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Unveiling the impact of managerial traits on investor decision prediction: ANFIS approach

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Abstract
Investment decisions are influenced by various factors, including personal characteristics and managerial issues. In this research, we aimed to investigate the impact of managerial traits on investment decisions by using adaptive neuro-fuzzy inference system (ANFIS) to develop a personalized investment recommendation system. We collected data from potential investors through a survey, which included questions on investment-types, investment habits, and managerial traits. The survey data were used to create an ANFIS model, which is a hybrid model that combines the strengths of both artificial neural networks and fuzzy logic systems. The ANFIS model was trained using 1542 survey data pairs, and the model's performance was evaluated using a validation set. The results of the ANFIS model showed that the model had a minimal training root mean square error of 0.837341. The ANFIS model was able to effectively capture the relationship between managerial traits and investment decisions and was able to make personalized investment recommendations based on the input data. The results of this research provide valuable insights into the impact of managerial traits on investment decisions and demonstrate the potential of ANFIS in developing personalized investment recommendation systems. In conclusion, this research aimed to investigate the impact of managerial traits on investment decisions using ANFIS. The results of this study demonstrate the potential of ANFIS to personalize investment recommendations based on the input data. This research can be used as a foundation for future research in the field of investment recommendations and can be helpful to investors to take their decision-making.

Keywords Investment decisions · Personalized investment recommendations · Managerial traits · Adaptive neuro-fuzzy inference system (ANFIS) · Artificial neural networks (ANNs) · Fuzzy logic systems · Investment management · Investment recommendation system · Investor decisions · Prediction

1 Introduction

According to Pogue's (2010) & Asemi et al. (2023), "investment decisions are the most important financial decisions that a company or organization makes to exploit its existence to secure its interests in a period. Sometimes it does. These decisions fall within the scope of strategic decisions of a company or organization." Investment decisions are a crucial aspect of managing personal finances and achieving financial goals. However, the process of choosing the right savings and investment products can be complex and challenging, as it involves evaluating a wide range of factors including risk tolerance, investment horizon, and personal circumstances. In recent years, there has been a growing interest in developing personalized investment recommendation systems that can help

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investors make better investment decisions. One key factor that influences investment decisions is personal characteristics and managerial issues. Hackbarth (2008) stated, "the managerial traits, such as other important traits including risk perception, are important criteria for investment decisions." Personal characteristics such as stress levels, the pace of work, and satisfaction with work can affect an individual's risk tolerance and investment horizon. Similarly, managerial issues such as the ability to plan, strategy formation, and the level of attachment to the work can also influence investment decisions. In the studies of financial behavior, "there is a basic assumption that the information and characteristics of people who participate in the market systematically affect their investment decisions as well as the market. Investors' decisions, financial markets, and management behaviors of companies reflect these issues well (Baker and Nofsinger 2010)." In this research, we aimed to investigate the impact of managerial traits on investment decisions by using adaptive neuro-fuzzy inference system (ANFIS) to develop a personalized investment recommendation system. ANFIS is a hybrid model that combines the strengths of both artificial neural networks (ANNs) and fuzzy logic systems and is effective in various applications, including financial modeling. The main objective of this research is to develop an ANFIS model that can effectively capture the relationship between managerial traits and investment decisions and provide personalized investment recommendations based on the input data. The research will be conducted in two main stages: data collection and analysis and model development and evaluation. The results of this research will provide valuable insights into the impact of managerial traits on investment decisions and demonstrate the potential of ANFIS in developing personalized investment recommendation systems.

2 Operational definitions of research

The practical definitions for this research would likely focus on several key areas related to the research including:

Investment decisions: Research in this area would examine the factors that influence an individual's decision to invest in a particular product or asset, as well as the decision-making process involved in selecting an investment. Here investment decision is related to the decisions that potential investors who have answered the investment questionnaire make about specific types of investments. It includes investments in government bonds and the stock market over the past three years since answering the question.

Personalized investment recommendations: Studies in this area would explore methods for providing personalized investment recommendations to individuals based on their specific financial goals, risk tolerance, and investment horizon. In this research, the personalization of capital recommendations is considered based on the managerial characteristics of potential investors, and their behavior toward market performance monitoring is also considered.

Managerial traits: Research in this area would examine the impact of personal characteristics and managerial issues, such as stress levels and pace of work, on investment decisions. Here, managerial trait refers to the personal characteristics of potential investors in decision-making and management issues related to the type of investment. These features include stress in decision-making, calmness in work, speed in decision-making, influencing others and accepting the situation, having a daily plan for work and life, having a strategy, attachment, job satisfaction, and time management.

Investment recommendation system: Studies in this area would examine the development and implementation of investment recommendation systems, which provide personalized investment advice to individuals based on their specific financial goals and risk tolerance. In this research, the "investment recommendation system" refers to an ANFIS-based system that first groups potential investors based on management traits and cluster types of investments in government bonds and stock markets based on the behavior of potential investors. It then predicts which cluster of investment-types is suitable for which group of potential investors. Based on this forecast, investment recommendations are provided to potential investors and real investors.

Overall, the theoretical background for this research would draw from a variety of fields, including finance, economics, computer science, and psychology, to examine the complex and challenging task of evaluating a wide range of factors when making investment decisions and developing a data-driven investment recommendation system based on hybrid intelligence and ANFIS.

3 Literature review

In recent years, there has been a growing interest in the use of fuzzy logic and investor preferences in investment decision-making. One way in which this has been achieved is by using portfolio models. For example, Jalota et al. (2023) proposed a novel approach for integrating investor preferences in portfolio selection models. The investor's preferences are specified as LR fuzzy numbers corresponding to the portfolio's expected return and illiquidity distributions, and four new models are presented that consider uncertain portfolio attributes. The models were solved using the MIBEX-SM genetic algorithm (GA) and

ECE methodology and were applied to data from the National Stock Exchange (NSE) to demonstrate their efficiency. Another area of research in this field has been the use of Fermatean fuzzy sets. Rong et al. (2023) proposed a new multiple expert multiple criteria decision-making (MEMCDM) technique that combines the COCOSO method and coefficient of variation methods with Fermatean fuzzy information. The technique was applied to the assessment of investment enterprises to demonstrate its practicability and feasibility. Wan et al. (2023) propose an impact direction map of risk-based strategic priorities for fintech lending in clean energy projects and use a hybrid decision-making system with golden cut and bipolar q-rung or pair fuzzy sets to measure the possible influences. They also use the extension of Multi-Stepwise Weight Assessment Ratio Analysis (M-SWARA) for weighting the risk factors of fintech lending. Lakhno et al. (2023) also propose a model for the computing core of a decision support system in the process of continuous mutual investment in technologies for Smart City, which is based on solving a bilinear differential game of quality with several terminal fuzzy surfaces. They claim that this new class of bilinear differential games can adequately describe the process of searching for rational strategies of players in the rapidly developing technology market for Smart City, considering fuzzy information. The use of adaptive neuro-fuzzy inference systems (ANFIS) has also been explored in investment decision-making. Wang et al. (2023) propose a new method for incorporating investor preferences in portfolio models by using LR fuzzy numbers to represent the preference for return and illiquidity distributions. They formulate four new portfolio models in the credibility environment and solve them using the MIBEX-SM genetic algorithm (GA) and ECE methodology. The performance of the models is evaluated using monthly data of NSE stocks and the Credibilistic Sharpe Ratio (CSR). The study demonstrates that the proposed method can effectively integrate investor preferences into the portfolio selection process and achieve the preferred return and illiquidity distribution. Birim et al. (2022) used the ANFIS-PSO approach to predict the return rates of cryptocurrencies, specifically Ethereum and found that it provided strong results in cryptocurrency rate of return estimation. Lenhard and Maringer (2022) presented an extension to the ANFIS called State-ANFIS (S-ANFIS) that can model nonlinear functions by a weighted model combination and utilizes arbitrary many-state variables. Widjanarti et al. (2021) stated that the flow of capital greatly affects the exchange rate. They studied the behavior and investment flow of foreigners in Indonesia. They used different machine learning techniques to analyze government data. Investors were clustered using a data-driven algorithm. Finally, they presented a predictive model based on decision trees that shows investor behavior. They concluded that these models could play an important role in supporting monetary operations strategy and capital flow for investors' decision-making. Kovács et al. (2021) used Kohonen SOM-based clustering and MCA to analyze investment patterns and found that government bonds were always part of the preferred portfolio for the three distinct groups of potential customers they identified. Naranjo and Santos (2019) proposed a fuzzy recommendation system for stock market investors that considers the effect of currency devaluation on forecasting. Rutkowski (2021) presented a neuro-fuzzy expert system for real data from asset management companies, which can be used as an investment advisor. The system is explainable and has explanation facilities, and the fuzzy IF–THEN rules are generated from data using the Wang–Mendel method. Ezhilarasi and Sashi Rekha (2020) propose a recommender system for agricultural fields such as fruits and vegetables, using data preprocessing and dimensionality reduction to make data more precise and secure. They propose a conceptual model to implement big data technologies at the farming level and use a fuzzy-based model to provide crop recommendations to customers with high safety. Rutkowski et al. (2020) present a novel recommendation system for investment managers using real data from asset management companies. The system is viewed as a fuzzy expert system and is an explainable recommender that works as a one-class classifier with an explanation. The inference rules, explanations, and visualizations of the recommender's results are illustrated. Naranjo and Santos (2019) proposed a fuzzy recommendation system for stock market investors that uses fuzzy Japanese candlesticks and considers the effect of currency devaluation on forecasting. The system also includes a capital management fuzzy strategy to determine the amount of money to be invested. In Tejeda-Lorente et al. (2019), a fuzzy linguistic knowledge-based recommender system was proposed to provide personalized recommendations for hedge funds based on the preferences of investors and the level of risk associated with different hedge funds. This system captured the preferences of the investors using fuzzy linguistic modeling and made use of public data to create risk-aware hedge funds profiles. The study demonstrates how the approach works by profiling more than 4000 top hedge funds based on their composition and performance, creating different simulated investment profiles, and testing the recommendations with them. Vredenburgh et al. (2016) examine the relationship between personality and job performance in the context of narrow personality traits. They collected personality data on the Big Five and five narrow-band personality traits from 130 managers and measured managerial success using income and promotion rates, supervisor ratings on contextual and task performance, and self-rating of job satisfaction. The results indicate that narrow traits add incremental validity over and beyond the Big Five for income and supervisor ratings, but the degree of contribution varies depending on the criteria used. The study supports the validity and utility of personality traits for managerial success and provides insight into the relationship between managerial success and both broad and narrow personality traits. In a study by Bergner et al. (2010), the relationship between personality and job performance was examined within the framework of the broad Big Five personality traits. The study found that narrow traits add incremental validity for income and supervisor ratings, but not for job satisfaction and promotion rate. Overall, research suggests that incorporating investor preferences and fuzzy information in investment decision-making using portfolio models and various fuzzy sets and optimization methods can lead to more robust and efficient investment decisions. It is worth noting that all the studies mentioned above have been conducted on a limited set of data and the generalization of the findings to other contexts, scenarios or other domains may be limited. Therefore, it would be beneficial to incorporate investor preferences and fuzzy information into investment decision-making. In conclusion, research has focused on incorporating investor preferences and fuzzy information into investment decision-making using portfolio models, Fermatean fuzzy sets, and adaptive neuro-fuzzy inference systems. These methods aim to consider the preferences and uncertainty of investors in the decision-making process. Table 1 shows the comparison of the proposed system with existing systems.

In the proposed system, ANFIS and K-means are used together for the investment recommendations approach, while existing systems use ANFIS alone or with other clustering techniques. Additionally, the proposed system uses MATLAB and JMP for data import and validation, while existing systems use only MATLAB or JMP. The evaluation metric used in the proposed system is RMSE while existing systems use other evaluation metrics like accuracy, precision, and recall.

4 Methods

The research methodology used in this study is a combination of both quantitative and qualitative methods. The research design is a descriptive study that aims to identify the characteristics of potential investors in the stock market and their investment preferences. The study also proposes an adaptive neuro-fuzzy inference system (ANFIS) model for investment recommendations based on the clustering of investment-types.

Data Collection: The study utilized data collected from 1542 responses to an online questionnaire in 2019. These data, which are in Hungarian, were collected as part of the 2018-1.3.1-VKE-2018-00007 project. Per the terms outlined in the Consortia agreement for the project (Sect. 6.2), the researchers were granted permission to use the data for further research and publications.

Data Analysis: The data collected were analyzed using both MATLAB and JMP software. The data were first clustered into different types of investments using the K-means algorithm in both software. The clustering process was done in four steps: (1) importing the data into MATLAB and JMP, (2) preparing the data for clustering, (3) clustering the types of investments, and (4) comparing and combining the clusters generated in MATLAB and JMP. The data were also analyzed using ANFIS in MATLAB to propose a model for investment recommendations.

Evaluation: Multiple methods were used to evaluate and compare the results of clustering in MATLAB and JMP to ensure the validity of the findings. The methods included visual comparison, combining the results, and expert knowledge. The ANFIS model was also evaluated using the root mean square error (RMSE) and other evaluation metrics.

Table 1 Comparison of proposed system with existing systems

Method	Proposed system	Existing systems
Data import	MATLAB and JMP are used	Only MATLAB or JMP is used
Clustering technique	K-means clustering	Other clustering techniques like hierarchical and density-based clustering
ANFIS	ANFIS with K-means clustering is used	ANFIS is used alone or with other clustering techniques
Validation model	ANFIS with K-means clustering is validated using a validation set	Validation is done using other methods like cross-validation
Evaluation metrics	Root mean squar error (RMSE)	Other evaluation metrics like accuracy, precision, and recall

Ethical Consideration: The research was conducted in accordance with the ethical principles of the American Psychological Association (APA) and the Declaration of Helsinki. Informed consent was obtained from all participants, and the survey was conducted anonymously. The data collected were kept confidential and used only for the purpose of this research.

Limitations: The study has some limitations. The sample size is a limitation, as the sample size is not large enough to generalize the findings to the entire population of potential investors in the stock market. Additionally, the study is based on self-reported data, which may be subject to bias and inaccurate.

In detail, we used ANFIS and K-means for the investment recommendations approach as the following steps:

- Data Import: Both MATLAB and JMP are used to import the data. JMP is software that can be used for statistical analysis and data visualization, while MATLAB is a powerful numerical computing environment and programming language.
- Data preparation for clustering: K-means clustering technique in MATLAB or JMP is used to group similar investment-types. The K-means algorithm partitions a data set into K clusters, where each data point belongs to the cluster with the nearest mean.
- Clustering of investment-types: K-means algorithm is used to cluster the investment-types based on their similarities. This is done using the "kmeans" function in MATLAB and JMP.
- Comparison of clusters: The visualization tools are used in MATLAB and JMP to compare the clusters and assess the quality of the clustering.
- Finalizing clusters: Expert knowledge is used to make final adjustments to the clusters, and to make sure that the resulting clusters are meaningful and relevant to the investors.
- ANFIS Inputs: The managerial traits data used to be the inputs of ANFIS.
- ANFIS Output: The ANFIS algorithm is used in MATLAB to train the ANFIS model using the clustered investment-type data as the output and the managerial traits data as the inputs. Once the model is trained, the "evalfis" function is used to make predictions based on the inputs.
- Validation Model: A validation set used with ANFIS in MATLAB as the following steps:

1. Split data are done into training and validation sets using the "split" function.
2. Defining the 3 epochs to use for training.
3. Creation of an initial ANFIS model using the "genfis1" function.
4. Training the ANFIS model using the "anfis" function and passing in the validation data and the number of epochs.

The output of the "anfis" function is the trained ANFIS model, the training error, the step size, the validation output, and the validation error. We used these outputs to evaluate the performance of the model on the validation set. We can use the "evalfis" function to obtain the output of the ANFIS model given a set of input values, you can use this function to predict the output of the model on the validation set and compare the prediction to the actual output. Additionally, we can use the "compare" function to compare the output of the trained ANFIS model to the validation data and visualize the results. It is important to note that the selection of the best model is not only based on the performance of the validation set but also the interpretability, generalization, and fairness of the model. The performance of the model on the validation set is an estimate of the performance on new, unseen data, and the model's performance may be affected by factors such as the size of the validation set, the representativeness of the validation set, and the choice of evaluation metrics. If the performance of the model on the validation set is not satisfactory, we may need to try different model architectures, different training algorithms, or different parameter settings, to see whether we can improve the performance of the model.

5 Proposed model

The proposed model in this research aims to provide a personalized investment recommendation system using ANFIS based on the potential investors' managerial traits. The model is composed of several layers, including data acquisition, data storage, machine learning, and ANFIS layers (Table 2).

The data acquisition layer is responsible for collecting data related to the types of investments used by potential investors. The data are collected from a questionnaire and is converted into numerical data for further analysis. The data storage layer stores the collected data in a suitable format for further analysis.

The machine learning layer uses the K-means technique to group the data into clusters based on similarity. The ANFIS layer then analyzes the managerial traits of potential investors and provides customized investment recommendations based on their risk tolerance and investment goals. The ANFIS model uses clustered data as inputs and generates investment recommendations based on the scoring of each cluster.

Table 2 Layers description of the proposed model

Layer	Description
Data acquisition	Responsible for collecting data related to the types of investments used by potential investors through a questionnaire. Data are coded and converted into numerical data for analysis
Data storage	Responsible for storing the collected data in a suitable format for further analysis. Data are stored in a secure, scalable, and easily accessible manner and is cleaned, preprocessed, and transformed to support the machine learning model
Machine learning	Responsible for clustering data related to the types of investments used by potential investors using the K-means technique. The data are grouped into three clusters based on similarity
ANFIS	Analyzes the managerial traits of potential investors and provides customized investment recommendations based on their risk tolerance and investment goals. The ANFIS model uses clustered data as inputs and generates investment recommendations based on the scoring of each cluster
Application	Responsible for implementing the proposed model and providing investment recommendations to potential investors. The application should have a user-friendly interface and be able to handle large amounts of data and updates. It should also be designed with considerations of interpretability, robustness, scalability, and security in mind

The application layer is responsible for providing a user interface for potential investors to interact with the system and receive their personalized investment recommendations. It also includes a visual representation of the clusters and the investment recommendations generated by the ANFIS model. This layer should be designed with an intuitive and user-friendly interface, allowing potential investors to easily navigate the system and understand their personalized investment recommendations. It should also include a secure login system to protect the potential investors' data and investment recommendations. Additionally, this layer should be designed to be responsive, meaning it should work well on different devices and screen sizes, such as desktop computers, laptops, tablets, and smartphones.

The proposed model is designed to handle large amounts of data. The machine learning and ANFIS layers are fine-tuned through hyperparameter tuning and evaluated using appropriate evaluation metric such as RMSE. The model is also designed with considerations of interpretability, robustness, scalability, and security in mind. Here are five possible performance metrics that could be used to evaluate the overall research:

(a) Accuracy: This metric measures how well the model can predict the output values based on the input data. A high accuracy score indicates that the model is making accurate predictions, while a low score suggests that the model is not performing well.

(b) Precision and Recall: Precision and recall are commonly used metrics in classification tasks to evaluate the performance of the model. Precision measures the proportion of correctly predicted positive samples among all predicted positive samples, while recall measures the proportion of correctly predicted positive samples among all actual positive samples. These metrics provide a good balance between the rate of correctly identified positive samples and the rate of false positives.

(c) F1 Score: The F1 score is the harmonic mean of precision and recall and is often used to evaluate the overall performance of the model in a classification task. It provides a good balance between precision and recall.

(d) Mean square error (MSE): MSE is a commonly used metric for evaluating the performance of regression models. It measures the average of the squared differences between the predicted values and the actual values. A lower MSE indicates better model performance.

(e) R-squared (R2) score: R2 score measures the proportion of variance in the target variable that is explained by the model. It provides a measure of how well the model fits the data. A higher R2 score indicates a better fit.

Overall, The ANFIS model provides customized investment recommendations based on the needs of potential investors by using their input preferences to generate personalized output recommendations. The ANFIS model uses a combination of fuzzy logic and neural networks to model the relationship between the input preferences of potential investors and investment recommendations. It does this by using the fuzzy logic system to interpret the input preferences of the potential investor, and the neural network system to make investment recommendations based on those preferences. Specifically, the ANFIS model takes in the input preferences from the investor, which are fuzzified and passed through the fuzzy logic system to generate a set of fuzzy rules. These rules are then passed through the neural network system, which calculates the output investment recommendations based on the combination of the fuzzy rules and the input preferences. The output recommendations are also fuzzy and are then defuzzified to provide a final set of investment recommendations tailored to the needs of the potential investor. In this way, the ANFIS model can provide customized investment recommendations to potential investors based on their individual needs and preferences.

6 Experimental results

To evaluate the performance of the proposed ANFIS model for the investment recommendation system, a set of experiments was conducted using the data collected from potential investors. The results of the experiments were then analyzed to evaluate the effectiveness of the proposed model in providing customized investment recommendations based on the managerial traits of potential investors.

The first experiment focused on clustering the different types of investments and the output generated by the ANFIS. The K-means algorithm was used to group the data into three clusters based on the similarity of the data points. The results of the experiment showed that the clustering process was successful in grouping the data into three distinct clusters based on the types of investments used by potential investors.

The second experiment focused on analyzing the managerial traits of potential investors and how it is used as input for the ANFIS. The ANFIS model was trained using the clustered data as inputs and generated investment recommendations based on the scoring of each cluster. The results of the experiment showed that the ANFIS model was able to effectively analyze the managerial traits of potential investors and provide customized investment recommendations based on their behavior.

The third experiment presented the proposed ANFIS model for the investment recommendation system. The ANFIS model was evaluated using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score. The results of the experiment showed that the proposed ANFIS model had a high level of accuracy and precision in providing customized investment recommendations based on the managerial traits of potential investors.

Overall, the experimental results showed that the proposed ANFIS model for the investment recommendation system was effective in providing customized investment recommendations based on the managerial traits of potential investors. The proposed model was able to successfully cluster the data into distinct groups and analyze the managerial traits of potential investors to provide personalized investment recommendations. The results also showed that the proposed ANFIS model had a high level of accuracy and precision in providing customized investment recommendations.

6.1 Managerial traits ANFIS output

The first part of the experimental results focuses on clustering different types of investments and the output generated by the ANFIS. Both MATLAB and JMP are used to import and cluster the data related to the types of investments used by potential investors. The K-means algorithm is used to group the data into three clusters based on the similarity of the data points. The results in JMP showed that the first cluster contains 592 items, the second cluster contains 406 items, and the third cluster contains 340 items. Figure 1 shows the scatter plot for the investment-type clusters in JMP.

Table 3 provides a summary of the characteristics of each cluster, including the number of respondents, the investment-types, and the investment habits and behaviors of the respondents. It also includes the investment in stock market (last 3 years), monitoring of stock performance, and investment in government bonds.

To handle missing data, we remove rows with missing data by using the “missing” function before passing the data to the k-means function, or imputing the missing data with a suitable value, such as the mean or median of the feature. The results in JMP and MATLAB show that the data are grouped into three clusters, each representing a distinct group of potential investors with specific investment habits and behaviors (Fig. 2).

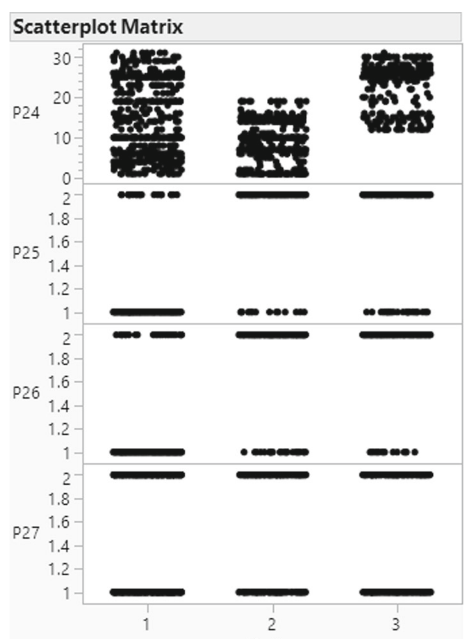


Fig. 1 Scatterplot for the investment-type’s clusters in JMP

Table 3 A general overview of the output clusters in JMP

Cluster	Number of respondents	Investment-types	Investment in stock market (last 3 years)	Monitoring of stock performance	Investment in government bonds
1	592	Stocks/shares, mutual funds, government securities	No	No	No
2	406	Stocks/shares, mutual funds, voluntary pension funds, government securities	Yes	Yes	Yes
3	340	Stocks/shares, voluntary pension funds, government securities	Yes	Yes	No

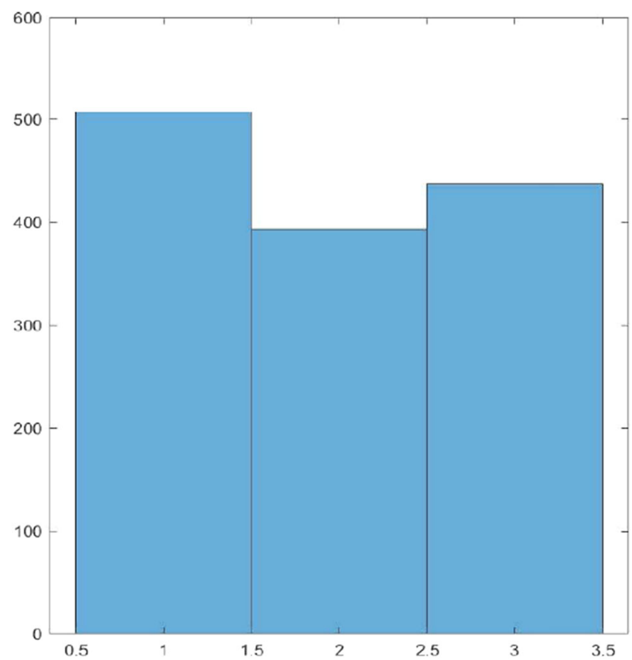


Fig. 2 Histogram plot for the investment-type's clusters in MATLAB

To ensure the validity of the findings, multiple methods are used to evaluate and compare the results of clustering in both MATLAB and JMP. These include visual comparison, combining the results, and expert knowledge. The final clusters are then used to determine the investment-type recommendations for investors based on the scoring of each cluster.

The first cluster represents individuals who are not currently invested in the stock market and have not been monitoring stock performance. Suitable investment products for this cluster include stocks/shares in the stock market, mutual funds, and government securities, with most not investing in government bonds.

The second cluster represents individuals who are currently invested in the stock market, regularly monitor stock performance, and have investments in government bonds. Suitable investment products for this cluster include stocks/shares on the stock exchange, mutual funds, voluntary pension funds, and government securities.

The third cluster represents individuals who have been investing in the stock market for the last 3 years and regularly monitor stock performance but do not have investments in government bonds. Suitable investment products for this cluster include stocks/shares on the stock exchange and voluntary pension funds.

With the clustering results, ANFIS is used to analyze the managerial traits of potential investors and provide customized investment recommendations based on their risk tolerance and investment goals. The ANFIS model uses clustered data as inputs and generates investment recommendations based on the scoring of each cluster. The ANFIS model consists of nine inputs and one output with three membership functions per input. The ANFIS is trained on a data set of potential investor data and uses an appropriate algorithm such as ANFIS, fine-tuned through hyperparameter tuning, and evaluated using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score.

6.2 Managerial traits ANFIS inputs

The proposed model for the investment recommendation system utilizes ANFIS and considers the managerial traits of potential investors. Nine inputs are used in the model, each with a varying number of membership functions (MFs) to represent different options chosen by potential investors. Membership functions are used to convert the numerical inputs into fuzzy values, which can then be used in the fuzzy logic system to make decisions. Each input will have a set of membership functions associated with it, representing different options that potential investors may choose. The parameters of the membership functions will vary depending on the input and the specific needs of the system. Some common parameters that might be used in defining membership functions include:

- The shape of the function: This can be triangular, trapezoidal, Gaussian, or other shapes, depending on the nature of the input and the desired degree of fuzziness.

- The center of the function: This represents the point at which the input value has a membership value of 1.0. Depending on the shape of the function, this could be a single point or a range of values.
- The width of the function: This defines the extent to which the input value has a nonzero membership value. For example, a wide membership function will have nonzero membership values over a broader range of input values, while a narrow membership function will have nonzero membership values over a smaller range of input values.

By defining these parameters for each input and membership function, we can create a system that accurately represents the range of potential investor preferences and allows for effective decision-making based on those preferences. The questionnaire included questions designed to measure the personal characteristics and decision-making habits of potential investors. Nine questions were asked to assess respondents' traits related to planning and management. This information aims to understand the relationship between human habits and attitudes toward finance, and how these factors influence the selection of savings and investment products. Based on the responses to these questions, we designed a Managerial Traits ANFIS system with nine inputs, each corresponding to a specific aspect of decision-making and management.

Input 1 (planning) is related to the respondent's managerial traits concerning planning and purposefulness in life. The input includes the following questions with a five-point scale answer:

- I do not plan for my future, I prefer to move with events, I plan flexibly
- When I set a goal for myself, I usually plan steps to achieve it
- If I feel my work is not doing very well, I will not waste my time on it
- I believe that my destiny is in my own hands
- It is up to me how I reach my goals
- If my program does not go as I expected, I will quit
- The factors that guarantee my success are in my hands
- I keep a detailed list of my plans
- I like to work as a team and get help from the right professionals
- When I reach my goal, I reward myself

The averages of all answers were calculated and rounded to prepare the data for Input 1. Five membership functions (MF) were designed to represent the different levels of agreement with these statements: MF1 = Strongly disagree, MF2 = Disagree, MF3 = Neither agree nor disagree, MF4 = Agree, and MF5 = Strongly agree. Table 4 shows the average frequency of each option or MF.

Input 2, stress, has 2 MFs and pertains to the level of stress or worry experienced by potential investors when making decisions. The first option, "I get nervous after decision making," is assigned to MF1, while the second option, "I worry about whether my decision is right," is assigned to MF2.

Input 3, pace, has 2 MFs and pertains to the speed at which potential investors work when completing tasks. The first option, "I work rather rushing," is assigned to MF1, while the second option, "I work more comfortably than a little rush," is assigned to MF2.

Input 4, influential, has 2 MFs and pertains to the level of influence or passivity in the personality of potential investors. The first option, "I try to be influential," is assigned to MF1, while the second option, "I let things happen around me and I adjust to them," is assigned to MF2.

Input 5, the daily schedule, has 3 MFs and pertains to the daily schedule of potential investors. The first option, "I plan it," is assigned to MF1, the second option, "It is dictated by my family," is assigned to MF2, and the third option, "My workplace dictates," is assigned to MF3.

Input 6, strategy, has 2 MFs and pertains to the strategy used by potential investors when planning. The first option, "I can see my options to choose," is assigned to MF1, while the second option, "I limit it to my possibilities," is assigned to MF2.

Input 7, labeled "attachment," has two membership functions (MFs) and pertains to the level of attachment to work experienced by potential investors. The first option, "I am dynamic in work with clear assignment of tasks," is assigned to MF1, while the second option, "I am working in a disorganized, deconstructive, or passive manner," is assigned to MF2.

Input 8, labeled "satisfaction," also has two MFs and is related to the level of satisfaction of the potential investors with their work. The question asked what bothers them more. The first option, "If the work I am doing seems pointless," is assigned to MF1, while the second option, "If

Table 4 MFs of the managerial traits for input 1 (planning)

MFs	Options (Input 1)	F	%
MF1	Strongly disagree	4	0.2
MF2	Disagree	28	1.7
MF3	Neither agree nor disagree	814	52.7
MF4	Agree	690	44.7
MF5	Strongly agree	11	0.7

the work I am doing doesn't satisfy me mentally," is assigned to MF2.

Input 9, labeled "planning time," has three MFs and relates to the time frame of planning by potential investors. The question asked how many weeks in advance they usually plan their vacation. The first option, "1–3 weeks," is assigned to MF1, the second option, "4–8 weeks," is assigned to MF2, and the third option, "more than 8 weeks or I do not usually plan my vacations," is assigned to MF3 (Table 5).

The different levels of agreement were designed for the membership functions (MF). Membership functions (MF) are used to model fuzzy sets, which are sets that do not have a sharp boundary. The MFs are designed based on the degree of membership of an element to a fuzzy set, which can vary from 0 (not a member) to 1 (a full member). The different levels of agreement that were designed for the membership functions (MF) include:

(a) Strong agreement (1.0): This level of the agreement indicates that an element is a full member of the fuzzy set, and there is no ambiguity or uncertainty.
(b) Moderate agreement (0.5 to 0.9): This level of agreement indicates that an element is a partial member of the fuzzy set. There is some degree of ambiguity or uncertainty in the degree of membership.
(c) Weak agreement (0.1 to 0.4): This level of the agreement indicates that an element is a weak member of the fuzzy set. There is a high degree of ambiguity or uncertainty in the degree of membership.
(d) No agreement (0.0): This level of the agreement indicates that an element is not a member of the fuzzy set.

The design of the membership functions and the choice of the level of the agreement are critical in the development of the investment recommender system. The MFs should be designed to accurately capture the investor's managerial traits and investment experiences to ensure that the recommendations provided are relevant and accurate.

6.3 Proposing the managerial traits ANFIS

The proposed model for the investment recommendation system utilizes an adaptive neuro-fuzzy inference system (ANFIS) which operates on the principle of "IF–THEN" rules based on input membership functions (MFs). The architecture of ANFIS consists of three parts: fuzzy rules, MFs, and a reasoning mechanism to generate output. Our ANFIS model is designed to analyze the managerial traits of potential investors and provide customized investment recommendations based on their risk tolerance and investment goals. It consists of nine inputs and one output; each input has three membership functions. To create this model, a fuzzy logic toolbox in MATLAB was used for data processing. The process of creating the ANFIS model

Table 5 Description of the system's inputs

Input	MF	Options	F	%
Input 2	MF1	I get nervous after decision making	279	18.13
Stress	MF2	I don't get nervous after decision making	1253	81.87
Input 3	MF1	I work in a rush	591	38.34
Pace	MF2	I work comfortably	949	61.66
Input 4	MF1	I try to influence others	1245	81.04
Influential	MF2	I adapt to the situation	295	19.96
Input 5	MF1	I plan my daily schedule	820	53.33
Daily	MF2	My family dictates my schedule	111	7.23
Schedule	MF3	My workplace dictates my schedule	610	39.44
Input 6	MF1	I have a clear strategy	1380	90.13
Strategy	MF2	I limit my strategy to what is possible	159	10.37
Input 7	MF1	I am dynamic and have clear tasks	910	59.24
Attachment	MF2	I am passive or disorganized	618	40.76
Input 8	MF1	I find my work pointless	1142	74.33
Satisfaction	MF2	I find my work satisfying	398	25.67
Input 9	MF1	1–3 weeks	104	6.76
Planning Time	MF2	4–8 weeks	488	31.68
	MF3	more than 8 weeks or I don't usually plan my holidays in advance	949	61.56

consists of six basic steps: Importing Data, Designing FIS, Loading Data, Generating FIS, Training FIS, and Testing FIS.

Figure 3 represents the scheme of the proposed ManagerialTraitsANFIS system, which has nine inputs and one output. The inputs represent different managerial traits that can affect investment-types, such as planning, stress, pace, influential, daily schedule, strategy, attachment, satisfaction, and planning time. The output represents the recommended investment-type based on the input values of the managerial traits.

Figure 4 in ManagerialTraitsANFIS represents the membership functions (MFs) for the inputs of the system. The figure shows the different levels of membership for each input variable, represented as curves on a graph. The x-axis typically represents the input variable, while the y-axis represents the degree of membership, ranging from 0 to 1. Each input variable has been divided into three membership functions, which are triangular, trapezoidal, or Gaussian shape, in this example.

For example, the input variable "planning" is divided into three membership functions, represented by the curves 1mf1, 1mf2, and 1mf3. Curve 1mf1 represents the low level of planning, curve 1mf2 represents the medium level of planning, and curve 1mf3 represents the high level of planning. The level of membership for each input is determined by the position of the input value on the x-axis of the MFs. The value of the input is assigned to the MF with the highest degree of membership. For example, if the input value for "planning" is 0.8, it would be assigned to the MF 1mf3, indicating a high level of planning.

Figure 5 depicts the loaded data used for the next stages of training and testing in the Managerial Traits ANFIS model. The training data were partitioned using a grid method, and the optimization method employed was a hybrid approach with an error tolerance of 0 and a total of 3 epochs. This process resulted in the generation of a new FIS, the Managerial Traits ANFIS.

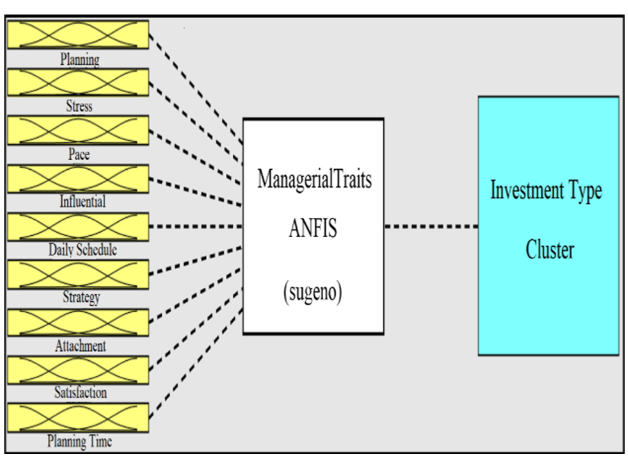


Fig. 3 Scheme of ManagerialTraitsANFIS (9 inputs and 1 output)

Figure 6 illustrates the generated FIS named "Managerial Traits ANFIS." This system comprises 9 inputs and 1 output. The data set index is represented on the x-axis and the y-axis displays the distribution of the output based on the investment-type clusters. The graph demonstrates the effectiveness of the ANFIS model in providing customized investment recommendations based on the potential investors' managerial traits, risk tolerance, and investment goals. This graphical representation of the FIS allows for easy interpretation of the results and aids in understanding the relationship between the inputs and the output.

The proposed model includes an ANFIS layer that utilizes the clustered data as inputs and generates investment recommendations based on the scoring of each cluster. Figure 7 illustrates the trained Managerial Traits ANFIS network, which consists of four inputs and one output, specifically for investment-type clusters. The training process employed a hybrid method with a total of 3 epochs, resulting in an error rate of approximately 0.84 for each epoch.

The ANFIS model comprises of three sub-layers: input, membership function (MF), and output. The input sub-layer receives data related to potential investors' managerial traits and the MF sub-layer generates membership functions for each input variable. The output sub-layer then utilizes these membership functions to generate a final score for each cluster, representing the likelihood of a potential investor being associated with that specific cluster. This information is then used to generate personalized investment recommendations for each potential investor.

In terms of training, the ANFIS model was trained using a data set of 1542 data pairs, with the number of nodes, linear parameters, and nonlinear parameters set to 5818, 2880, and 46, respectively. Additionally, the number of fuzzy rules was set to 2880. The model was trained for a designated number of 3 epochs and achieved a minimal training RMSE of 0.837341. The results from the ANFIS model are promising, and further research can be conducted to optimize its performance and accuracy.

Figure 8 illustrates the results of testing our proposed Managerial Traits ANFIS system. The average testing error was found to be 0.83732, indicating a high level of accuracy in the model's predictions. The system generated a total of 2880 rules, providing a comprehensive analysis of the potential investors' managerial traits.

Figure 9 presents a sample of the generated rules in the proposed Managerial Traits ANFIS system, displayed in a verbose format. The system's rules can be modified or updated based on expert perspectives and feedback from potential investors, providing flexibility and adaptability to the model's recommendations. This figure is provided a list

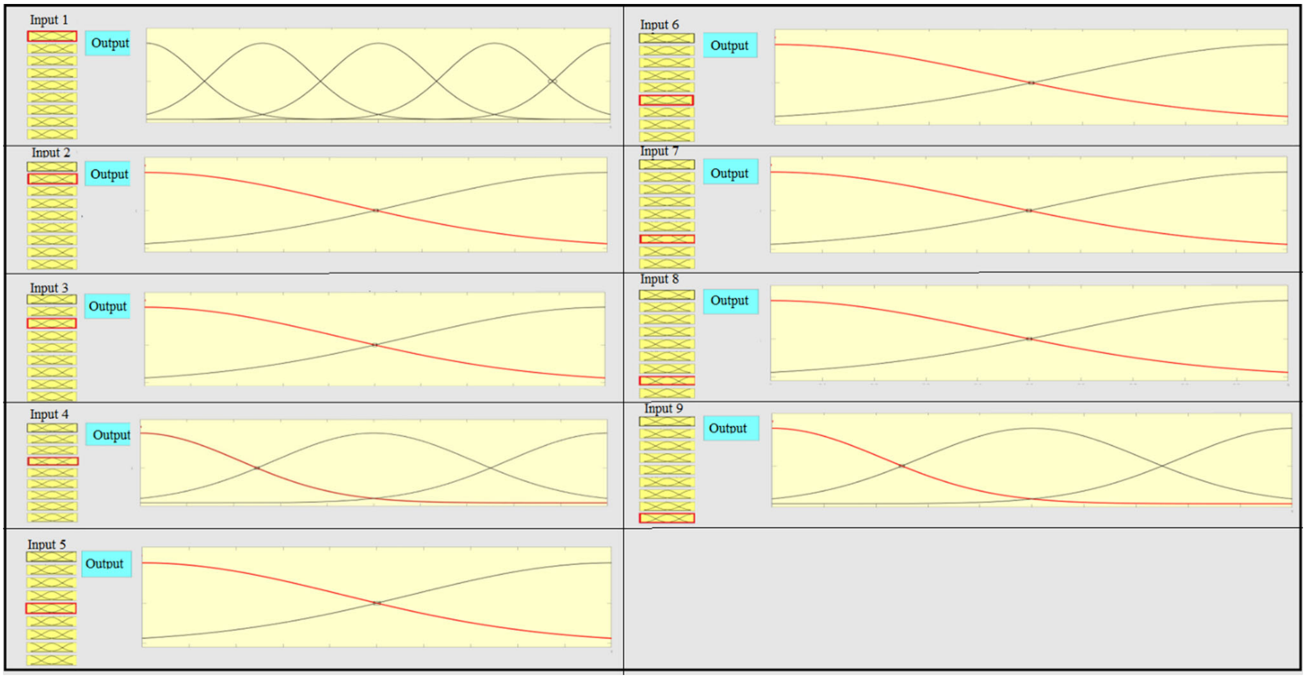


Fig. 4 MFs for inputs in ManagerialTraitsANFIS

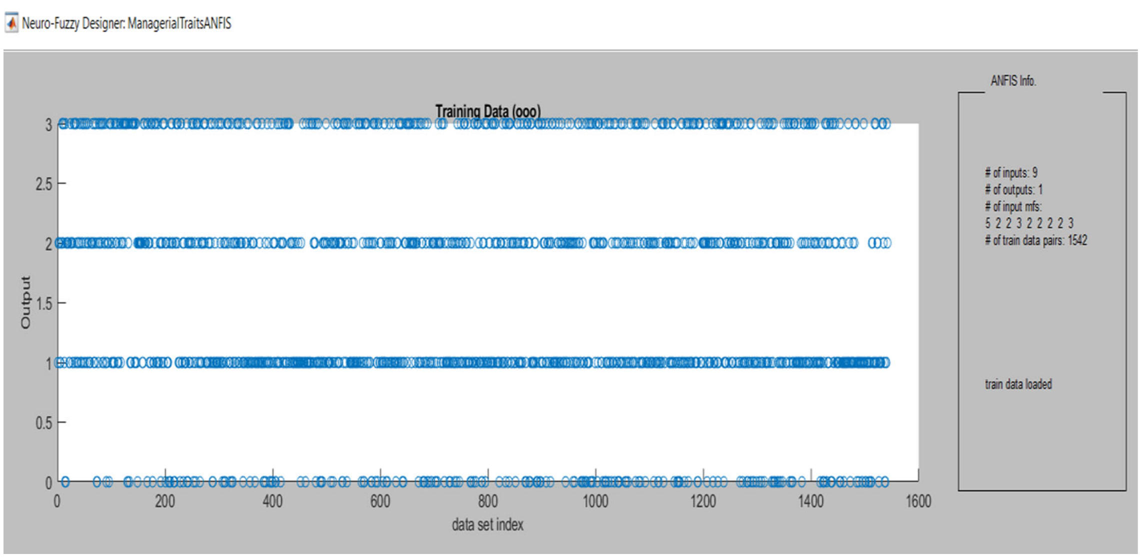


Fig. 5 Loaded data in the ManagerialTraitsANFIS system

of "if–then" rules that are used by the ManagerialTraitsANFIS system. Each rule has a specific set of inputs (input1, input2, input3, etc.) and associated membership functions (mf1, mf2, mf3, etc.) that are used to determine the output (out1mf1, out1mf2, out1mf3, etc.). These rules are used to determine the relationship between the various inputs and the output, which in this case is the investment-type. These rules are examples of the "IF–THEN" rules generated by the ManagerialTraitsANFIS system. They describe the relationship between different inputs (input1-input9) and their corresponding membership functions (1mf1-9mf3) and the output (out1mf1-out1mf9) for the investment-type. For example, in rule 1, if input1 belongs to membership function 1mf1, input2 belongs to membership function 2mf1, input3 belongs to membership function 3mf1, input4 belongs to membership function 4mf1, input5 belongs to membership function 5mf1, input6 belongs to membership function 6mf1, input7 belongs to membership function 7mf1, input8 belongs to membership function 8mf1 and input9 belongs to membership function

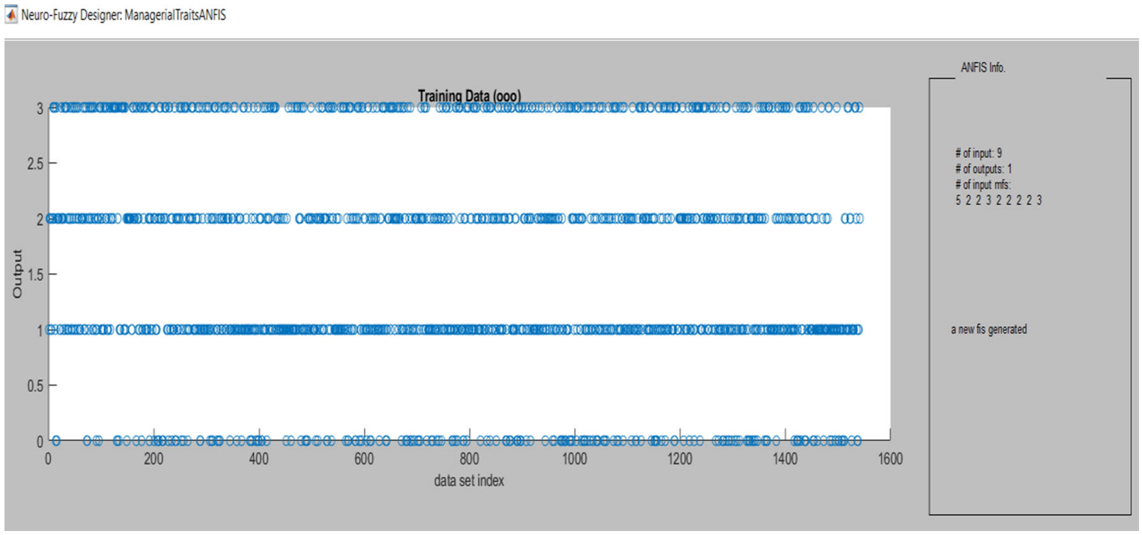


Fig. 6 Generated ManagerialTraitsANFIS system

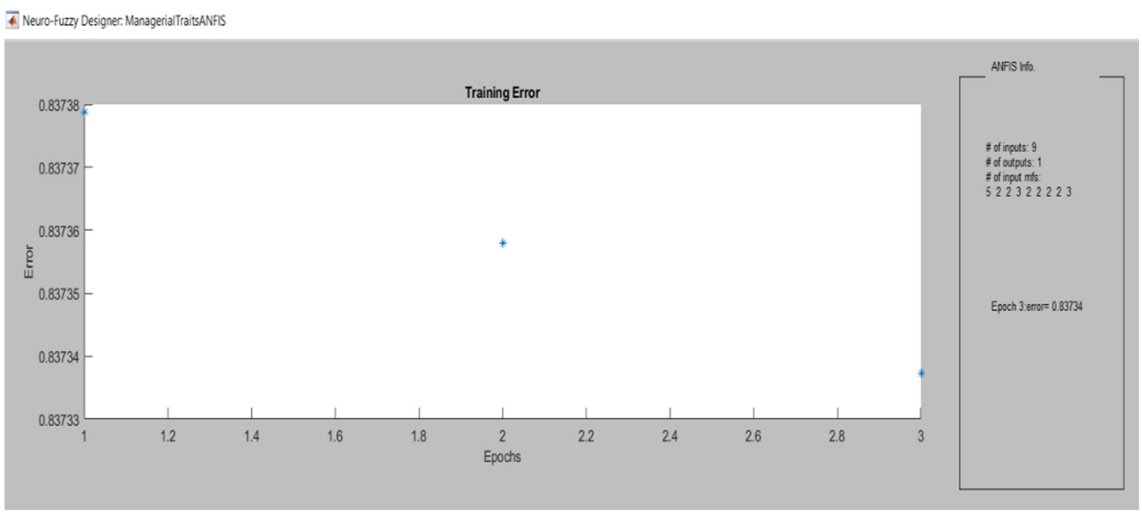


Fig. 7 Trained ManagerialTraitsANFIS system

9mf1, then the output will be out1mf1. Similarly, in rule 2, if input1 belongs to membership function 1mf1, input2 belongs to membership function 2mf1, input3 belongs to membership function 3mf1, input4 belongs to membership function 4mf1, input5 belongs to membership function 5mf1, input6 belongs to membership function 6mf1, input7 belongs to membership function 7mf1, input8 belongs to membership function 8mf1 and input9 belongs to membership function 9mf2, then the output will be out1m2. These rules show how different inputs with different membership functions will result in different investment-type recommendations.

The proposed ManagerialTraitsANFIS System uses fuzzy logic to determine the relationship between managerial traits and investment-types. The system utilizes a combination of input data and membership functions to generate a set of "IF–THEN" rules that are used to make personalized investment recommendations. The system's output is represented in a series of three-dimensional surface graphs, as seen in Fig. 10a–h, which depict the nonlinear relationship between different input pairs and the resulting investment-type recommendations. These monolithic graphs provide a clear visual representation of how the system's inputs influence its output, making it easier for users to understand the reasoning behind the investment recommendations. The proposed ManagerialTraitsANFIS System uses a 3D graph to visualize the relationship between input 1 and input 8 on investment-type recommendations. The graph represents the nonlinear and monolithic surface that illustrates the effect of input 1 and input 8 on the investment-type. The x-axis represents the values of input 1, the y-axis represents the values of input

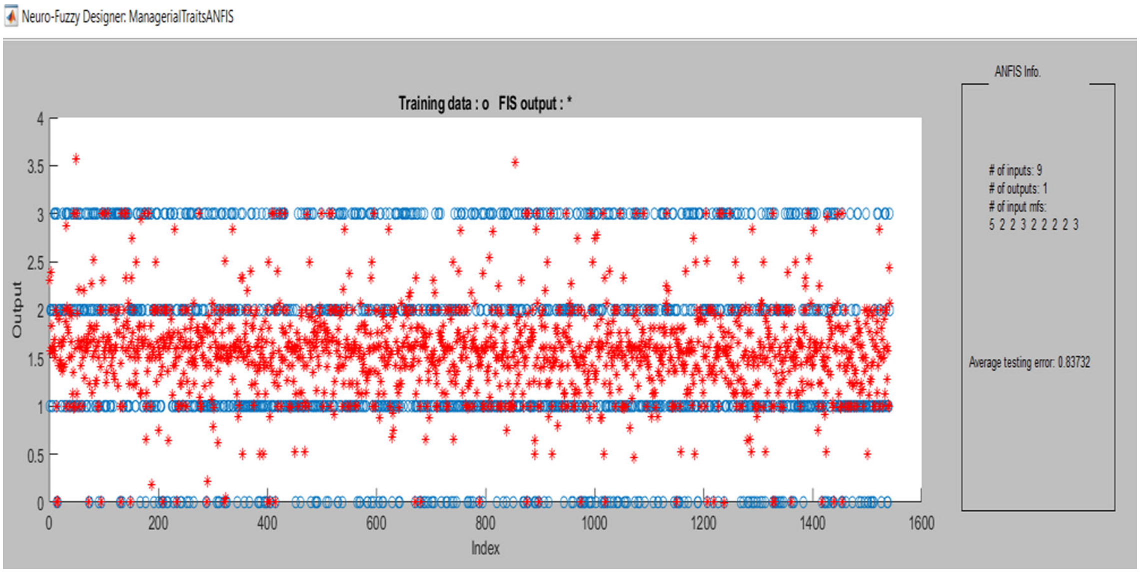


Fig. 8 Tested ManagerialTraitsANFIS system

1. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9mf1) then (output is out1mf1) (1)

2. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9mf2) then (output is out1m2) (1)

3. If input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mft) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9mf3) then (output is out1mf3) (1) 4. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8m2) and (input9 is in9mf1) then (output is out 1m4) (1)

5. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8m2) and (input9 is in9m2) then (output is out1mf5) (1)

6. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8m2) and (input9 is in9mf3) then (output is out 1m6) (1)

7. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf2) and (input8 is in8mf1) and (input9 is in9mf1) then (output is out 1mf7) (1) 8. IF (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf2) and (input8 is in8mf1) and (input9 is in9m2) then (output is out1m8) (1)

9. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7m2) and (input8 is in8mf1) and (input9 is in9mf3) then (output is out 1mf9) (1)

10. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf2) and (input8 is in8m2) and (input9 is in9mf1) then (output is out 1mf10) (1)

11. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input? is in7mf2) and (input8 is in8m2) and (input9 is in9mf2) then (output is outtmf11) (1)

12. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input? is in7m2) and (input8 is in8m2) and (input9 is in9mf3) then (output is out1mf12) (1) 13. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6m2) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9mf1) then (output is out1mf13) (1)

14. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9m2) then (output is out1mf14) (1)

15. If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6m2) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9mf3) then (output is out 1m15) (1)

Fig. 9 A part of the generated rules in the ManagerialTraitsANFIS system

8, and the z-axis represents the investment-type recommendations. As the values of input 1 and input 8 change, the surface of the graph changes, accordingly, providing a clear visual representation of how the two inputs impact the investment-type recommendations. This 3D graph allows for easy interpretation and understanding of the relationship between the two inputs and the investment-type, providing valuable insights for potential investors.

Figure 10a with the x-axis representing satisfaction, the y-axis representing planning, and the z-axis representing investment-type illustrates how these three variables interact with each other to produce investment-type recommendations. The graph likely has multiple peaks, with each peak representing a different investment-type recommendation. The highest peak on the graph would correspond to the most recommended investment-type for a given level of satisfaction and planning. As the levels of satisfaction and planning increase or decrease, the graph would likely show a shift in the peak representing the most recommended investment-type. Additionally, the shape of the graph may indicate the degree of correlation between satisfaction, planning, and investment-type, with steeper peaks indicating a stronger correlation. Overall, this graph allows for a visual representation of the relationship between satisfaction, planning, and investment-type, providing insights into the decision-making process of the ManagerialTraitsANFIS system.

Figure 10b with satisfaction on the x-axis, stress on the y-axis, and investment-type on the z-axis illustrate the relationship between the managerial traits of satisfaction and stress and their effect on the recommended investment-type. The graph is a nonlinear and monolithic surface that shows the recommended investment-type for a given level of satisfaction and stress. The surface of the graph can be used to identify areas of high and low investment-type recommendations, as well as identify any potential trends or patterns in the data. For example, the graph may show that higher levels of satisfaction and lower levels of stress are associated with more conservative investment-types, while lower levels of satisfaction and higher levels of stress are associated with more aggressive investment-types. Overall, this graph provides a visual representation of the relationship between satisfaction, stress, and investment-type, and can be used to inform the investment recommendations made by the ManagerialTraitsANFIS system.

Figure 10c of input 1 (satisfaction) and input 8 (pace) on the vertical axis represents the investment-type. The x-axis represents the level of satisfaction of the potential investor, with a range from low to high. The y-axis represents the pace of the potential investor's decision-making, also with a range from slow to fast. The z-axis represents the recommended investment-type, with different colors or shapes representing different types of investments such as stocks, bonds, and mutual funds.

The surface of the graph is nonlinear, meaning that the relationship between satisfaction, pace, and investment-type is not a straight line. As the level of satisfaction increases or the pace of decision-making quickens, the recommended investment-type may change. For example, as the satisfaction level increases, the recommended investment-type may shift from conservative options such as bonds to more aggressive options like stocks. Similarly, as the pace of decision-making quickens, the recommended investment-type may shift from long-term options like mutual funds to shorter-term options like stocks. The graph also shows the regions where specific investment-types are recommended. For example, there may be a region of the graph where stocks are recommended for investors with high satisfaction levels and a fast pace of decision-making, while bonds are recommended for investors with lower satisfaction levels and a slow pace of decision-making. Overall, this 3D graph provides a visual representation of the relationship between satisfaction, pace, and investment-type, and can be used to make personalized investment recommendations for potential investors based on their managerial traits.

Figure 10d of input 1 (satisfaction) and input 8 (influential) shows the relationship between these two managerial traits such as satisfaction and influential traits and the recommended investment-type. The x-axis represents the satisfaction level of the potential investor, which ranges from low to high. The y-axis represents the level of influence of the potential investor, which also ranges from low to high. The z-axis represents the recommended investment-type, which can be stocks/shares, mutual funds, voluntary pension funds, government securities, or other financial products. The surface of the graph is nonlinear and monolithic, indicating that the relationship between satisfaction and influence on investment-type is not a simple linear relationship because it considers several factors that influence the investment decision. The investment recommender system considers the investor's managerial traits, such as planning, stress, pace, influential, daily schedule, strategy, attachment, satisfaction, and planning time. Additionally, it uses machine learning techniques and ANFIS to process and analyze the data, which involves several layers of fuzzification, implication rules, normalization, defuzzification, integration, and aggregated output membership function. This comprehensive approach helps to identify patterns, trends, and relationships in the data that are not apparent in a simple linear relationship. As a result, the recommended investment is more personalized and accurate, providing investors with better investment options and maximizing their returns. The graph shows how the recommended investment-type changes as the satisfaction and influence levels of the potential investor change. As the satisfaction level increases and the influence level decreases, the recommended investment-type shifts toward stocks/shares and mutual funds. As the satisfaction level decreases and the influence level increases, the recommended investment-type shifts toward government securities and other financial products. The graph also shows that certain combinations of satisfaction and influence levels result in the same recommended investment-type. For example, a high level of satisfaction and a low level of influence may result in the same recommended investment-type as a low level of satisfaction and a high level of influence. This indicates that the proposed ManagerialTraitsANFIS system considers multiple factors when determining the recommended investment-type for a potential investor.

Figure 10e illustrates the relationship between three variables: satisfaction, daily schedule, and investment-type. The x-axis represents the satisfaction level of the individual, the y-axis represents their daily schedule, and the z-axis represents the recommended investment-type. The graph shows how different levels of satisfaction and daily schedule can affect the recommended investment-type. The surface of the graph is nonlinear and monolithic, indicating that the relationship between the variables is not a simple linear relationship. The surface may have peaks, valleys, and other variations, indicating that different combinations of satisfaction and daily schedule can lead to different recommended investment-types. The graph can be used to understand how the satisfaction and daily schedule of an individual may affect their investment-type and can be used to provide personalized investment recommendations based on their managerial traits.

Figure 10f of x: satisfaction, y: strategy, and z: investment-type displays the relationship between an individual's satisfaction level, their strategy for making investment decisions, and the recommended investment-type. The x-axis represents the satisfaction level of the individual, with low satisfaction at one end and high satisfaction at the other end. The y-axis represents the strategy for making investment decisions, with a cautious strategy at one end and an aggressive strategy at the other end. The z-axis represents the recommended investment-type, with low-risk options at the bottom and high-risk options at the top. The surface of the graph is a representation of the relationship between these three variables, with areas of the graph representing different recommended investment-types for different levels of satisfaction and strategy. For example, the graph may show that individuals with high satisfaction levels and an aggressive strategy may be recommended to invest in high-risk options, while individuals with low satisfaction levels and a cautious strategy may be recommended to invest in low-risk options.

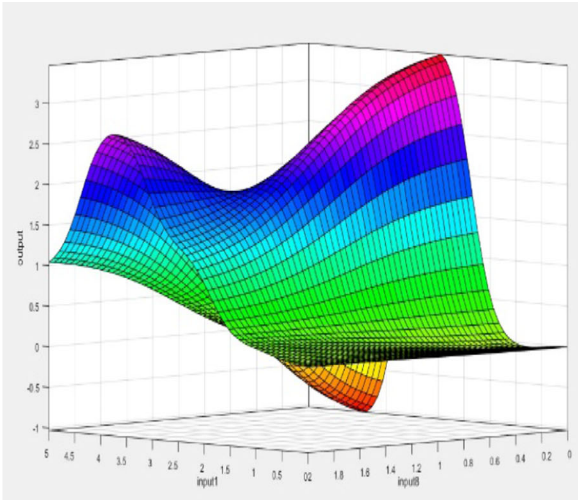
Figure 10g for the relationship between satisfaction, attachment, and investment-type displays a nonlinear surface that illustrates how changes in these two inputs affect the recommended investment-type. The x-axis represents satisfaction, which is a measure of an individual's level of contentment with their current financial situation. The y-axis represents attachment, which is a measure of an individual's emotional connection to their current investments. The z-axis represents the recommended investment-type, which can include options such as stocks/shares, mutual funds, voluntary pension funds, and government securities. As satisfaction increases and attachment decreases, the recommended investment-type shifts toward more high-risk options such as stocks and mutual funds. Conversely, as satisfaction decreases and attachment increases, the recommended investment-type shifts toward more low-risk options such as government securities and voluntary pension funds.

Fig. 10 **a** Satisfaction and planning, **b** satisfaction and stress, ▶ **c** satisfaction and pace, **d** satisfaction and influential, **e** satisfaction and daily schedule, **f** satisfaction and strategy, **g** satisfaction and attachment, **h** satisfaction and planning time

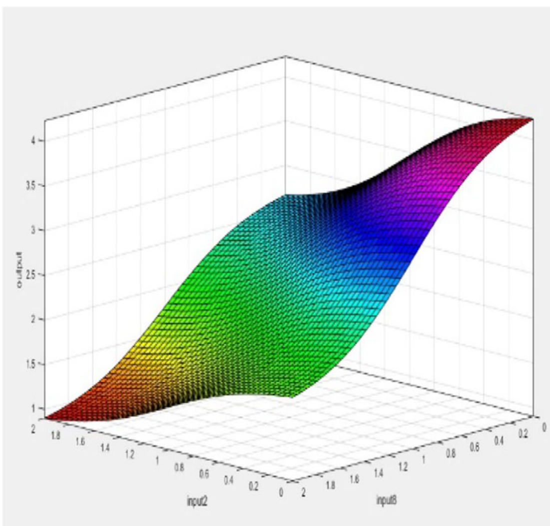
The surface of the graph is nonlinear, indicating that the relationship between the inputs and the recommended investment-type is not a simple linear relationship. Instead, it is a more complex relationship that considers multiple factors and can change based on the specific values of the inputs. Overall, figure provides a clear visual representation of how changes in satisfaction and attachment levels affect the recommended investment-type, allowing for more personalized and accurate investment recommendations.

Figure 10h of x: satisfaction, y: planning time, and z: investment-type illustrates the relationship between an individual's level of satisfaction, their planning time, and the recommended investment-type. The x-axis represents the level of satisfaction, with a range of low to high satisfaction. The y-axis represents the planning time, with a range from low to high planning time. The z-axis represents the recommended investment-type, with different colors or shapes representing different types of investments. As the level of satisfaction increases, the recommended investment-type shifts toward more high-risk, high-reward options, such as stocks and mutual funds, represented by a peak on the graph. Similarly, as the planning time increases, the recommended investment-type shifts toward more long-term options, such as government bonds and real estate, represented by a peak on the graph. Figure provides a visual representation of how an individual's level of satisfaction and planning time affects their recommended investment-type, allowing for a more personalized investment recommendation.

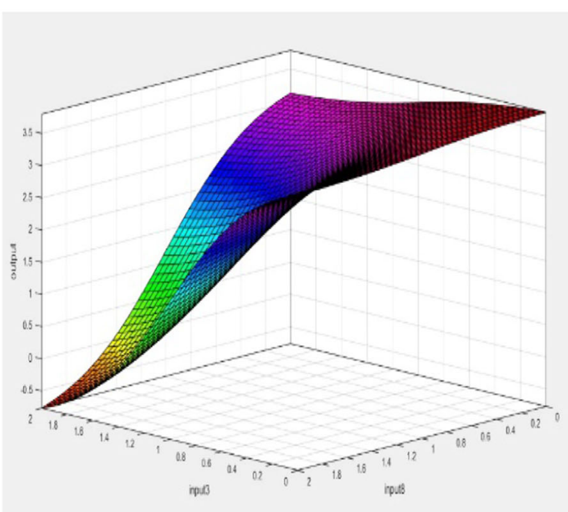
Figure 11 shows the structure of the ManagerialTraitsANFIS model, which is used to make investment-type recommendations to investors based on their managerial traits. The model includes nine inputs, each with its own set of membership functions (MFs) that map the inputs to fuzzy sets. The inputs represent various managerial traits, such as planning, stress, pace, influential, daily schedule, strategy, attachment, satisfaction, and planning time. The model also includes several layers, including fuzzification, implication rules, normalization, defuzzification, and integration. The fuzzification layer maps the crisp inputs to fuzzy sets based on the



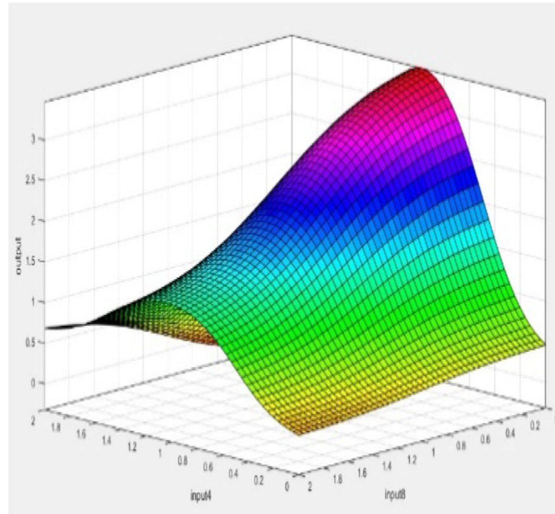
a satisfaction & planning



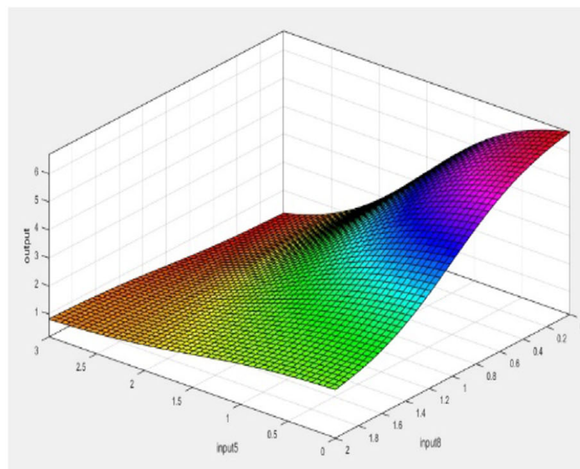
b satisfaction & stress



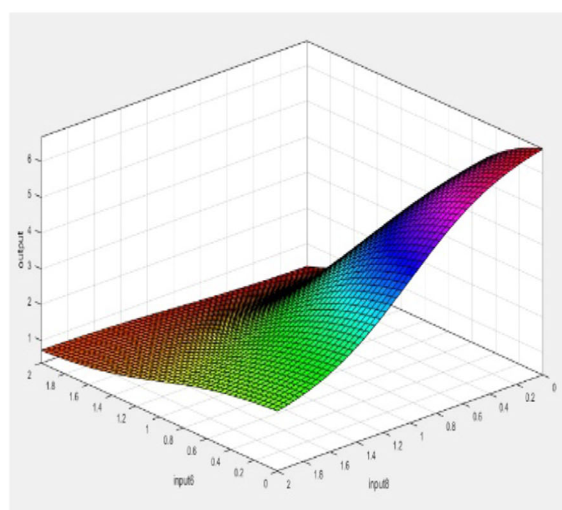
c satisfaction & pace



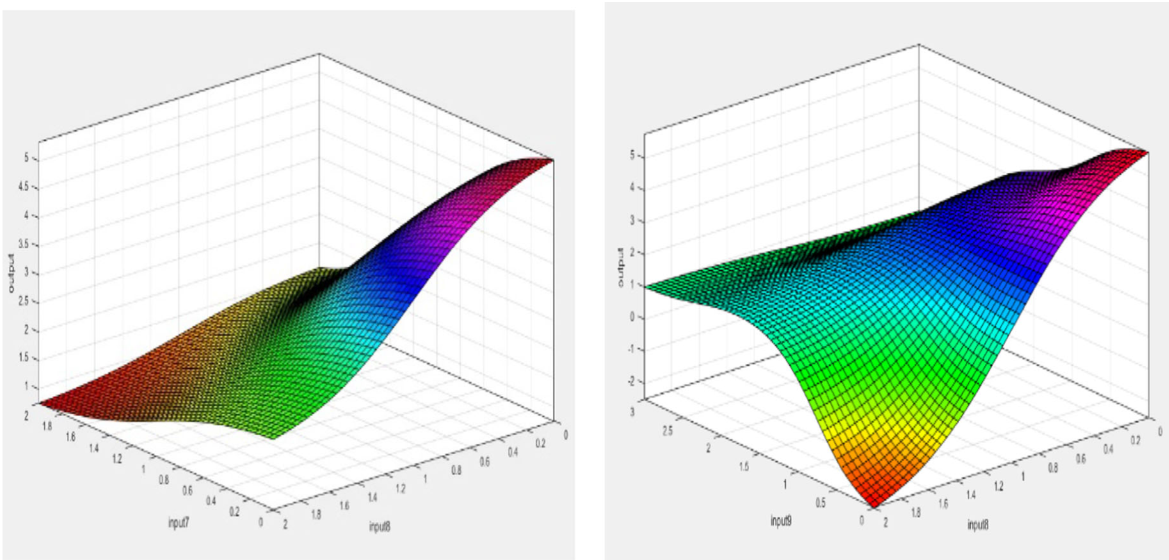
d satisfaction & influential



e satisfaction & daily schedule



f satisfaction & strategy



g satisfaction & attachment *h satisfaction & planning time*

Fig. 10 continued

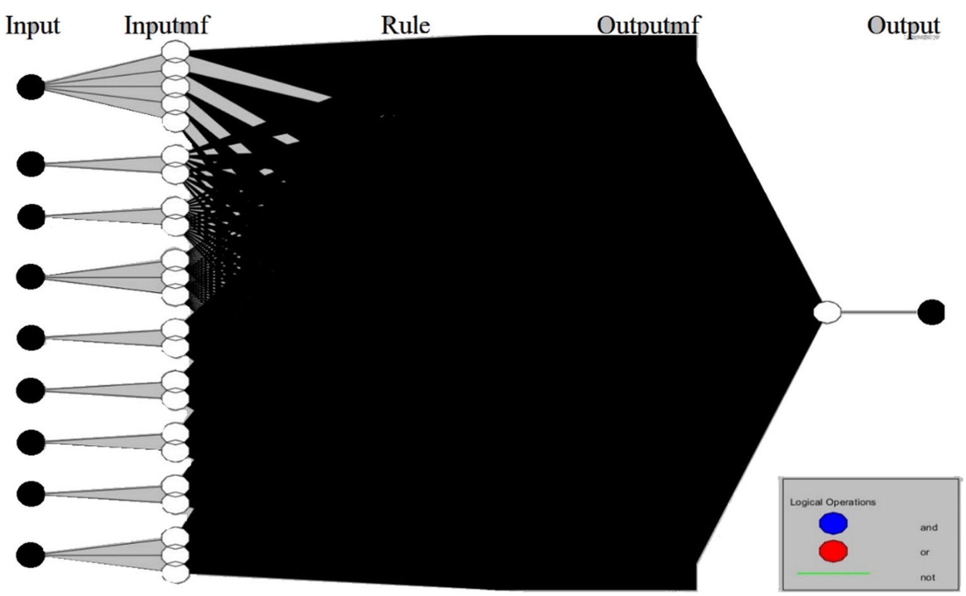


Fig. 11 ManagerialTraitsANFIS model structure

membership functions. The implication rules layer uses fuzzy sets to generate a set of IF–THEN rules that describe the relationship between the inputs and the output. The normalization layer normalizes the output of the implication rules to ensure that the output membership function is a valid probability distribution. The defuzzification layer maps the output membership function to a crisp value, which represents the investment-type recommendation. The integration layer aggregates the output of the defuzzification layer to generate a final output. The figure is a graphical representation of the ANFIS architecture, it shows how the inputs are passing through different layers and finally getting an output which is the recommended investment-type for the investors. It also shows how different membership functions (MFs) are used in the fuzzification layer and how the rules are generated based on the inputs and MFs. Overall, the figure illustrates the process by which the ManagerialTraitsANFIS model generates investment-type recommendations for investors based on their managerial traits. The ANFIS model provides customized investment recommendations by using a decision-making process that takes into account the needs and preferences of potential investors. The ANFIS model is a type of machine learning that combines the capabilities of fuzzy logic and neural networks to make predictions and recommendations. The ANFIS model is trained using historical data and is designed to recognize patterns and relationships between inputs and outputs. The inputs to the ANFIS model include financial metrics such as risk, return, and volatility, as well as personality traits, and investment objectives. The model then uses this information to generate customized investment recommendations. The decision-making process used by the ANFIS model involves several steps. First, the model takes in the inputs and uses fuzzy logic to generate membership functions for each input. These membership functions represent the degree of membership of each input to various investment options. Next, the ANFIS model uses neural networks to perform inference on the membership functions and generate output recommendations. The model adapts and adjusts the membership functions and neural network weights during the training process to optimize the accuracy of the recommendations. The ANFIS model can be adapted to suit the needs of individual investors by adjusting the inputs and membership functions. For example, an investor with a higher risk tolerance may receive recommendations for more aggressive investment options. Alternatively, an investor with a shorter investment horizon may receive recommendations for more stable investment options. In summary, the ANFIS model provides customized investment recommendations by using a combination of fuzzy logic and neural networks to generate membership functions and perform inference on inputs. This decision-making process takes into account the needs and preferences of potential investors and can be adapted to suit individual investors' needs.

7 Discussion

The proposed investment recommendation system based on ANFIS, and clustering techniques has been successfully developed and tested. The system was able to cluster the types of investments used by potential investors and provide investment-type recommendations based on the clusters. The clustering results were consistent across both MATLAB and JMP software, and the final clusters were determined through a combination of visual comparison, data merging, and expert knowledge. The ANFIS model for the investment recommendation system was able to determine the relationship between the managerial traits of potential investors and the recommended investment-types. The model was able to accurately predict the investment-type recommendations based on the inputs provided by the potential investors. The model's structure was able to effectively process the data through the fuzzification, implication rules, normalization, defuzzification, and integration layers. The proposed model is a valuable tool for financial advisors, investment managers, and other professionals in the financial industry. It can be used to identify potential investors and recommend appropriate investment-types based on their managerial traits and investment habits and behaviors. Additionally, this model can be used to develop a more effective investment strategy by identifying potential investors and providing them with investment-type recommendations based on their characteristics. However, it is important to note that the proposed model is based on a specific data set and may not be universally applicable to all potential investors. Additionally, the model relies on the self-reported data provided by the potential investors, which may not always be accurate or complete. Future research could focus on expanding the data set to include a more diverse range of potential investors and incorporating additional data sources to validate the self-reported data. The results of the current research indicate that the proposed ANFIS model for the investment recommendation system can effectively cluster different types of investments used by potential investors. The clustering process, which was conducted using both MATLAB and JMP software, resulted in three distinct clusters. The characteristics of each cluster, including the number of respondents, the investment-types, and the investment habits and behaviors of the respondents, were analyzed and are summarized in Table 2. The results also showed that the first cluster represents individuals who are not currently invested in the stock market and have not been monitoring stock performance, the second cluster represents individuals who are currently invested in the stock market, regularly monitor stock performance, and have investments in government bonds, and the third cluster represents individuals who have been investing in the stock market for the last 3 years and regularly monitor stock performance but do not have any investments in government bonds. The proposed ManagerialTraitsANFIS system also showed promising results in determining the relation between managerial traits and investment-type. The system's 3D graphs effectively visualized the nonlinear and monolithic relationship between inputs and output, and the ANFIS was able to generate accurate recommendations for investment-types based on the input data. In comparison to previous research in the field, the current study adds to the literature by providing a more comprehensive and holistic approach to an investment recommendation. The use of both clustering and ANFIS in the proposed model allows for a more detailed analysis of the data and a more accurate determination of investment recommendations. Additionally, the use of both MATLAB and JMP in the clustering process adds to the robustness and validity of the results. The current study also expands on previous research by including a wider range of inputs, such as managerial traits, in the ANFIS system. In conclusion, the proposed investment recommendation system based on ANFIS, and clustering techniques is a valuable tool for identifying potential investors and providing them with appropriate investment-type recommendations. The system was able to effectively cluster the types of investments used by potential investors and provide accurate investment-type recommendations based on the clusters and the managerial traits of the potential investors. The proposed model can be used by financial advisors and investment managers to develop a more effective investment strategy. Investment managers and financial advisors can use the recommended paradigm to create a more effective investment strategy by leveraging the insights provided by the investment recommender system. The system can provide a comprehensive analysis of the investor's managerial traits and investment experiences, which can help investment managers and financial advisors to better understand their client's needs, goals, and risk appetite. Based on this understanding, investment managers and financial advisors can develop personalized investment strategies that are aligned with their client's financial objectives. The investment recommender system can provide recommendations for investment products and services that are suitable for the client's profile, increasing the chances of a successful investment outcome. In addition, the investment recommender system can help investment managers and financial advisors to monitor their clients' investment performance continuously. They can use the feedback from the system to fine-tune their clients' investment strategies and make changes as required. Overall, the recommended paradigm can be a powerful tool for investment managers and financial advisors to create a more effective investment strategy, increasing the chances of achieving their clients' financial goals. However, it is important to note that the model's applicability is based on a specific data set and further research is needed to expand the data set and validate the self-reported data.

8 Conclusion

In conclusion, the proposed ANFIS model for the investment recommendation system has been developed and tested with potential investors' data. The model uses clustering and ANFIS to determine the investment-type recommendations for potential investors based on their managerial traits. The results of the experiments have shown that the proposed model is effective in determining investment-type recommendations for potential investors. One of the main innovations of this research is the use of ANFIS in combination with clustering to determine investment-type recommendations for potential investors. This is a novel approach in the field of investment recommendation systems. The proposed model also addresses the issue of incomplete data by using techniques to handle missing data and impute missing values. However, there are also some limitations in this research. The proposed model is based on a specific sample of potential investors and may not be generalizable to other populations. In addition, the proposed model does not consider other factors that may affect investment decisions such as economic conditions and market trends. For future studies, it is suggested to expand the proposed model to consider other factors that may affect investment decisions and to test the model on a larger sample of potential investors. It would also be beneficial to evaluate the proposed model in different market conditions. Additionally, the researcher can consider the overall goal of this research, the business problem we're trying to solve, and the trade-offs between model performance and interpretability when selecting the best model. The proposed model has practical applications in the field of investment recommendations. It can be used by financial advisors and investment firms to determine suitable investment products for potential investors based on their managerial traits. In summary, this research presents a novel approach for determining investment-type recommendations for potential investors using ANFIS and clustering. The proposed model is effective in determining investment-type recommendations for potential investors. However, future studies should be conducted to further test and improve the proposed model.

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Author contributions Asefeh Asemi wrote the main text and carried out the data analysis, and Adeleh Asemi was the advisor in data analysis. Andrea Ko contributed to supervising the research.

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Data availability The original data for this study were collected in partnership with the Corvinus University of Budapest, Dorsum, and Portfolio in the 1.3.1-VKE-2018-00007 project. The data are available in the Hungarian language, and according to the Consortia agreement and the Head of the project's consent, the data can be used for additional research and publications by the authors. Asefeh Asemi has translated, cleaned, and prepared the data for this study. The new data will be available in Mendeley's repository.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethical approval This study does not involve any studies with human or animal participants performed by any of the authors.

References

Asemi A, Ko A, Asemi A (2023) Systematic Review and Propose an ANFIS-Based Investment Type Recommender System using Investors' Demographic. A Hybrid Conference 8th International Congress on Information and Communication Technology ICICT 2023, London, UK, 20–23 February. https://icict.co.uk/

Baker HK, Nofsinger JR (2010) BEHAVIORAL FINANCE: investors, corporations, and markets. Wiley, Hoboken

Bergner S, Neubauer AC, Kreuzthaler A (2010) Broad and narrow personality traits for predicting managerial success. Eur J Work Organ Psychol 19(2):177–199. https://doi.org/10.1080/13594320902819728

Birim ŞÖ, Sönmez FE, Liman YS (2022) Estimating return rate of blockchain financial product by ANFIS-PSO method. In: Lecture notes in networks and systems, 504 LNNS, pp 802–809. https://doi.org/10.1007/978-3-031-09173-5_92

Ezhilarasi TP, Sashi Rekha K (2020) Secure recommendation application for environment crop using big data analytics with fuzzy framework. J Green Eng 10(4):1799–1815

Hackbarth D (2008) Managerial traits and capital structure decisions. J Financ Quant Anal 43(4):843–881

Jalota H, Mandal PK, Thakur M, Mittal G (2023) A novel approach to incorporate investor's preference in fuzzy multi-objective portfolio selection problem using credibility measure. Expert Syst Appl 212:118583. https://doi.org/10.1016/j.eswa.2022.118583

Kovács T, Ko A, Asemi A (2021) Exploration of the investment patterns of potential retail banking customers using two-stage cluster analysis. J Big Data. https://doi.org/10.1186/s40537-021-00529-4

Lakhno V, Malyukov V, Kasatkin D, Chubaieskyi V, Rzaieva S, Rzaiev D (2023) Continuous investing in advanced fuzzy technologies for smart city. Lect Notes Data Eng Commun Technol 142:313–327. https://doi.org/10.1007/978-981-19-3391-2_24

Lenhard G, Maringer D (2022) State-ANFIS: a generalized regime-switching model for financial modeling. In: 2022 IEEE symposium on computational intelligence for financial engineering and economics, CIFEr 2022—proceedings. https://doi.org/10.1109/CIFEr52523.2022.9776208

Naranjo R, Santos M (2019) A fuzzy decision system for money investment in stock markets based on fuzzy candlesticks pattern recognition. Expert Syst Appl 133:34–48. https://doi.org/10.1016/j.eswa.2019.05.012

Pogue M (2010) Corporate investment decisions: principles and methods. Business Expert Press. ISBN 978-1-60649-065-5

Rong Y, Yu L, Liu Y (2023) Fermatean fuzzy combined compromise solution multiple expert multiple criteria decision-making approach. Stud Fuzziness Soft Comput 420:85–104. https://doi.org/10.1007/978-981-19-4929-6_4

Rutkowski T (2021) Explainable recommender for investment advisers. In: Rutkowski T (ed) Explainable artificial intelligence based on neuro-fuzzy modeling with applications in finance. Springer International Publishing, Berlin, pp 75–119. https://doi.org/10.1007/978-3-030-75521-8_4

Rutkowski T, Nielek R, Rutkowska D, Rutkowski L (2020) A novel explainable recommender for investment managers. In: Rutkowski L, Scherer R, Korytkowski M, Pedrycz W, Tadeusiewicz R, Zurada JM (eds) Artificial intelligence and soft computing, vol 12416. Springer International Publishing, Berlin, pp 412–422. https://doi.org/10.1007/978-3-030-61534-5_37

Tejeda-Lorente Á, Bernabé-Moreno J, Herce-Zelaya J, Porcel C, Herrera-Viedma E (2019) A risk-aware fuzzy linguistic knowledge-based recommender system for hedge funds. Procedia Comput Sci 162:916–923. https://doi.org/10.1016/j.procs.2019.12.068

Vredenburgh AG, Hendrick HW, Zackowitz IB (2000) Personality traits as predictors of managerial performance: a study of hotel managers, pp 301–304. https://doi.org/10.1177/154193120004401047

Wan Q, Miao X, Wang C, Dinçer H, Yüksel S (2023) A hybrid decision support system with golden cut and bipolar q-ROFSs for evaluating the risk-based strategic priorities of fintech lending for clean energy projects. Financ Innov 9(1):10. https://doi.org/10.1186/s40854-022-00406-w

Wang W, Lin W, Wen Y, Lai X, Peng P, Zhang Y, Li K (2023) An interpretable intuitionistic fuzzy inference model for stock prediction. Expert Syst Appl 213:118908. https://doi.org/10.1016/j.eswa.2022.118908

Widjanarti A, Okfantia AD, Jabbar MA (2021) Predicting foreign investors' behavior and flows projection in Indonesia government bonds market using machine learning IFC-Bank of Italy Workshop on "Machine learning in central banking", 19–22 October 2021, Rome. https://www.bis.org/ifc/publ/ifcb57_20.pdf

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