International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 11-No.1 (2025) pp. 508-515
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

Enhancing Trading Strategies: Mandani Fuzzy Logic Forecasting for Borsa Istanbul Stocks Using Important Indicators

Erman ÖZER[1]*, Nurullah SEVİNÇKAN[2], Erdem DEMİROĞLU[3],Hasan AYDOS[4]

[1]Recep Tayyip Erdoğan University, Faculty of Engineering and Architecture, Computer Engineering Department, Rize-Turkey
***Corresponding Author Email:** erman.ozer@erdogan.edu.tr - **ORCID:** 0000-0002-9638-0233

[2]Recep Tayyip Erdoğan University, Faculty of Engineering and Architecture, Computer Engineering Department, Rize-Turkey
Email: nurullah_sevinckan20@erdogan.edu.tr - **ORCID:** 0009-0001-1207-9444

[3]Recep Tayyip Erdoğan University, Faculty of Engineering and Architecture, Computer Engineering Department, Rize-Turkey
Email: erdem_demiroglu20@erdogan.edu.tr - **ORCID:** 0009-0007-4084-6392

[4]Recep Tayyip Erdoğan University, Faculty of Engineering and Architecture, Computer Engineering Department, Rize-Turkey
Email: hasan_aydos20@erdogan.edu.tr - **ORCID:** 0009-0008-1197-4093

Article Info:

DOI: 10.22399/ijcesen.695
Received : 27 November 2024
Accepted : 14 January 2025

Keywords :

Financial Forecast,
Fuzzy Logic,
Technical Analysis,
Mamdani.

Abstract:

Recent years have seen significant financial market advancements, predicting stock or crypto exchange prices is a complex and risky process. Developments in the financial world are becoming increasingly interesting, especially for traders and investors who want to maximise profits. Nowadays, financial forecasting analysis is changing as conditions change and popular methods are preferred instead of traditional methods. Current changes and developments in the markets have become very important with the fuzzy logic method and the selection of indicators. In this study demonstrates that significant success was achieved by combining the strengths of six popular indicators RSI, SO, MACD, OBV, BB, and CCI to mitigate their weaknesses and enhance prediction accuracy. This study provides forecasting analysis with mandani fuzzy logic method to facilitate the operation of 655 companies listed in Borsa Istanbul (BIST). FROTO stock data belonging to Ford Otosan company on BIST is used as data. This study aims to enable traders and investors to maximize their profits or increase their portfolios. The most accurate results were obtained using membership functions created for the indicators and 34 rules created using the Mamdani fuzzy method.

1. Introduction

Technical analysis plays a crucial role in the financial world by focusing on price movement dynamics and the supply-demand interactions that drive these movements. Unlike fundamental analysis, it deliberately disregards factors such as government policies, economic conditions, and other macroeconomic influences.

While technical analysts rely on charts to identify patterns and trends, fuzzy logic offers an innovative approach by processing imprecise data more effectively. By incorporating aspects such as investor psychology and market participant reactions to price changes, fuzzy logic provides deeper insights into the complexities of human behaviour, market conditions, and economic factors. In financial markets, where investment decisions are often driven by expectations rather than tangible factors, securities are frequently valued based on perception rather than intrinsic worth. A core principle of technical analysis is to grasp these market participants' expectations and observe their actions in anticipation of future developments [1-5].

Fuzzy logic focuses on connecting financial analysis to a set of fuzzy indicators that aid in making effective stock trading decisions. This paper discusses the fundamental principles of fuzzy logic, its application in financial analysis, and

demonstrates its utility through a practical example. The use of fuzzy logic in financial forecasting and analysis has garnered significant attention in both academic and professional circles. As the financial industry becomes increasingly complex, traditional forecasting methods [6-10] often fall short in addressing the nuances and uncertainties inherent in financial data. With its ability to process imprecise and uncertain information, fuzzy logic emerges as a promising alternative, enhancing the accuracy and reliability of financial forecasting and analysis.
Zadeh's development of fuzzy sets in 1965 laid the groundwork for the fundamental principles of fuzzy logic, which are widely used today. Unlike traditional sets, fuzzy sets allow partial membership. This allows to distinguish between items of limited importance that contain uncertainty about events of interest [11]. In order to design a fuzzy model, a rule base should be created using expert knowledge or information gathered from historical data. The rules can include, for example, statements such as "the technical trading signal is a strong sell signal if the long-term moving average is high and the short-term moving average is very low "[12]. In a fuzzy system, the process of trade recommendation generation starts with the fuzzification of inputs by components of technical indicators (e.g. moving averages or filter values) followed by the application of rules. Fuzzy results are generated for each rule. The results of the active rules used in the decision-making process are combined to obtain a fuzzy result about the output variable. After defuzzification, a trading position is generated with a single value [13,14].

2. Literature Review

A lot of work has been done in the financial sector since the 2000s. Chang et al. developed the Sugeno fuzzy system using stock price movements in different sectors in the Taiwan Stock Exchange and claimed that they achieved an accuracy of approximately 97.6% [15].
Muzzioli and De Baets found that most of the papers using fuzzy logic for option pricing address the direct pricing problem in both discrete and continuous time settings. The focus of this paper is to make a contribution to option pricing under fuzziness from a practical point of view. They obtain a non-triangular price using the Black-Scholes option pricing method. However, they improve the applicability of the fuzzy version of this formula by constructing and testing triangular fuzzy numbers for the underlying asset price, volatility and free interest rate. To check the quality of these approaches, they first evaluate their closeness to the true values of the fuzzy Black and Scholes model and claim that they achieve good results [16].
Modern indicators for financial solutions have been identified with the technique developed through the Dow Hypothesis. As reported by Vanstone and Hahn [17], they obtained pattern match and esoteric indicators. Brock et al. based on information from the Dow, using the average closing prices over a range of days and the Moving Average method [18] obtained important indicators in the financial field. Mallikarjuna and Rao [19] combine some indicators such as MACD, RSI and SO to obtain the direction of the moving trend of the stock.
Nowadays, studies collectively highlight the critical interplay between advanced modeling techniques, preprocessing strategies, and domain-specific adaptations in financial forecasting. The evaluation of normalization techniques for transformer-based models emphasizes the importance of tailored preprocessing, especially when technical indicators are incorporated—an insight mirrored in the Gradient Boosting study, which demonstrates how high-quality data and feature engineering are pivotal for capturing nonlinear relationships in bank ROE forecasting [20]. Similarly, machine and deep learning models for option pricing underscores the necessity for scalable, interpretable, and region-specific models, aligning with the need for adaptable preprocessing methods and sector-specific approaches identified in the normalization study [21,22]. The analysis of technical indicators, such as MACD and Bollinger Bands, further reinforces the value of capturing momentum and volatility, foundational metrics that underpin the effectiveness of predictive models across financial domains [23]. In this study, SO, RSI, MACD, OBV, Bollinger Bands (BB), and Commodity Channel Index (CCI) indicators are utilized in analyzing BIST Ford Otosan stock to enhance predictive accuracy and provide the best solutions in the financial field. Ford Otosan was chosen for this study due to its large market capitalization, which results in lower volatility and stable price movements during significant trading activity. As a prominent company ranked in the BIST30 index, it is a reliable and important entity for analysis in the Turkish stock market. Together, this work suggests a unified framework where preprocessing, model interpretability, and domain-specific insights converge to advance the precision and applicability of financial prediction systems across diverse markets.

3. System Architecture

The finance system architecture using Mamdani fuzzy logic method is shown in Figure 1. Data are

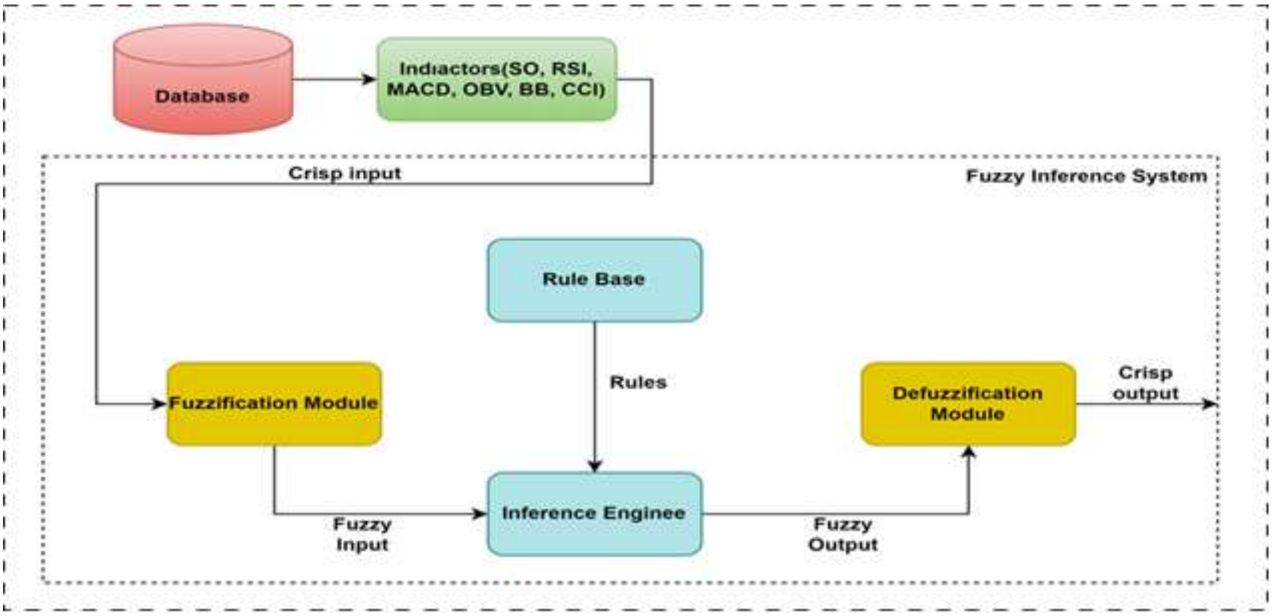


Figure 1. *Fuzzy Logic Based Finance System Architecture*

4. Indicators

In our study, six popular indicators widely used in the stock market are selected to analyze the share prices of Ford Otosan, one of the leading companies in Turkey, on Borsa Istanbul. These indicators SO, RSI, MACD, OBV, BB and CCI are proven tools in financial analysis in different market scenarios. Each indicator, with its unique functionality, is used in different areas of analysis such as overbought/sold, momentum, trend analysis, volume correlation, volatility measurement and market anomaly detection.
RSI helps to identify overbought or oversold conditions. SO provides momentum insight based on recent price movements. MACD combines momentum and trend analysis to provide clearer signals. OBV adds a deeper perspective on trends by correlating price movements with volume. BB measures price volatility and identifies potential trend reversals. CCI helps detect market anomalies by evaluating price deviations from historical averages. With their complementary features, these indicators are integrated with the Mamdani fuzzy logic method to provide a balanced and powerful analysis framework for generating buy, sell and hold signals.

4.1 Relative Strength Indicator (RSI)

This indicator takes into account whether the price is overpromoted. It starts with a numerical range from 0 to 100. If the RSI is greater than 70, a sell trade is formed. If the RSI value is between 70 and 30, a hold trade is formed. If the RSI value is below 30, a buy trade is formed.

$$\mathrm{RSI} = 100 - 100(1 + \mathrm{RS}) \qquad (1)$$

$$\mathrm{RS} = \text{Average Gain} \,/\, \text{Average Loss} \qquad (2)$$

RS is the average daily value of the upside close/downside close values obtained based on N days.

4.2 Stochastic Indicator(SO)

This indicator is a momentum indicator. The worth range is between 0 and 100. If the worth is above 80, a buy trade is formed. If the worth is below 20, a sell trade is formed. If the worth is between 80 and 20, a hold trade is formed.

$$\mathrm{SO} = 100 * (\text{Last Close} - \text{Low Bottom Level}(n)) / (\text{Highest Peak Level}(n) - \text{Lowest Bottom Level }(n)) \quad (3)$$

4.3 Moving Average Convergence Divergence (MACD)

This indicator is a momentum and trend indicator used in financial markets. MACD shows the momentum and trend of asset prices using two moving averages. This indicator has two values, positive and negative. If the value is positive, a buy trade is generated. If the value is negative, a sell trade is formed.

$$\mathrm{MACD} = \mathrm{EMA}_{12} - \mathrm{EMA}_{26} \qquad (4)$$

EMA_{12} = 12 period moving average
EMA_{26} = 26 period moving average

4.4 On Balance Volume(OBV)

This indicator is calculated from the total volume in a given time interval. This indicator has two values. They are positive and negative. If the OBV is rising, it indicates that the volume in the coming days is greater than the volume in the past days and this creates positive buying in the price. If the OBV is falling, it indicates that the volume on the down days is greater than the volume on the up days, and this creates a negative sell trade. If the OBV is flat, there is a equilibrium among buying and selling. This creates a hold position in the price.

$$\mathrm{OBV} = \mathrm{OBV}_{prev} \begin{cases} \text{volume, if close} > \text{close}_{prev} \\ 0, \quad \text{if close} = \text{close}_{prev} \\ \text{-volume, if close} < \text{close}_{prev} \end{cases} \quad (5)$$

4.5 Bollinger Bands (BB)

BB %B is an indicator within the BB that measures the position of the cost within the BB range. This indicator takes high values when the cost is near the upper band and low values when the cost is near the lower band. These situations may indicate that the cost is approaching overbought or oversold territory. %B approaching 1 indicates that the cost is near the upper band, while a %B approaching 0 indicates that the cost is near the lower band. In a sideways trend, the %B value may be approximately 0.5, indicating that the cost is in the middle of the Bollinger Bands range

$$\%B = (\text{cost} - \text{Subband})/(\text{Topband} - \text{Subband} \quad (6)$$

4.6 Commodity Channel Index (CCI)

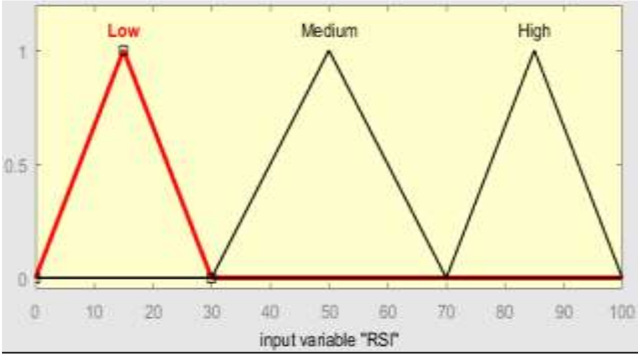
CCI is an indicator that measures the average fluctuations of prices within a given time frame. This indicator does not measure the position of the price within the BB range, but rather its overall volatility levels and its proximity to overbought or oversold zones.

$$\mathrm{CCI} = (\text{Typical Price - Moving Average})/(0.015^* \text{ Mean Absolute Deviation of Typical Price pband - Subband}) \quad (7)$$

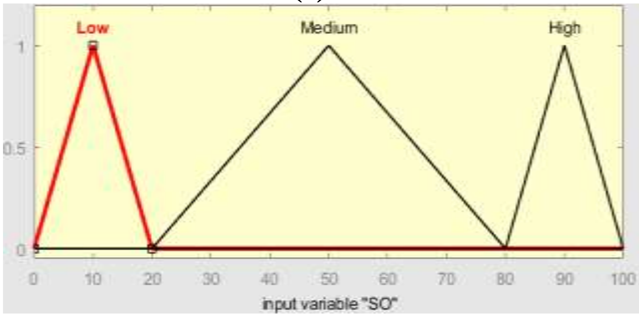
The CCI usually moves between -100 and +100. When the CCI value is above +100, the asset may be in overbought territory and prices may retrace. When the CCI value falls below -100, the asset may be in oversold territory and prices may make an upward move.

5. Proposed Design

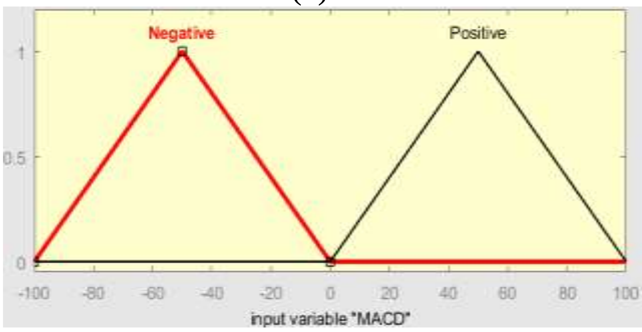
Inputs and outputs were defined using the Mamdani fuzzy method. So that the method can provide a



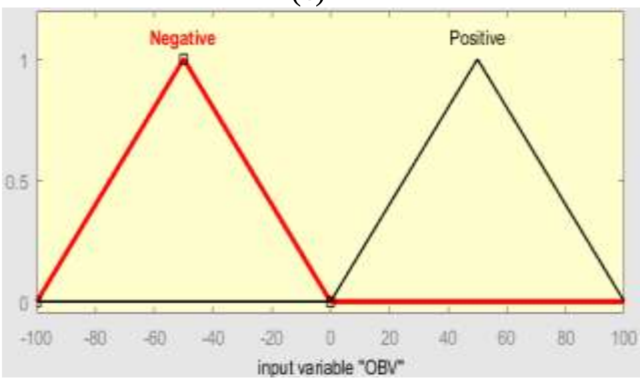
(a)



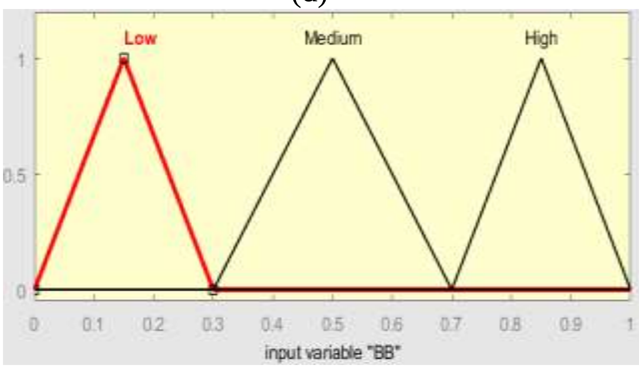
(b)



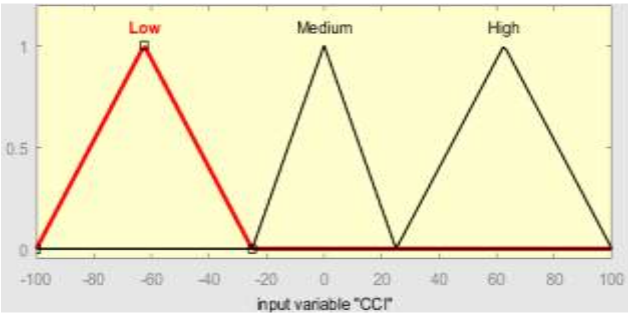
(c)



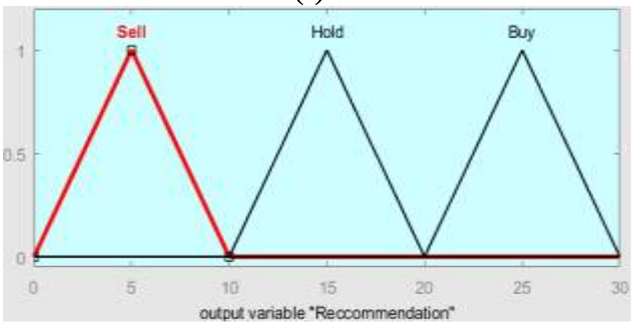
(d)



(e)



(f)



(g)

Figure 2. *Membership functions of (a) RSI, (b) SO, (c) MACD, (d) OBV, (e) BB, (f) CCI, (g) Reccommendation*

financial analysis, 6 inputs and 1 output state were defined as displayed in Figure 2. Our output values are Buy, Sell and Hold. If the Buy transaction occurs, the recommended signal is the buy signal. If a Hold transaction occurs, the recommended signal is a hold signal. If a Sell transaction occurs, the recommended signal is the sell signal. The development of fuzzy logic rules for stock analysis facilitates decision-making under uncertain market conditions by enabling the evaluation ofstock values, risk levels, and optimal trading times. Within the system architecture, 34 fuzzy logic rules were established, incorporating indicators such as RSI (Low, Medium, High), SO (Low, Medium, High), OBV (Negative, Positive), BB (Low, Medium, High), and CCI (Low, Medium, High), yielding promising results in their application. (Figure. 3). The fifth of these rules is RSI high SO high MACD negative OBV negative BB low CCI Medium. What we need to understand here is that according to the RSI indicator, there is an excessive purchase, but the SO indicator has produced a buy signal, in this case we need to look at other indicators, here the MACD indicator is negative, which means that we can say that there is a slowdown in the purchase of those who bought the asset. Since our OBV indicator is negative, we can say that the volume of buyers has decreased. BB is Low, which indicates that the price has reached the lower base moving average. According to CCI, there is a balance in buying and selling. Considering all of these, a sell signal is given in the exchange rate. Although SO gives a buy signal, according to the MACD indicator, the pace of asset purchases has decreased, and according to OBV, the decreasing pace of asset purchases also indicates a decrease in volume. According to the BB, the price based on the lower base should normally support the lower moving average band, while the majority of the indicators give a sell signal, indicating that this support is more likely to be broken. In this way, our rule gives a sell signal. In the 3rd rule, RSI low SO high MACD positive OBV positive BB medium CCI low. Here, in contrast to our first rule, the RSI and CCI show low values, indicating less buying and more selling. In contrast, the SO indicator gives a buy signal, while the MACD and OBV indicators show that buying is accelerating and the volume is high. BB shows that the price is at the mid-moving average and a rise is more likely. In this case, our rule gives a buy signal.

6. Conclusions

Forecasting asset prices in today's financial markets is a complex and uncertain process. Predicting price movements of assets like stocks, cryptocurrencies, or metals is not always accurate. Various mathematical methods have been developed to address this challenge, evolving into different indicators over time. In this study, six different indicators (RSI, SO, MACD, OBV, BB, CCI) predict company stock prices. The combination of these indicators aims to improve forecasting accuracy by generating buy, sell and hold signals. Each indicator has its pros and cons, and therefore, using fuzzy logic, rules were created to combine these different indicators in a balanced way. These rules serve traders who focus mainly on technical analysis and short-term strategies. However, long-term investments are often evaluated with fundamental analysis. In the future, they may also be combined with fundamental analysis inputs and developed for long-term results.

7.Discussion

The integration of fuzzy logic into technical analysis introduces a robust methodology to address the uncertainties inherent in financial markets. Traditional technical analysis often relies on rigid thresholds and binary decisions, which can struggle with the complexities of real-world data. By combining multiple indicators such as RSI, SO, MACD, OBV, BB, and CCI fuzzy logic provides anuanced framework that reconciles conflicting signals to produce more reliable trading

1. If (RSI is High) and (SO is Medium) and (MACD is Negative) and (OBV is Positive) and (BB is High) and (CCI is High) then (Reccommendation is Sell) (1)
2. If (RSI is Low) and (SO is High) and (MACD is Negative) and (OBV is Positive) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Hold) (1)
3. If (RSI is Low) and (SO is High) and (MACD is Positive) and (OBV is Positive) and (BB is Medium) and (CCI is Low) then (Reccommendation is Buy) (1)
4. If (RSI is Medium) and (SO is Low) and (MACD is Positive) and (OBV is Positive) and (BB is Medium) and (CCI is High) then (Reccommendation is Hold) (1)
5. If (RSI is High) and (SO is High) and (MACD is Negative) and (OBV is Negative) and (BB is Low) and (CCI is Medium) then (Reccommendation is Sell) (1)
6. If (RSI is Low) and (SO is Low) and (MACD is Positive) and (OBV is Positive) and (BB is High) and (CCI is Medium) then (Reccommendation is Buy) (1)
7. If (RSI is Medium) and (SO is Medium) and (MACD is Negative) and (BB is Low) and (CCI is Low) then (Reccommendation is Buy) (1)
8. If (RSI is High) and (SO is High) and (MACD is Positive) and (OBV is Positive) and (BB is Low) and (CCI is Medium) then (Reccommendation is Buy) (1)
9. If (RSI is Low) and (SO is Medium) and (OBV is Positive) and (BB is High) and (CCI is Low) then (Reccommendation is Hold) (1)
10. If (RSI is Low) and (SO is Low) and (MACD is Positive) and (OBV is Positive) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Buy) (1)
11. If (RSI is Medium) and (SO is High) and (MACD is Negative) and (BB is Medium) and (CCI is High) then (Reccommendation is Sell) (1)
12. If (RSI is Low) and (SO is Low) and (MACD is Positive) and (OBV is Negative) and (BB is High) and (CCI is High) then (Reccommendation is Hold) (1)
13. If (RSI is High) and (SO is High) and (MACD is Negative) and (OBV is Negative) and (BB is Low) and (CCI is Low) then (Reccommendation is Sell) (1)
14. If (RSI is Medium) and (SO is High) and (MACD is Positive) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Buy) (1)
15. If (RSI is High) and (SO is Medium) and (OBV is Positive) and (BB is High) and (CCI is High) then (Reccommendation is Sell) (1)
16. If (RSI is High) and (SO is Low) and (MACD is Positive) and (OBV is Positive) and (BB is High) and (CCI is High) then (Reccommendation is Sell) (1)
17. If (RSI is Low) and (SO is High) and (MACD is Negative) and (OBV is Negative) and (BB is Low) and (CCI is Medium) then (Reccommendation is Buy) (1)
18. If (RSI is Medium) and (SO is Medium) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Hold) (1)
19. If (RSI is High) and (SO is High) and (MACD is Positive) and (OBV is Positive) and (BB is High) and (CCI is High) then (Reccommendation is Sell) (1)
20. If (RSI is Low) and (SO is Low) and (OBV is Negative) and (BB is Low) and (CCI is Low) then (Reccommendation is Sell) (1)
21. If (RSI is Low) and (SO is High) and (MACD is Negative) and (OBV is Positive) and (BB is Low) and (CCI is Low) then (Reccommendation is Buy) (1)
22. If (RSI is Low) and (SO is High) and (MACD is Positive) and (OBV is Positive) and (BB is Low) and (CCI is Low) then (Reccommendation is Buy) (1)
23. If (RSI is Low) and (SO is Medium) and (MACD is Negative) and (OBV is Positive) and (BB is Low) and (CCI is Low) then (Reccommendation is Buy) (1)
24. If (RSI is Low) and (SO is Medium) and (MACD is Positive) and (OBV is Negative) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Sell) (1)
25. If (RSI is Low) and (SO is High) and (MACD is Negative) and (OBV is Positive) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Buy) (1)
26. If (RSI is Medium) and (SO is High) and (MACD is Positive) and (OBV is Positive) and (BB is Low) and (CCI is Low) then (Reccommendation is Buy) (1)
27. If (RSI is High) and (SO is Low) and (MACD is Negative) and (OBV is Negative) and (BB is High) and (CCI is High) then (Reccommendation is Sell) (1)
28. If (RSI is High) and (SO is Medium) and (MACD is Negative) and (OBV is Negative) and (BB is Medium) and (CCI is High) then (Reccommendation is Sell) (1)
29. If (RSI is High) and (SO is Medium) and (MACD is Positive) and (OBV is Positive) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Hold) (1)
30. If (RSI is High) and (SO is Medium) and (MACD is Negative) and (OBV is Negative) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Sell) (1)
31. If (RSI is Medium) and (SO is Medium) and (MACD is Positive) and (OBV is Positive) and (BB is Low) and (CCI is Low) then (Reccommendation is Hold) (1)
32. If (RSI is Low) and (SO is Low) and (MACD is Negative) and (OBV is Negative) and (BB is Low) and (CCI is Low) then (Reccommendation is Sell) (1)
33. If (RSI is Medium) and (SO is Medium) and (MACD is Positive) and (OBV is Positive) and (BB is Medium) and (CCI is Medium) then (Reccommendation is Hold) (1)
34. If (RSI is Medium) and (SO is Medium) and (MACD is Positive) and (OBV is Positive) and (BB is Medium) and (CCI is High) then (Reccommendation is Hold) (1)

Figure 3. *Rules*

recommendations. For instance, while one indicator might signal a buy, another might suggest caution, and fuzzy logic balances these inputs by considering the interplay between them. This approach mirrors the decision-making process of experienced traders, offering a more comprehensive perspective on market dynamics.

Despite its advantages, implementing fuzzy logic comes with challenges. The development of an effective rule base requires deep domain expertise and extensive historical data. Moreover, the system's performance must be periodically updated to reflect changing market conditions, and computational complexity can limit its utility in high-frequency trading. However, these challenges also present opportunities for future enhancements, such as integrating machine learning to refine rules dynamically or incorporating sentiment analysis to capture market psychology. By bridging technical and fundamental analysis, fuzzy logic offers a flexible and adaptive tool for addressing the complexities of financial forecasting. Fuzzy is interesting system and applied in different fields in the literature [24-33].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Vanstone, Bruce; Hahn, Tobias Designing stock market trading systems. With and without soft computing , 2010. ISBN 1906659583, 9781906659585

[2] BROCK, WILLIAM; LAKONISHOK, JOSEF; LeBARON, BLAKE (1992): Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *The Journal of Finance* 47 (5), pp. 1731–1764. DOI: 10.1111/j.1540- 6261.1992.tb04681.x.

[3] Mallikarjuna, M.; Rao, R. Prabhakara (2019): Evaluation of forecasting methods from selected stock market returns. *Financ Innov* 5 (1). DOI: 10.1186/s40854-019-0157-x.

[4] Dourra, H., & Siy, P. (2002). Investment using technical analysis and fuzzy logic. *Fuzzy sets and systems*, 127(2), 221-240.

[5] Ahmad, M., Soeparno, H., & Napitupulu, T. A. (2020, October). Stock Trading Alert: With fuzzy knowledge-based systems and technical analysis. In 2020 *International Conference on Information Technology Systems and Innovation (ICITSI)* (pp. 155-160). IEEE.

[6] D. Bernardo, H. Hagras, and E. Tsang, (2013). A genetic type-2 fuzzy logic based system for the generation of summarized linguistic predictive models for financial applications, *Soft Computing*, 17(12);2185-2201.

[7] W. J. Banks and P. L. Abad, (1994). On the performance of linear programming heuristics applied on a quadratic transformation in the classification problem, *European Journal of Operational Research*, 72(1);23-28.

[8] J. H. Min and Y.-C. Lee, (2005). Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters, *Expert systems with applications*, 28(4);603-614,

[9] K. Y. Tam, (1991). Neural network models and the prediction of bank bankruptcy, *Omega*, 19(5),429-445.

[10] P. R. Kumar and V. Ravi, (2007) Bankruptcy prediction in banks and firms via statistical and intelligent techniques–A review, *European journal of operational research*, 180(1);1-28, 2007.

[11] L.A. Zadeh, (1965). Fuzzy sets, *Information and Control*, 8(3);338-353, https://doi.org/10.1016/S0019-9958(65)90241-X.

[12] W. Chen, Z. Fei, X. Zhao and S. Ren, (2022). Event–triggered asynchronous control for switched T–S fuzzy systems based on looped functionals, *J Franklin Inst* 359 (12), 6311–6335.

[13] Gradojevic, N., & Gençay, R. (2013). Fuzzy logic, trading uncertainty and technical trading. *Journal of Banking & Finance*, 37(2), 578-586.

[14] E. Özer, N. Sevinçkan and E. Demiroğlu, "Comparative Analysis of Computational Intelligence Techniques in Financial Forecasting: A Case Study on ANN and ANFIS Models," *2024 32nd Signal Processing and Communications Applications Conference (SIU)*, Mersin, Turkiye, 2024, pp. 1-4, doi: 10.1109/SIU61531.2024.10600769.

[15] Pei-Chann Chang, Jheng-Long Wu, Jyun-Jie Lin, (2016). A Takagi–Sugeno fuzzy model combined with a support vector regression for stock trading forecasting, *Applied Soft Computing*, 8,831-842, https://doi.org/10.1016/j.asoc.2015.10.030.

[16] Silvia Muzzioli & Bernard De Baets, (2011). Assessing the information content of option-based volatility forecasts using fuzzy regression methods, *Department of Economics 0669, University of Modena and Reggio E., Faculty of Economics* "Marco Biagi".

[17] Vanstone, Bruce; Hahn, Tobias (2010): Designing stock market trading systems. With and without soft computing / by Bruce Vanstone, *Tobias Hahn. Petersfield: Harriman House.*

[18] BROCK, WILLIAM; LAKONISHOK, JOSEF; LeBARON, BLAKE (1992): Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *The Journal of Finance* 47 (5), pp. 1731–1764. DOI: 10.1111/j.1540- 6261.1992.tb04681.x.

[19] Mallikarjuna, M.; Rao, R. Prabhakara (2019): Evaluation of forecasting methods from selected stock market returns. *Financ Innov* 5 (1). DOI: 10.1186/s40854-019-0157-x.

[20] V. Suthiponpisal and D. Tancharoen, (2024) A Comparative Evaluation of Noise Reduction Versus Data Normalization Techniques in Stock Market Prediction Using Transformer Models, *8th International Conference on Information Technology (InCIT)*, Chonburi, Thailand, 2024, pp. 775-780, doi: 10.1109/InCIT63192.2024.10810587.

[21] A. Das, S. De, T. Mukherjee, M. Dey and K. Das Ghosh, (2024) Forecasting Bank ROE with Gradient Boosting: A Machine Learning Approach, 2024 *5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)*, Tirunelveli, India, pp.448-452, doi:10.1109/ICDICI62993.2024.10810845.

[22] S. Premsundar, V. Prabhu H and V. N Bahadurdesai, (2024) Deep Learning Model for Option Pricing - Review, *2024 8th International Conference on Computational System and Information Technology for Sustainable Solutions (CSITSS)*, Bengaluru, India, , pp. 1-6, doi: 10.1109/CSITSS64042.2024.10816734.

[23] T. Islam and K. Kapinchev, (2024). Evaluation of the Effectiveness of Technical Indicators, 2024 *17th International Conference on Signal Processing and Communication System (ICSPCS)*, Surfers Paradise, Australia, 2024, pp. 1-6, doi: 10.1109/ICSPCS63175.2024.10815753.

[24] R. Logesh Babu, K. Tamilselvan, N. Purandhar, Tatiraju V. Rajani Kanth, R. Prathipa, & Ponmurugan Panneer Selvam. (2025). Adaptive Computational Intelligence Algorithms for Efficient Resource Management in Smart Systems. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.836

[25] S.D.Govardhan, Pushpavalli, R., Tatiraju.V.Rajani Kanth, & Ponmurugan Panneer Selvam. (2024). Advanced Computational Intelligence Techniques for Real-Time Decision-Making in Autonomous Systems. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.591

[26] Bhanu Sekhar OBBU, & Zamrooda JABEEN. (2024). Integrated Fuzzy Cognitive Map and Chaotic Particle Swarm Optimization for Risk Assessment of Ischemic Stroke. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.540

[27] S. Krishnaveni, Devi, R. R., Ramar, S., & S.S.Rajasekar. (2025). Novel Architecture For EEG Emotion Classification Using Neurofuzzy Spike Net. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.829

[28] D. Neguja, & A. Senthilrajan. (2024). An improved Fuzzy multiple object clustering in remodeling of roofs with perceptron algorithm. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.773

[29] M. Venkateswarlu, K. Thilagam, R. Pushpavalli, B. Buvaneswari, Sachin Harne, & Tatiraju.V.Rajani Kanth. (2024). Exploring Deep Computational Intelligence Approaches for Enhanced Predictive Modeling in Big Data Environments. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.676

[30] S.P. Lalitha, & A. Murugan. (2024). Performance Analysis of Priority Generation System for Multimedia Video using ANFIS Classifier. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.707

[31] RamaKishore K., Ramprasad C.H., & Varma P.L.N. (2024). Description of Regular m-Bipolar Fuzzy Graphs. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.605

[32] Hadi Athab Hamed, & Ahmed Kareem ABDULLAH. (2025). M-ary Pulse Ampplitude Modulation Recognition Using Discrete Meyer Wavelet and Reverse Biorthogonal Wavelet. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.749

[33] Nasti, S. M., Najar, Z. A., & Chishti, M. A. (2024). A Comprehensive Review of Path Planning Techniques for Mobile Robot Navigation in Known and Unknown Environments. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.797