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AI-Enhanced Fuzzy Precision in Stock Investment Decisions with Integrated Weighted Aggregation and Multivariate

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Abstract— This paper presents a decision support system designed for stock trading, utilizing Fuzzy IF-THEN Rules. The system utilizes three key linguistic variables as input parameters: Price-to-Earnings Ratio (PE), Earnings per Share (EPS), and Price-to-Book Ratio (PB). Its primary aim is to assist investors in making informed decisions regarding their stock investments, aiming to maximize profits in the complex and challenging stock market environment. To simplify and improve decision-making in this intricate realm, Artificial Intelligence (AI) is employed through the implementation of Fuzzy Logic (FL). The stock Investment decider is constructed by developing a Mamdani Type 2 Fuzzy Logic System using MATLAB. Previous research has highlighted the effectiveness of FL in navigating the complexities of stock trading environments. The study thoroughly assesses and validates the fuzzy rules through the application of a Fuzzy Inference System in MATLAB, ensuring a comprehensive evaluation of the proposed system's effectiveness. The model demonstrated an highest accuracy rate of 99.35% concerning real-time investment decisions and with other Machine Learning Models.

Keywords— Fuzzy logic, Mamdani Fuzzy type -2, MATLAB, crisp values, stock investment decision

I. INTRODUCTION

The business landscape is undeniably intricate and highly competitive, demanding businesses to recognize the essential need for integrating information technology (IT) applications. These applications enhance operational efficiency and elevate the quality of products and services [1]. The pivotal role of IT in the business environment is evident as businesses seamlessly integrate various applications, with e-commerce being a notable example. E-commerce stands out as a widely acknowledged advancement due to its user-friendly nature and manifold benefits, streamlining and expediting business processes for greater convenience and efficiency. Expanding the scope of information technology to sectors like the stock market holds the promise of offering fresh perspectives and exploration opportunities in this field. The stock market is a favored destination for investments due to its potential for substantial profits [2]. Operating within a complex business environment, the stock market demands perpetual updates for investors as stock values are in a constant state of flux. The inherently unpredictable price patterns necessitate investors to exercise prudence in their investment strategies, emphasizing the importance of sound decisions before taking any actions related to their stocks.

In the context of stock trading, individuals must stay perpetually informed about the latest stock value updates, given the continuously changing nature of these values. Subsequently, they are tasked with making judicious decisions regarding their stock portfolios, aiming for advantageous outcomes and significant gains. Novice investors in stock trading often face challenges in decision-making, leading to errors in buying or selling stocks. It becomes evident that all investors must make informed decisions to maximize profits or minimize losses. The overarching objective of this study is to establish decision-making guidelines for buying and selling shares in the stock market, assisting investors, regardless of their experience level,

in making informed and sound decisions for favorable outcomes. The specific objectives include creating an algorithm grounded in fuzzy rules for a decision support system in stock trading, formulating a comprehensive set of fuzzy rules drawing from empirical stock data and expert insights, and providing actionable recommendations for stock trading decisions, covering both buying and selling strategies.
The stock Investment decider is built using a Mamdani Type 2 Fuzzy Logic System with Mat Lab. The paper is organized with a literature survey in section 2, experimentation and methodology in section 3, results and discussion in section 4, and conclusion and future enhancements in section 5.

II. LITERATURE SURVEY- THE ADVENT OF TECHNOLOGY IN THE BANKING SECTOR

A substantial body of literature explores the utilization of decision support systems grounded in fuzzy logic. This research emphasizes the intricacies of the stock market, prompting the integration of expert systems to navigate its dynamic landscape effectively. Consequently, recent years have witnessed a surge in research dedicated to decision-making within the stock market, resulting in numerous related projects and studies. In a notable 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 assigned a specific role in facilitating intelligent meeting scheduling support. The subagents include the Meeting Negotiation Agent (MNA), responsible for managing the negotiation process for meetings; the Fuzzy Inference Sample (FIA), assisting in fuzzy inference to help the meeting host organize and conduct meetings effectively; and the Genetic Learning Agent (GLA), playing a crucial role in the learning process and contributing to the optimization of meeting-related decisions. These three agents collaborate closely to efficiently compute results. The MNA collects the names of meeting attendees from the meeting host and communicates this information to the FIA. Moreover, 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 referenced study [5], researchers delved into the development of a Fuzzy Logic-Based Stock Trading System, aiming to leverage fuzzy expert systems to enhance decision-making in stock trading, emulating human skills. The primary objective was to create and evaluate a decision support system for trading processes employing soft computing techniques. The approach involved the application of fuzzy logic to formulate a decision-making algorithm, incorporating both expert knowledge and stock trading data. Expert knowledge and stock data were translated into the language of fuzzy variables, culminating in a set of fuzzy rules. The experimental outcomes aligned successfully with the study's objectives, substantiating the effectiveness of their approach.
Accurate stock predictions play a pivotal role in guiding investors on opportune moments for buying and selling stocks, given the intricacies of the stock market. Y. F. Wang addressed the challenges of predicting stock movements with the study "Prediction of Stock Price Using Fuzzy Grey Prediction System," aiming to instantly forecast stock prices by combining fuzzification techniques with grey theory [6]. Additionally, Hiemstra, Y. delved into stock prediction in the research titled "Stock Market Forecasting Support System Based on Fuzzy Logic," introducing the architecture of a fuzzy logic-based forecasting support system. They justified their selection of fuzzy logic as the most suitable method, focusing on objectives such as defining and storing knowledge for stock market prediction, modeling vagueness and imperfections, and providing a declarative, interactive, and explanatory prediction framework [7]. Another pertinent 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, specifically through technical analysis, with the goal of emulating human behavior in stock trading, covering 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].

III. METHODOLOGY AND EXPERIMENTATION

Fuzzy Logic extends traditional logic by introducing the concept of partial truth, residing between the absolutes of "completely true" and "completely false" [9]. Dr. L. A. Zadeh introduced this extension in the 1960s to effectively model the inherent uncertainty present in natural language. Fuzzy logic fundamentally finds application in the domain of fuzzy expert systems. A fuzzy expert system, in this context, refers to an expert system utilizing a collection of fuzzy membership functions and rules, in contrast to Boolean logic, to reason with data. The set of rules within a fuzzy expert system is commonly termed the rule base or knowledge base. According to Simutis, the connection between input and output in stock trading can be expressed through IF-THEN fuzzy rules, as given in equation (1) [10].

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

where p is the fuzzy set

$x = \{x_1, x_2, .., x_n\}$ 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.

Advantages of Fuzzy Logic -Fuzzy logic offers distinct advantages over other prediction models, making it a preferred choice for certain applications. One key strength lies in its adept handling of uncertainty and vagueness within data. Fuzzy logic excels when faced with imprecise information or situations involving gradual transitions between categories. The rule-based nature of fuzzy logic systems further contributes to their appeal, as rules are expressed in natural language (if-then statements), fostering intuitive and interpretable models. This transparency enhances the model's interpretability, allowing stakeholders to understand and trust the decision-making process.

A notable advantage of fuzzy logic is its ability to readily incorporate expert knowledge into the model. This is particularly valuable in fields where human expertise plays a crucial role, such as medical diagnosis or financial forecasting. Fuzzy logic systems also demonstrate efficiency with limited data, producing meaningful results even with small datasets. Their effectiveness in modelling complex systems with nonlinear relationships is another key strength, enabling the capture of intricate patterns without the need for extensive mathematical formulations. The natural language representation used in fuzzy logic, involving linguistic variables and terms, facilitates a clear expression of knowledge. This feature is advantageous when working with non-experts or translating human intuition into a computational model. Fuzzy logic systems are often less computationally demanding compared to certain machine learning models, making them suitable for applications with limited computational resources. Moreover, fuzzy logic excels in dynamic adaptability, adjusting to changes in input conditions. This capability is particularly valuable in real-time applications where the system must respond to evolving situations. While these advantages position fuzzy logic as a powerful tool, it's crucial to recognize that its effectiveness depends on the nature of the problem. For tasks involving massive datasets, complex patterns, or where a higher degree of predictive accuracy is required, other models like machine learning algorithms might be more suitable. The choice between models should align with the specific characteristics and requirements of the prediction problem at hand.

Mamdani Type-2 Fuzzy Logic Systems (T2-FLS) and Classic Fuzzy Logic Systems (C-FLS) exhibit distinctive characteristics. Classic Fuzzy Logic deals with uncertainty using crisp membership values, assigning elements complete or no membership to a set. In contrast, Mamdani Type-2 Fuzzy Logic extends this concept by introducing "fuzzy uncertainties" in membership functions, allowing a nuanced representation of uncertainty. While Classic Fuzzy Logic employs simpler, single-level membership functions, Mamdani Type-2 Fuzzy Logic uses more complex functions with additional parameters to model uncertainty. Classic Fuzzy Logic assumes a fixed level of uncertainty for each membership value, whereas Mamdani Type-2 Fuzzy Logic acknowledges that uncertainty itself can be fuzzy, providing greater flexibility. Classic Fuzzy Logic typically involves single-level fuzzy sets, while Mamdani Type-2 Fuzzy Logic employs multiple levels, each corresponding to a different degree of uncertainty. In terms of rule base complexity, Classic Fuzzy Logic utilizes straightforward IF-THEN rules with crisp conclusions. On the other hand, Mamdani Type-2 Fuzzy Logic introduces additional parameters and rules to account for uncertainty in both antecedents and consequents. Regarding defuzzification, Classic Fuzzy Logic employs standard methods like centroid or max membership, while Mamdani Type-2 Fuzzy Logic requires more sophisticated methods due to additional uncertainty levels in the output.

In essence, Mamdani Type-2 Fuzzy Logic extends Classic Fuzzy Logic by incorporating fuzzy uncertainties, enabling a more nuanced representation of uncertainty and flexible handling of complex information. Hence, in this study, Mamdani Type-2 Fuzzy Logic is implemented and evaluated for stock investment prediction.

A. Mamdani Typ-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.

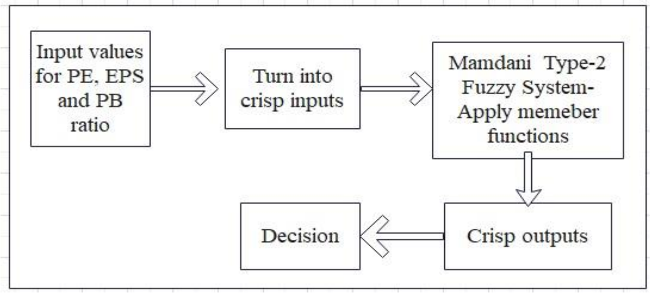

Figure 1. Architecture of the stock investment advisor

B. Stock Trading Decision-Making

The primary objective for individuals involved in stock trading is profit maximization. To achieve this goal, it is crucial to develop a robust strategy. A commonly recommended strategy, advocated by most experts, is the "buy low" and "sell high" approach [11]. This strategy entails purchasing stocks when their prices are low and selling them when their value appreciates. However, it is essential to recognize 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, individuals interested in the stock market should gain a fundamental understanding of the history and performance of the company or shares they intend to invest in. This knowledge enables investors to make more informed decisions, enhancing their chances of achieving financial objectives in the volatile realm of stock trading. Figure 2 illustrates the architecture of the Mamdani Type 2 Fuzzy controller designed for stock investment decisions.

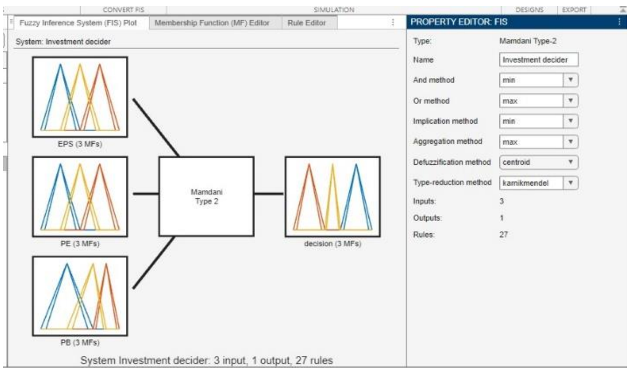

Figure 2. Architecture of Investment Advisor

C. Experimentation

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

1.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 Price-to-Earnings (P/E) ratio serves as a crucial indicator of how the market assesses a company's stock concerning its earnings. A high P/E ratio generally indicates that investors hold optimistic expectations for future earnings growth, whereas a low P/E ratio may suggest lower growth expectations or undervaluation. Consequently, fluctuations in the P/E ratio can have a direct impact on a stock's price. When a company's P/E ratio increases, it has the potential to drive up the stock price, assuming that earnings remain stable or are anticipated to improve. The P/E ratio assumes a pivotal role in

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stock pricing, acting as a reflection of investor sentiment. It provides a foundation for comparative analysis and swiftly responds to changes in earnings expectations. This metric proves invaluable for both investors and analysts in the evaluation of a stock's attractiveness and forms a basis for informed investment decisions. Alterations in the P/E ratio wield direct influence over stock prices by signifying shifts in market perception regarding a company's growth prospects and valuation. As a dynamic tool, the P/E ratio captures the evolving sentiment of investors, thereby contributing to the ongoing assessment of a company's stock in the market.

Earnings per Share (EPS) stands as a fundamental financial metric that furnishes valuable insights into a company's profitability, exerting a significant influence on stock prices. EPS serves as a direct measure of a company's profitability, representing the portion of its earnings allocated to each outstanding share of common stock. Investors commonly interpret higher EPS as a positive signal, signifying that a company generates more profits per share. Consistent reporting of increasing EPS by a company has the potential to attract more investors, fostering heightened demand for its stock. This heightened demand can potentially lead to an increase in the stock price, as investors perceive the company as generating robust profits on a per-share basis. EPS is a pivotal factor in determining the valuation of a company's stock. Investors often employ the price-to-earnings (P/E) ratio, calculated as the stock's price divided by its EPS, to gauge whether a stock is overvalued or undervalued. A high P/E ratio concerning 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, attracting value-oriented investors, and contributing to an increase in the stock's price.
The growth of EPS, when positive and surpassing earnings expectations, can stimulate demand for a stock and contribute to price appreciation. Conversely, disappointing EPS figures or guidance misses can have the opposite effect, leading to a decline in the stock price. Therefore, EPS plays a crucial role in investor perceptions and decision-making, influencing the attractiveness and valuation of a company's stock in the market.

The Price-to-Book Ratio (P/B ratio) serves as a financial metric comparing a company's market value (stock price) to its book value (the value of its assets minus liabilities). This ratio holds significance in stock pricing and influences investor decision-making. Frequently utilized to assess whether a stock is undervalued or overvalued, the P/B ratio provides insights into its relative attractiveness for investors. A low P/B ratio suggests that the stock may be undervalued concerning its book value, presenting an appealing investment opportunity for value-oriented investors. Conversely, a high P/B ratio may indicate that the stock is trading at a premium to its book value, potentially making it less attractive to value investors. Changes in the P/B ratio directly impact a stock's price as investors adjust their valuations based on this metric. Investors commonly employ the P/B ratio for comparisons, evaluating a company's valuation against that of its industry peers or competitors. If a company exhibits a lower P/B ratio than its peers, it may be perceived as a more attractive investment. This perception can lead to higher demand for its stock and contribute to an increase in its price. Conversely, a higher P/B ratio relative to competitors may signal overvaluation, potentially resulting in a lower stock price as investors seek more reasonably priced alternatives.
In the context of this study, the crisp input variables considered for stock investment decisions are EPS, PE, and PB. These variables are categorized into three ranges of values: Low, Medium, and High, as depicted in Figures 3, 4, and 5, respectively. The fuzzification process is applied to these variables, enhancing the precision and adaptability of the decision-making system.

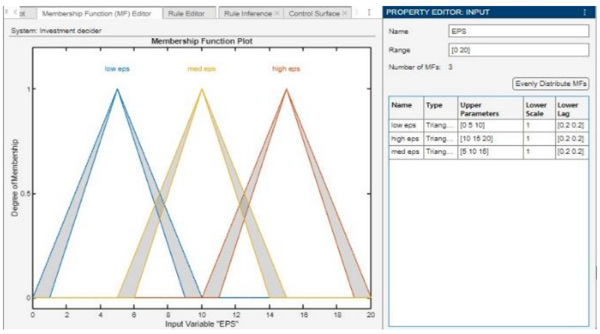

Figure 3. Initializing EPS

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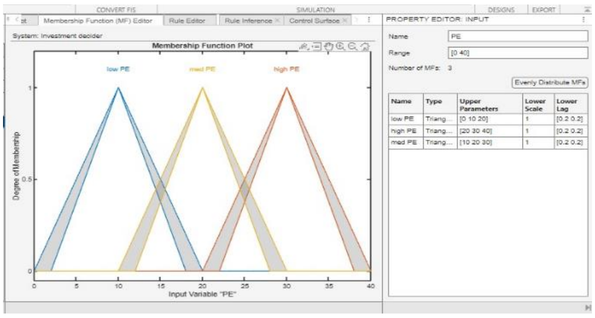


Figure 4. Intitalizing PE

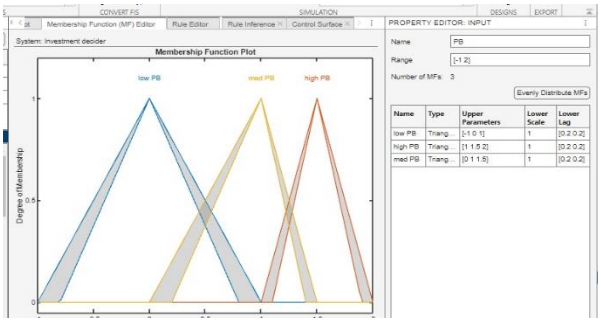


Figure 5. Initializing PB

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

2. Construction of member function for input variables
Figure 6, 7 and 8 show initialization member functions for the input variables.

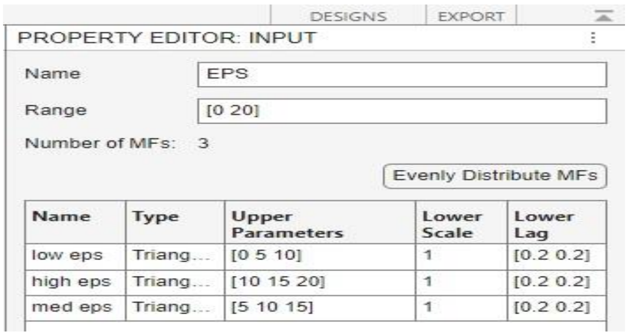
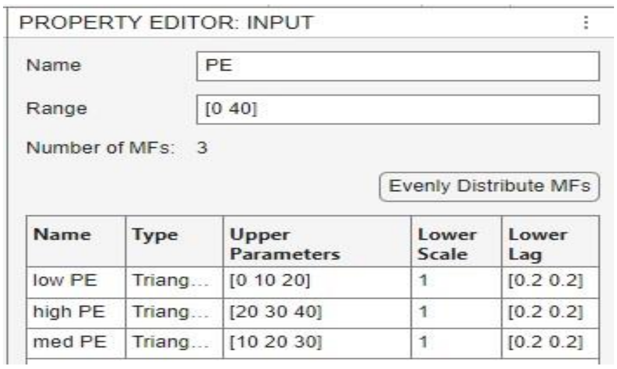


Figure 6. Initialization of member functions



PROPERTY EDITOR: INPUT

Name: PE

Range: [0 40]

Number of MFs: 3

Evenly Distribute MFs

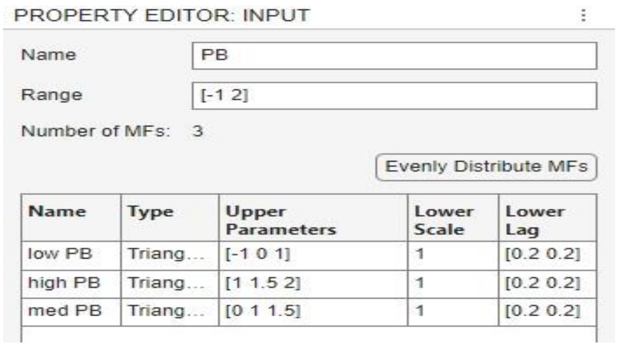
Name	Type	Upper Parameters	Lower Scale	Lower Lag
low PE	Triang...	[0 10 20]	1	[0.2 0.2]
high PE	Triang...	[20 30 40]	1	[0.2 0.2]
med PE	Triang...	[10 20 30]	1	[0.2 0.2]

Figure 7. Initialization of PE

3.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 investing 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.



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

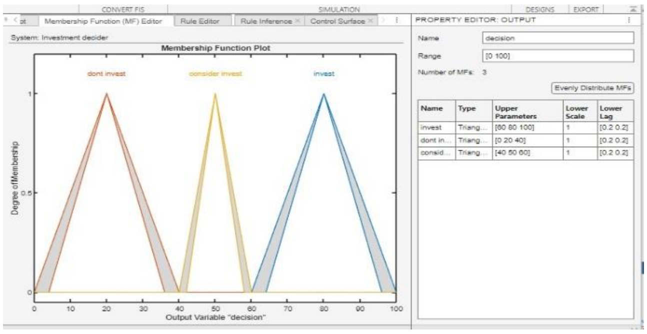
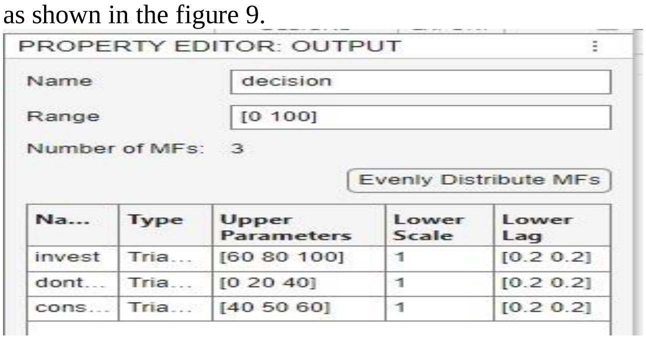


Figure 9. Initialization of Output variable

4. 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.



PROPERTY EDITOR: OUTPUT

Name: decision

Range: [0 100]

Number of MFs: 3

Evenly Distribute MFs

Na...	Type	Upper Parameters	Lower Scale	Lower Lag
invest	Tria...	[60 80 100]	1	[0.2 0.2]
dont...	Tria...	[0 20 40]	1	[0.2 0.2]
cons...	Tria...	[40 50 60]	1	[0.2 0.2]

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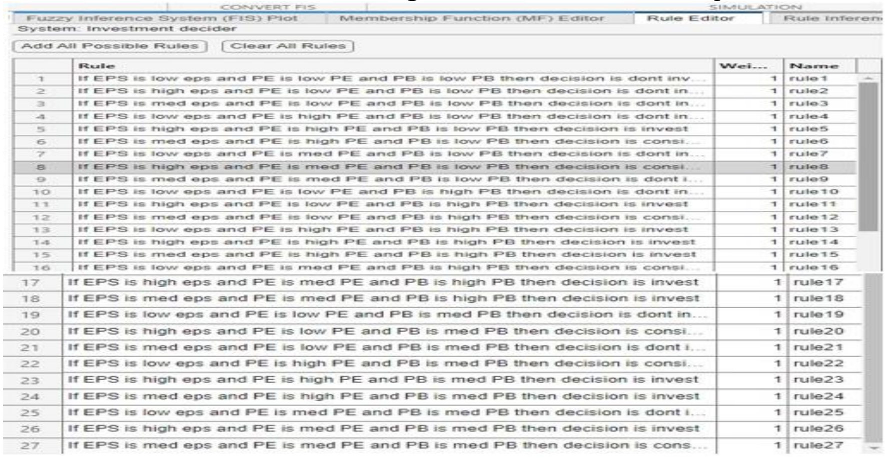
Figure 10. Output member functions

5.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.



CONVERT FIS | SIMULATION

Fuzzy Inference System (FIS) Plot | Membership Function (MF) Editor | Rule Editor | Rule Inferen

System: Investment decider

Add All Possible Rules | Clear All Rules

	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. Construction of Rules

IV. 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.

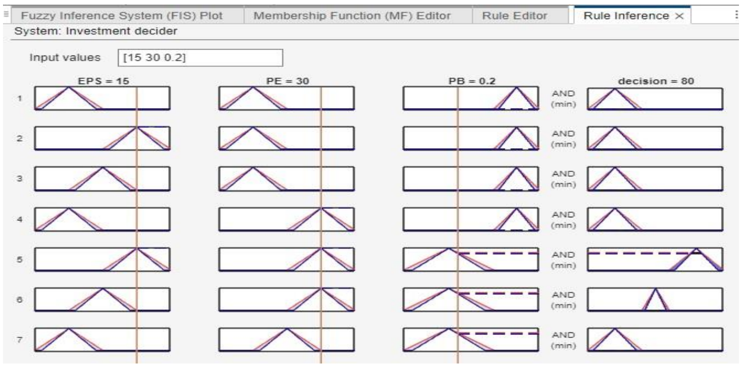


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Figure 12. investment decision 1

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.

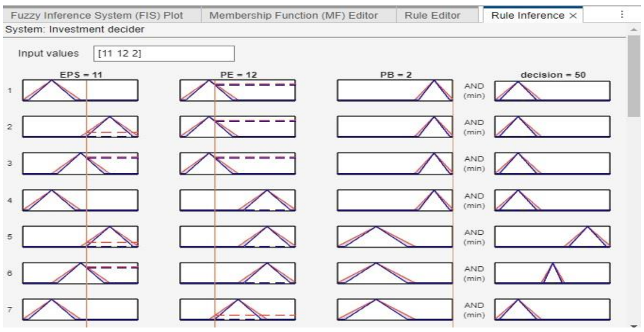

Figure 13. investment decision 2

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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.

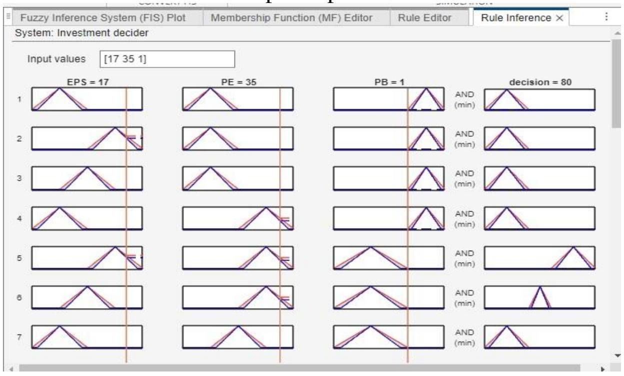

Figure 14. investment decision 3

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, UTI, Vodaphone, BHEL, Dalmia. 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 Livings, Dish Networks., Meritage Housing Ltd, and Perfect Decors. 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

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defuzzification visuals of the variables. The model showed accuracy of 99.35% with respect to real time investment decisions.

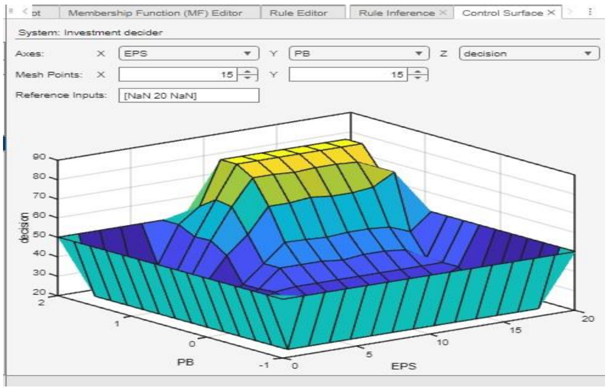

Figure 17. Fuzzification and defuzzification visualization

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.

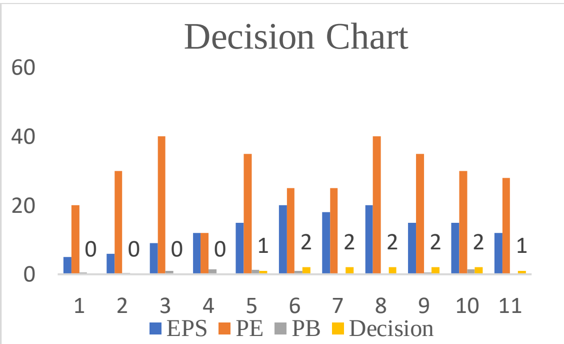

Figure 18. Decision Chart

The built model is cross evaluated with other Machine Learning (ML) models like Logistic Regression (LR), Navie Baye's classifier (NB), Support Vector Machine (SVM) and Random Forest (RF). The dataset containing EPS, PE and PB values from the past 10 years of 13 different companies are built and tested. The accuracy obtained is LR - 97.52%, NB - 95.34%, SVM - 96.45%, RF - 95.87 %.

V. Conclusion and Future Enhancement

In conclusion, the development and implementation of an Intelligent Fuzzy Stock Investment Advisor signify a notable advancement in the realm of financial technology and investment strategies. This innovative system harnesses the capabilities of fuzzy logic to make nuanced and human-like investment decisions, acknowledging the inherent uncertainties and imprecisions within financial markets. The model exhibited an impressive accuracy of 99.35% concerning real-time investment decisions, surpassing the accuracy achieved by other machine learning models.

The primary strengths of this Intelligent Fuzzy Stock Investment Advisor lie in its capacity to process intricate financial data, adapt to evolving market conditions, and offer personalized investment recommendations aligned with individual risk tolerance and financial objectives. By employing fuzzy logic, it adeptly navigates the volatility of stock markets, enabling well-informed investment choices. The Intelligent Fuzzy Stock Investment Advisor stands as a valuable tool for investors seeking a more sophisticated and adaptive approach to stock market investments. It holds the potential to enhance decision-making in the ever-changing financial landscape. However, users should exercise vigilance and stay well-informed to make prudent investment choices, recognizing that no investment strategy is entirely foolproof, and market dynamics can be unpredictable. The system's recommendations should be considered alongside other factors in the investment decision-making process.

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