025). Simulation-based on multi-objective optimization in complex system: A meta-modeling approach. *Complexity Analysis and Applications*, *2*(1), 25-38.

Mendonça, G. H., Ferreira, F. G., Cardoso, R. T., & Martins, F. V. (2020). Multi-attribute decision making applied to financial portfolio optimization problem. *Expert Systems with Applications*, *158*, 113527.

Mousavi, S. , Jafari Nodoushan, A. , Sangestani, M. and Moradi, M. (2022). Cardinality-constrained Value at Risk based Portfolio Optimization Using Krill Herd Metaheuristic Algorithm (Case study: Tehran Stock Exchange). *Financial Management Perspective*, 12(39), 147-169. (In persian). doi: 10.52547/JFMP.12.39.147

Nozari, H. (Ed.). (2023). Building Smart and Sustainable Businesses with Transformative Technologies. IGI Global.

Roudaki, M., Pourghader Chobar, A., Nagahi, A., Keihani, H., & Alamiparvin, R. (2025). Evaluation of supply chain performance using combination of DEA and fuzzy TOPSIS: A case from Iranian electric industry. *Journal of industrial engineering and management studies*, *12*(1), 114-124.

Samieifard, M., Abolghasemian, M., & Pourghader Chobar, A. (2024). The impact of innovation, performance, and e-commerce development in the online shop on online marketing: A case study in the industry. *Interdisciplinary Journal of Management Studies*, *18*(1), 1-17.

Sutiene, K., Schwendner, P., Sipos, C., Lorenzo, L., Mirchev, M., Lameski, P., ... & Cerneviciene, J. (2024). Enhancing portfolio management using artificial intelligence: literature review. *Frontiers in artificial intelligence*, *7*, 1371502.

Yang, M., Qian, W., Yang, L., Hou, X., Yuan, X., & Dong, Z. (2024). A Synergistic multi-objective evolutionary algorithm with diffusion population generation for portfolio problems. *Mathematics*, *12*(9), 1368.

Yordanova, Z., & Nozari, H. (2025). Harnessing Cyber-Physical Systems and Digital Twins for Industrial Innovation and Economic Resilience. In Dynamic and Safe Economy in the Age of Smart Technologies (pp. 33-48). IGI Global Scientific Publishing.

Zhang, Z. X., Chen, W. N., & Hu, X. M. (2023). A knowledge-based constructive estimation of distribution algorithm for bi-objective portfolio optimization with cardinality constraints. *Applied Soft Computing*, *146*, 110652.