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A Mamdani Fuzzy System with Multivariate Analysis and Weighted Aggregation for Precision Stock Investments Decisions -An AI Approach

Nirmala M S [1], Lata Kulkarni [2], *Jyothi N M [3]

[1]Department of Computer Science, Government College for Women (Autonomous), Manday, Karnataka, India
[2] Department of Electronics, Government Science College, Hassan, Karnataka, India
[3] Dept. of Computer Science Engineering, Koneru Lakshmaiah Education Foundation, Vddeswaram, AP, India

Abstract

This paper introduces a decision support system for stock trading, employing Fuzzy IF-THEN Rules. The system leverages three crucial linguistic variables as input parameters: Price-to-Earnings Ratio (PE), Earnings per Share (EPS), Price-to-Book Ratio (PB). Its primary objective is to aid investors in making rational decisions regarding their stock investments, with the goal of maximizing profits in the stock market—a notably intricate and challenging environment. To simplify and enhance decision-making for investors in this complex realm, this study harnesses Artificial Intelligence (AI) through the application of Fuzzy Logic (FL). The stock Investment decider is built by building Mamdani Type 2 Fuzzy Logic System using Mat Lab. Numerous prior research efforts have demonstrated the efficacy of FL in navigating the intricacies of stock trading environments. The study rigorously evaluates all the fuzzy rules through the utilization of a Fuzzy Inference System implemented in MATLAB. This comprehensive approach ensures that the proposed system's effectiveness is thoroughly assessed and validated.

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CORRESPONDING AUTHOR:

Jyothi N M

jyothiarunkr@gmail.com

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INTRODUCTION

The realm of business is undeniably intricate and fiercely competitive, replete with a myriad of tasks and challenges. In the contemporary landscape, most businesses have recognized the imperative need to harness information technology (IT) applications to enhance their operational efficiency and elevate the quality of their products and services [1]. This underscores the pivotal role that IT plays within the business environment. In recent times, a multitude of applications have been seamlessly integrated into the business milieu, with e-commerce being a prominent example. E-commerce has emerged as a widely acknowledged advancement in the realm of business due to its user-friendly nature and manifold benefits. It streamlines and expedites business processes, rendering them more convenient and efficient. Expanding the purview of information technology to encompass other sectors, such as the stock market, holds the promise of offering fresh perspectives and avenues for exploration in this field.

The stock market stands out as the most favored destination for investments due to its potential for substantial profits [2]. It falls within the realm of complex business environments, primarily because stock values are in a constant state of flux, demanding perpetual updates for investors. The price patterns are inherently unpredictable, necessitating investors to exercise prudence in their investment strategies. Sound decisions are imperative before taking any actions related to their stocks.

Considering the circumstances, we can distill this into a straightforward problem statement. In the context of stock trading, individuals involved must perpetually stay informed about the latest stock value updates, given the continuously changing nature of these values. After receiving these updates, they are tasked with making judicious decisions regarding their stock portfolios. These decisions must be advantageous and have the potential for significant gains. It is particularly challenging for novice investors in stock trading, who often err in their decisions to buy or sell stocks. It becomes evident that all investors must make informed decisions to maximize profits or minimize losses.

Hence, the overarching objective of this study is to establish a set of decision-making guidelines for buying and selling shares in the stock market. These guidelines aim to assist investors, regardless of their level of experience, in making informed and sound decisions that can lead to favorable outcomes. The following objectives delineate the focus of this research:

1.The primary aim is to create an algorithm grounded in fuzzy rules to underpin a decision support system for stock trading.

2.The formulation of a comprehensive set of fuzzy rules draws from both empirical stock data and expert insights.

3.This study endeavors to furnish actionable recommendations for stock trading decisions, encompassing both buying and selling strategies.

The stock Investment decider is built by building Mamdani Type 2 Fuzzy Logic System using Mat Lab. The rest of the paper is organized as follows section 2 contains literature survey, section 3 contains experimentation and methodology, section 4 contains results and discussion, and section 5 contains conclusion and future enhancements.

Literature Review

Extensive literature exists that delves into the concept of decision support systems employing fuzzy logic as their knowledge base. Moreover, this body of work underscores the complexity of the stock market, necessitating the integration of expert systems to effectively operate within its dynamic environment. Consequently, in recent years, the realm of decision-making within the stock market has gained substantial traction among researchers, leading to a proliferation of related projects and studies. In their research paper, Chang-Shing Lee et al. introduced an innovative Intelligent Fuzzy Meeting Agent designed for a Decision Support System. This system comprises three interconnected subagents, each tasked with facilitating intelligent meeting scheduling support. These subagents include Meeting Negotiation Agent (MNA): Responsible for managing the negotiation process for meetings. Fuzzy Inference Sample (FIA): This agent assists in fuzzy inference and aids the meeting host in organizing and conducting meetings effectively. Genetic Learning Agent (GLA): The GLA plays a crucial role in the learning process and contributes to optimizing meeting-related decisions. These three agents collaborate closely to compute results efficiently. The MNA collects the names of meeting attendees from the meeting host and communicates this information to the FIA. Furthermore, the rapid advancements in intelligent agent and multi-agent technologies within the domain of distributed artificial intelligence have ushered in a new era of in-depth research in the realm of distributed decision support systems [4].

In a study referenced as [5], researchers explored the development of a Fuzzy Logic-Based Stock Trading System, which focused on leveraging fuzzy expert systems to support decision-making in stock trading, rooted in human skills. The overarching goal was to construct and assess a decision support system for trading processes using soft computing techniques. Their approach involved the utilization of fuzzy logic to formulate a decision-making algorithm, integrating both expert knowledge and stock trading data. Expert knowledge and stock data were both translated into the language of fuzzy variables, ultimately resulting in a set of fuzzy rules. The experimental outcomes successfully aligned with the study's objectives, demonstrating the efficacy of their approach.

Stock prediction constitutes another critical facet of stock trading. Accurate stock predictions hold immense significance for investors, as they dictate the opportune moments for buying and selling stocks. Given the intricate nature of the stock market, predicting its movements poses considerable challenges. Consequently, Y. F. Wang undertook a study titled "Prediction of Stock Price Using Fuzzy Grey Prediction System" to address this issue. The study's aim was to instantaneously forecast stock prices by combining fuzzification techniques with grey theory [6]. Furthermore, Hiemstra, Y. delved into the domain of stock prediction with their research titled "Stock Market Forecasting Support System Based on Fuzzy Logic." They introduced the architecture of a fuzzy logic-based forecasting support system, justifying their choice of fuzzy logic as the most suitable method for their research objectives. These objectives encompassed defining and storing knowledge for stock market prediction, modeling vagueness and imperfections in knowledge, and providing a declarative, interactive, and explanatory prediction framework [7]. An additional relevant work in the intersection of stock market analysis and fuzzy logic is the research conducted by Doura, H. et al., titled "Investment Using Technical Analysis and Fuzzy Logic." This study applied fuzzy informational technologies to investment, particularly through technical analysis. The research aimed to emulate human behavior in stock trading, encompassing reactions to stock price movements, pattern formation, and buy/sell recommendations. Impressively, the results of this work were validated through testing across various companies [8].

Methodology and Experimentation

Fuzzy Logic represents an expansion of traditional logic, encompassing the concept of partial truth, which resides between the absolutes of "completely true" and "completely false" [9]. Dr. L. A. Zadeh of UC/Berkeley introduced this extension in the 1960s to effectively model the inherent uncertainty present in natural language. Fundamentally, fuzzy logic finds its application in the domain of fuzzy expert systems. A fuzzy expert system can be defined as an expert system that employs a collection of fuzzy membership functions and rules, in contrast to Boolean logic, for the purpose of reasoning with data. The ensemble of rules within a fuzzy expert system is commonly referred to as the rule base or knowledge base. As per Simutis, the connection between input and output in stock trading can be expressed through IF-THEN fuzzy rules as given in equation (1) [10].

$$A^{(i)}: If\ x_i\ is\ p_i^l\ And\ \dots, And x_n is\ q_i^l\quad then\ y\ is\ R^l \qquad (1)$$

where p is the fuzzy set

$x = \{x_1, x_2, \ldots, x_n\}$ represents elements of fuzzy set x

The output variables and their corresponding terms are represented by R^l. A fuzzy set, denoted as 'x,' can be described as a membership function that assigns every point within 'x' to the real interval [0.0, 1.0]. This concept aligns with one of the definitions of a fuzzy expert system, which characterizes a fuzzy expert system as a representation of truth values through membership values in fuzzy sets. These values are expressed as points on the scale ranging from 0.0 (indicating absolute falseness) to 1.0 (representing absolute truth). In contrast, 'y' can be defined as something else.

Mamdani Type -2 Fuzzy System

The architecture of a Mamdani Type-2 Fuzzy System is an extension of the traditional Mamdani Fuzzy System, designed to handle even higher levels of uncertainty and imprecision. It consists of Crisp Input Variables: At the beginning of the process, crisp input values are provided to the system. These crisp inputs represent specific, measured data or conditions relevant to the problem at hand.

Fuzzification of Crisp Inputs: The crisp input values are then fuzzified, which involves mapping each crisp input to the appropriate linguistic terms (e.g., "cold," "warm," "hot") using membership functions. These membership functions define how much each input belongs to each linguistic term and are typically expressed as Type-1 fuzzy sets. The fuzzification process captures the inherent uncertainty in the crisp input data, albeit at a Type-1 fuzzy level.

Inference Engine: The inference engine processes fuzzy rules that are constructed using these fuzzified linguistic terms based on the Type-1 fuzzy sets. The rules are expressed in IF-THEN format, and they determine the system's response based on the fuzzified input values.

Rule Aggregation: The results of applying the rules are aggregated to form a fuzzy output set. This fuzzy output set represents the system's output as a fuzzy value, considering the rules' implications for each linguistic term.

Defuzzification: The final step involves defuzzification, which converts the fuzzy output set into a single crisp value. This process provides a tangible, non-fuzzy output that can be used for control or decision-making. Techniques like centroid defuzzification are commonly used to obtain this crisp output.

While the primary focus of a Mamdani Type-2 Fuzzy System is to manage and reason with higher-order uncertainties using Type-2 fuzzy sets, crisp inputs are the initial data points that initiate the fuzzification process. The fuzzification and subsequent inference steps allow the system to deal with the inherent vagueness and imprecision in these crisp inputs, providing a more flexible and robust decision-making framework. Figure 1 shows the overall architecture of stock investment advisor model built using Mamdani Type-2 Fuzzy Logic.

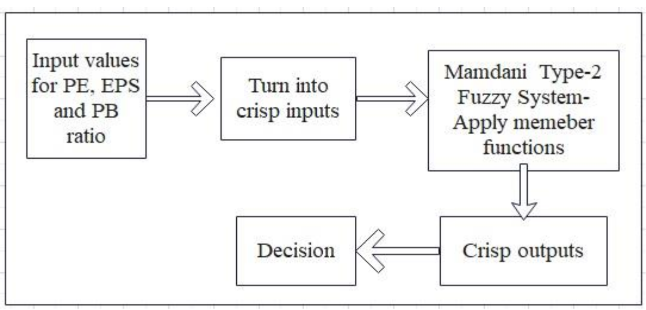


Figure 1. Architecture of the stock investment advisor

Stock Trading Decision-Making

The primary goal for individuals engaging in the world of stock trading is to maximize their profits. To achieve this, it is imperative to develop a sound strategy. Most experts recommend a strategy commonly known as "buy low" and "sell high" [11]. This approach involves purchasing stocks when their prices are low and selling them when they have appreciated in value. However, it's important to note that if the stock price remains consistently low and eventually experiences a significant drop, investors may not realize their intended gains. To mitigate this risk, those interested in the stock market should acquire a fundamental understanding of the history and performance of the company or shares they intend to invest in. By doing so, investors can make more informed decisions and increase their chances of achieving their financial objectives in the volatile world of stock trading. Figure 2 shows the architecture of Mamdani Type 2 Fuzzy controller designed for stock investment decisions

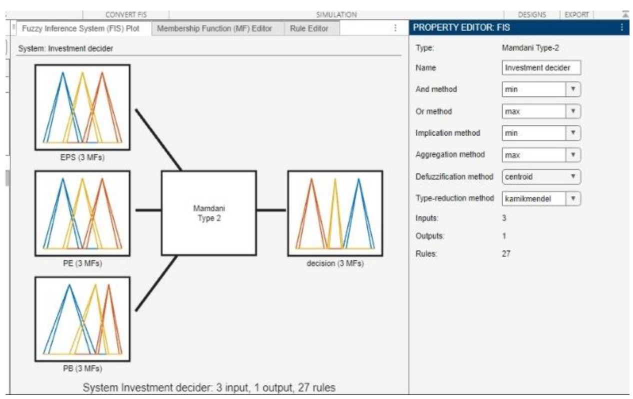


Figure 2. Architecture of Investment Advisor

Experimentation

The following streps are implemented in building fuzzy based stock investment advisor

Construction of Crisp Input variables

Three variables are considered in this research for stock investment decision. The Price-to-Earnings Ratio (P/E ratio) is a fundamental financial metric used in stock analysis. It provides valuable insights into a company's performance and its stock valuation.

The P/E ratio is a key indicator of how the market values a company's stock in relation to its earnings. A high P/E ratio typically suggests that investors have high expectations for future earnings growth, while a low P/E ratio may indicate lower growth expectations or undervaluation. Therefore, changes in the P/E ratio can directly impact a stock's price. If a company's P/E ratio increases, it can drive up the stock price, assuming earnings remain stable or are expected to improve. The P/E ratio plays a critical role in stock pricing by reflecting investor sentiment, providing a basis for comparative analysis, and responding to changes in earnings expectations. It is a valuable tool for both investors and analysts when evaluating the attractiveness of a stock and making investment decisions. Changes in the P/E ratio can directly influence stock prices as they signal shifts in market perception regarding a company's growth prospects and valuation.

Earnings per Share (EPS) is another fundamental financial metric that provides valuable information about a company's profitability and can have a significant role in influencing stock prices. EPS is a direct measure of a company's profitability. It represents the portion of a company's earnings that is allocated to each outstanding share of common stock. Investors often view higher EPS as a positive sign, indicating that a company is generating more profits per share. When a company consistently reports increasing EPS, it can attract more investors and drive-up demand for its stock, potentially leading to an increase in its stock price. PS is a critical factor in determining the valuation of a company's stock. Investors often use the price-to-earnings (P/E) ratio, which is the stock's price divided by its EPS, to assess whether a stock is overvalued or undervalued. A high P/E ratio relative to industry peers may suggest that investors are willing to pay a premium for the company's earnings, potentially driving up the stock price. Conversely, a low P/E ratio may indicate that the stock is undervalued, which could attract value-oriented investors and lead to an increase in the stock's price. Positive EPS growth and beats against earnings expectations can drive demand for a stock and contribute to price appreciation, while disappointing EPS figures or guidance misses can have the opposite effect, causing a decline in stock price.

The Price-to-Book Ratio (P/B ratio) is a financial metric that compares a company's market value (stock price) to its book value (the value of its assets minus liabilities). This ratio plays a role in stock pricing and investor decision-making. The P/B ratio is often used to assess whether a stock is undervalued or overvalued. A low P/B ratio suggests that the stock may be undervalued relative to its book value, making it an attractive investment for value-oriented investors. Conversely, a high P/B ratio can indicate that the stock is trading at a premium to its book value, potentially making it less appealing to value investors. Changes in the P/B ratio can directly impact a stock's price as investors adjust their valuations based on this metric. Investors often use the P/B ratio to compare a company's valuation to that of its industry peers or competitors. If a company has a lower P/B ratio than its peers, it may be perceived as a more attractive investment, potentially leading to higher demand for its stock and an increase in its price. Conversely, a higher P/B ratio relative to competitors may signal overvaluation, which could result in a lower stock price as investors seek more reasonably priced alternatives.

In this study, EPS, PE and PB crisp input variables are considered for stock investment decision with three ranges of values Low, Medium, and High and shown in figure 3 ,4 and 5 respectively. The fuzzification of the variables is done.

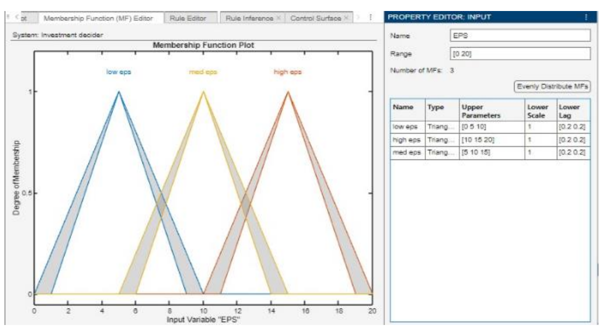


Figure 3. Initializing EPS

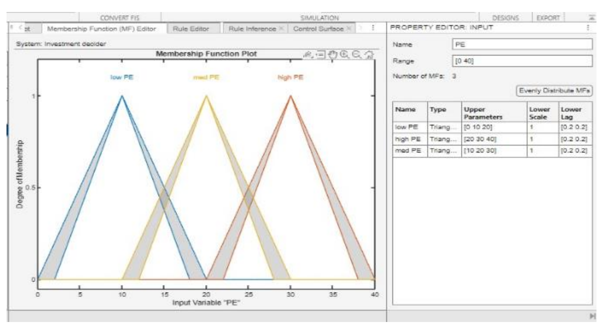


Figure 4. Intitalizing PE

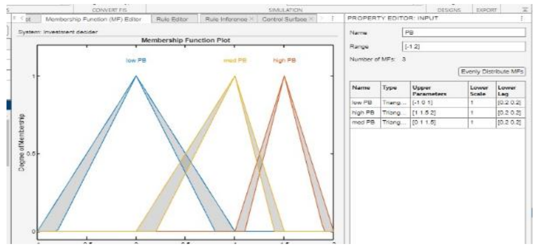


Figure 5. Initializing PB

The EPS ratio is calculated by

EPS=Net earnings/ Outstanding shares

The PE ratio is calculated by

P/E = Stock Price / EPS EPS Ratio

PB ratio is calculated by

PB=Market Price per Share/Book value per share

Input variables are given following crisp values for fuzzification.

0 > Low <=10, 10>Medium<=15, 15>High<=20

PE Ratio

0 > Low <=20, 20>Medium<30, 30>High<=40

PB Ratio

-1 > Low < =1, 1 >Medum <= 1.5, 1.5 > High <= 2

Construction of member function for input variables

Figure 6, 7 and 8 show initialization member functions for the input variables.

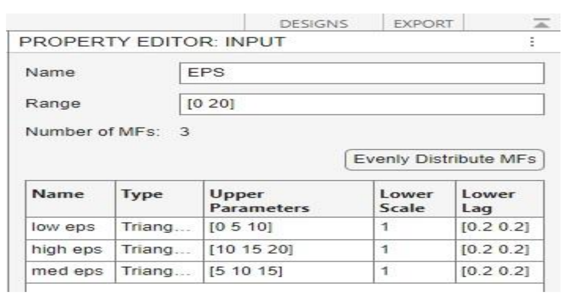
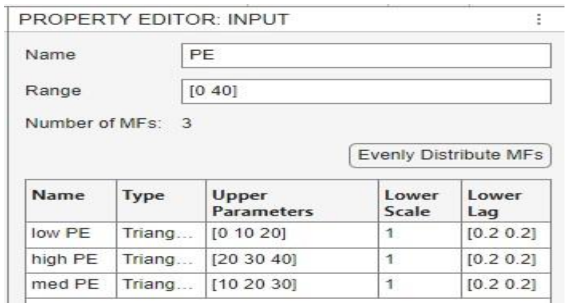


Figure 6. Initialization of member functions


PROPERTY EDITOR: INPUT

Name PE

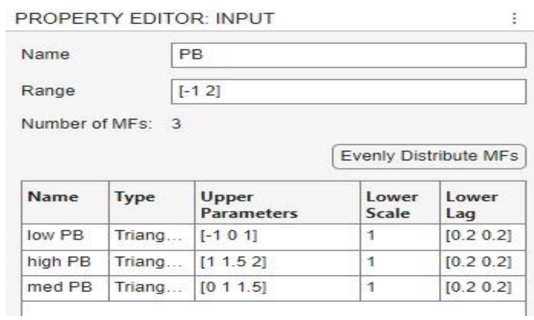
Range [0 40]

Number of MFs: 3

Evenly Distribute MFs

Name	Type	Upper Parameters	Lower Scale	Lower Lag
low PE	Triang...	[0 10 20]	1	[0.2 0.2]
high PE	Triang...	[20 30 40]	1	[0.2 0.2]
med PE	Triang...	[10 20 30]	1	[0.2 0.2]

Figure 7. Initialization of PE


PROPERTY EDITOR: INPUT

Name PB

Range [-1 2]

Number of MFs: 3

Evenly Distribute MFs

Name	Type	Upper Parameters	Lower Scale	Lower Lag
low PB	Triang...	[-1 0 1]	1	[0.2 0.2]
high PB	Triang...	[1 1.5 2]	1	[0.2 0.2]
med PB	Triang...	[0 1 1.5]	1	[0.2 0.2]

Figure 8. Initialization of PB

Construction of output variable

Defuzzification is done to get the output variable for investment decision. Three types of decision can be made. They are i. invest ii. Consider invest iii. Don't invest

Invest is a strong decision with greater than 50 percent of decision value which ensures high return. Consider investing decision is moderate level decision which has decision value of 50 where it is safe to invest but with moderate returns. Don't invest is recommended when the decision value is below 50 percent where investment does not lead to profitability. Figure 9 shows the construction of output variable decision.

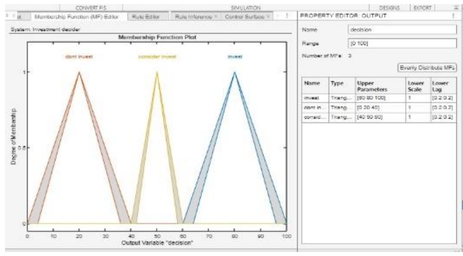


Figure 9. Initialization of Output variable

Construction of member function for output variable

Three member functions are constructed namely invest, consider invest and don't invest along with range of decision value as shown in the figure 9.

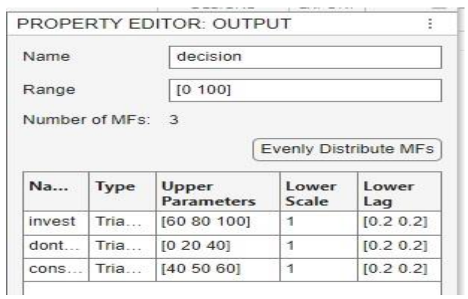
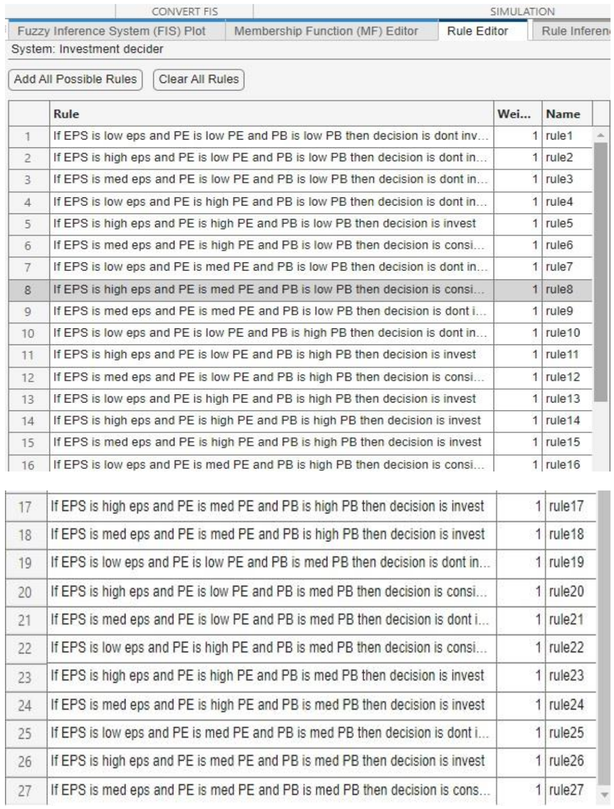


Figure 10. Output member functions

Construction of rules

A total of 27 rules are constructed to cover all possible combinations of the input variables. Figure 11 shows the construction of if then rules combining all three functions of the input variables.



	Rule	Wei...	Name
1	If EPS is low eps and PE is low PE and PB is low PB then decision is dont inv...	1	rule1
2	If EPS is high eps and PE is low PE and PB is low PB then decision is dont in...	1	rule2
3	If EPS is med eps and PE is low PE and PB is low PB then decision is dont in...	1	rule3
4	If EPS is low eps and PE is high PE and PB is low PB then decision is dont in...	1	rule4
5	If EPS is high eps and PE is high PE and PB is low PB then decision is invest	1	rule5
6	If EPS is med eps and PE is high PE and PB is low PB then decision is consi...	1	rule6
7	If EPS is low eps and PE is med PE and PB is low PB then decision is dont in...	1	rule7
8	If EPS is high eps and PE is med PE and PB is low PB then decision is consi...	1	rule8
9	If EPS is med eps and PE is med PE and PB is low PB then decision is dont i...	1	rule9
10	If EPS is low eps and PE is low PE and PB is high PB then decision is dont in...	1	rule10
11	If EPS is high eps and PE is low PE and PB is high PB then decision is invest	1	rule11
12	If EPS is med eps and PE is low PE and PB is high PB then decision is consi...	1	rule12
13	If EPS is low eps and PE is high PE and PB is high PB then decision is invest	1	rule13
14	If EPS is high eps and PE is high PE and PB is high PB then decision is invest	1	rule14
15	If EPS is med eps and PE is high PE and PB is high PB then decision is invest	1	rule15
16	If EPS is low eps and PE is med PE and PB is high PB then decision is consi...	1	rule16
17	If EPS is high eps and PE is med PE and PB is high PB then decision is invest	1	rule17
18	If EPS is med eps and PE is med PE and PB is high PB then decision is invest	1	rule18
19	If EPS is low eps and PE is low PE and PB is med PB then decision is dont in...	1	rule19
20	If EPS is high eps and PE is low PE and PB is med PB then decision is consi...	1	rule20
21	If EPS is med eps and PE is low PE and PB is med PB then decision is dont i...	1	rule21
22	If EPS is low eps and PE is high PE and PB is med PB then decision is consi...	1	rule22
23	If EPS is high eps and PE is high PE and PB is med PB then decision is invest	1	rule23
24	If EPS is med eps and PE is high PE and PB is med PB then decision is invest	1	rule24
25	If EPS is low eps and PE is med PE and PB is med PB then decision is dont i...	1	rule25
26	If EPS is high eps and PE is med PE and PB is med PB then decision is invest	1	rule26
27	If EPS is med eps and PE is med PE and PB is med PB then decision is cons...	1	rule27

Figure 11. Constuction of Rules

Results and Discussion

Defuzzification -The next step is to test the stock investment advisor with different values of the input variables. Afte the application of rules, the decision value is output. The decision value represents defuzzification of the fuzzy output variables into crisp value. The following figures show the rule inference applied on different input variables and defuzzification of decision value obtained.

Figure 12 shows rule inference for input values [15, 30,0.2] for EPS, PE and PB respectively. The decision value obtained by the model is 80 which means investor can take decision to invest. The obtained decision is cross checked with expert opinion and it proved to be correct.

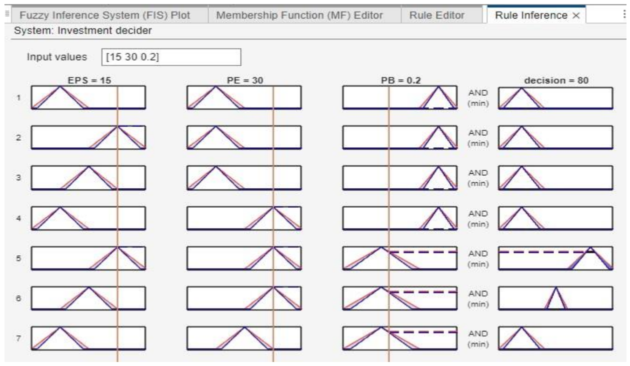


Figure 12. investment decision 1

Figure 13 shows the input values [20,10,1] and decision value output is 50 which means consider investment decision. This decision also matches with the expert opinion.

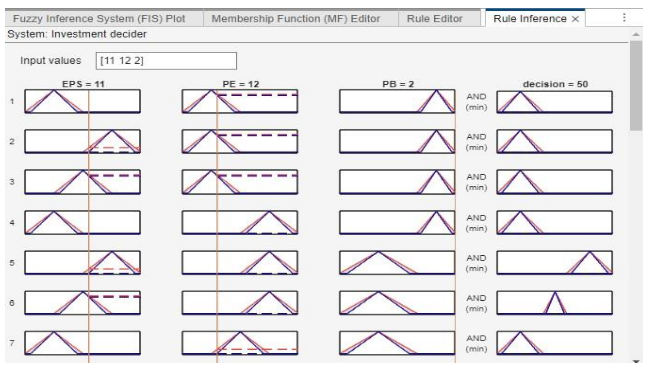


Figure 13. investment decision 2

Figure 14 shows the input values [17, 35, 1] and decision value output is 80 which means investment decision. This decision also matches with the expert opinion.

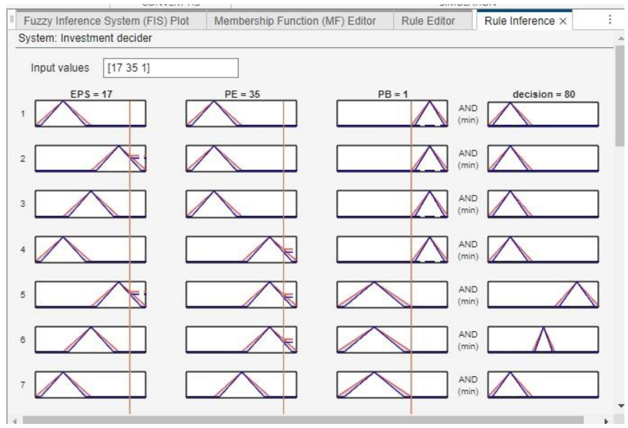


Figure 14. investment decision 3

Figure 15 shows the input values [6,13,1] and decision value output is 22.7 which means don’t invest decision. This decision also matches with the expert opinion.

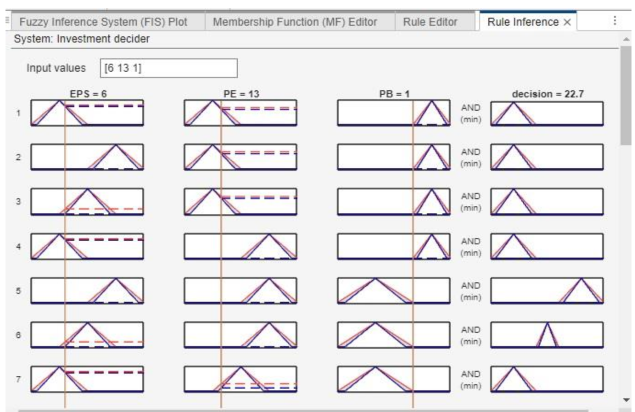


Figure 15. investment decision 4

Figure 16 shows the input values [20,10,1] and decision value output is 50 which means consider invest decision. This decision also matches with the expert opinion.

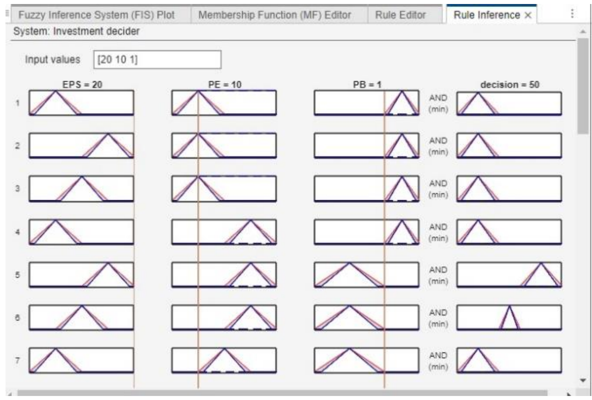


Figure 16. investment decision 5

The model is tested with real time input values of companies like Walmart, Tesla, Reliance, and the model predicted with the decision invest which is very much true as per the expert opinion. Next, the model is tested with input values of companies whose stock market value is moderate like Nippon Assets, UTI, Vodafone, BHEL, Dalmia Bharath. Since they are mid cap companies, the investment decision expected is consider investment. The built model also predicted with the same decision with value 50 which means consider investment. Next, the model is tested with input values of companies with low price EPS, PE and high PB like Brookdale Senior Living Inc., Dish Network Corp., Meritage Homes, and Perfect World Co. As per the expert opinion, these companies are not advisable to invest. The model output obtained is 22.37 as decision value which means don't invest decision. This also proved correct with the real time scenario.

Figure 17 shows the fuzzification and defuzzification visuals of the variables.

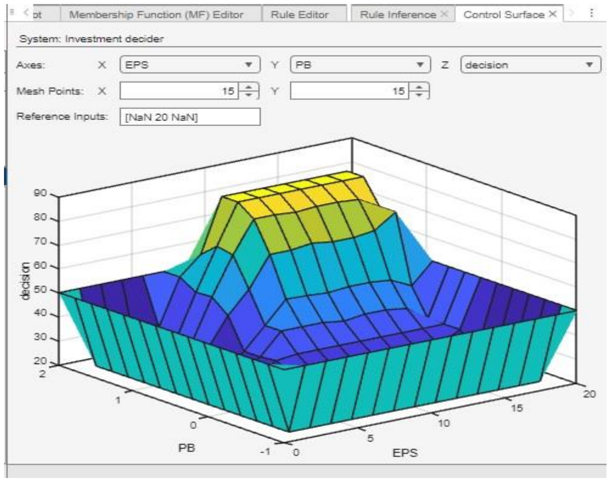


Figure 17. Fuzzification and defuzzification visualization

Figure 18 shows the graph of various investment decision made for different combination of input variables. Value 0 inidacates don't invest decision, 1 indicates consider invest decision and 2 indicates invest decsion.

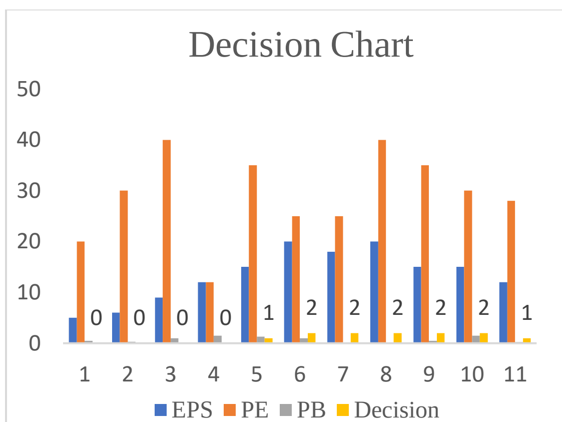


Figure 18. Decision Chart

Conclusion and Future Enhancement

In conclusion, the development and implementation of an Intelligent Fuzzy Stock Investment Advisor represents a significant advancement in the field of financial technology and investment strategies. This innovative system harnesses the power of fuzzy logic to make investment decisions in a more nuanced and human-like manner, considering the uncertainties and imprecisions inherent in financial markets.

The key strengths of this Intelligent Fuzzy Stock Investment Advisor lie in its ability to process complex financial data, adapt to changing market conditions, and provide personalized investment recommendations tailored to individual risk tolerance and financial goals. By leveraging fuzzy logic, it can navigate the volatility of stock markets more effectively and make informed investment choices. The Intelligent Fuzzy Stock Investment Advisor represents a valuable tool for investors seeking a more sophisticated and adaptive approach to stock market investments. It offers the potential for improved decision-making in an ever-changing financial landscape, but users should remain vigilant and well-informed to make prudent investment choices.

However, it's important to acknowledge that no investment strategy is foolproof, and the Intelligent Fuzzy Stock Investment Advisor is not exempt from risks. Market dynamics can be unpredictable, and past performance is not always indicative of future results. Users should exercise caution and consider the system's recommendations as one of several factors in their investment decision-making process.

Currently only three investment factors are considered for decision making. But the dynamic factors of the market may also contribute indirectly to the changing stock price. Future enhancement can be made by integrating with machine learning, considering more dynamic input factors, and feeding with real time dataset. Model can scale up to give decisions on equity, bonds, and cryptocurrencies etc., by incorporating risk assessment factors.

COMPETING INTERESTS

The authors have no competing interests to declare.

Author's Affiliation

Nirmala M S [1], Lata Kulkarni [2], *Jyothi N M [3]

[1]Department of Computer Science, Government College for Women (Autonomous), Manday, Karnataka, India
[2] Department of Electronics, Government Science College, Hassan, Karnataka, India
[3] Dept. of Computer Science Engineering, Koneru Lakshmaiah Education Foundation, Vddeswaram, AP, India

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