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Developing a model based on fuzzy logic for identifying reversal points in capital markets derived from technical analysis

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Abstract

This research aims to present a model for identifying reversal points in capital markets using technical analysis based on fuzzy logic. From the perspective of its objectives, this is an applied research, meaning it seeks to acquire the necessary knowledge to develop a tool that addresses key needs of shareholders, such as identifying reversal points, which are crucial in decision-making for buying and selling. Additionally, since the study aims to find relationships between variables to identify reversal points and assess the impact of their changes on the overall outcome, it is classified as causal or experimental research in terms of its methodology. From the perspective of data type, this research is based on quantitative data. In terms of timing, this study employs a cross-sectional design followed by a prospective approach. In this research, fuzzy logic and genetic algorithms were used to provide a method for identifying reversal points in financial markets. For this purpose, a Mamdani fuzzy system was employed. After implementing the proposed structure, the optimized membership functions were evaluated to ensure their alignment with the research objective (identifying reversal points). The proposed method, due to its desirable accuracy in identifying reversal points, has increased the returns from trading. If users enter or exit trades based on alerts with a probability higher than 85%, according to the type of reversal point, they will enter or exit trades at the right time in about 94% of cases, which will significantly contribute to improving the profitability of their trades.

Keywords: Return points, capital market, technical analysis, fuzzy logic
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1 Introduction

An examination of the performance trends of financial markets from the past to the present in various countries shows that these countries have consistently sought to attract more capital through financial innovations. In general, investment can be considered a fundamental pillar of a country's economy, and if done properly, it leads to an increase in national production and economic growth [7]. One of the prominent features of the economies of various countries in recent decades has been the significant growth of financial markets and institutions [14]. The scope and importance of

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financial transactions have consistently grown, with financial markets and institutions increasingly gaining a prominent position in the global economy [1]. In such conditions, without access to financial resources, many activities cannot be carried out, and as a result, achieving goals becomes impossible.

Today, financial managers of companies and economic enterprises are fully focused on identifying financial markets and their instruments in order to secure the necessary resources [6]. At the macro level, stock and debt markets play a significant role in economic growth and development, which in turn brings about social welfare [9]. Currently, success in stock trading largely depends on making correct decisions regarding timely and accurate entry and exit [23]. This requires analyzing information and having expertise to evaluate investment opportunities [8]. In fact, the main concern in today's investment markets is having access to comprehensive information and knowledgeable analysts who can assist investors in making optimal investment decisions.

Another approach that has been accepted and validated by investors over the years through experience is the adoption of automated systems. These systems are capable of efficiently analyzing financial data with a high level of confidence and supporting investment decisions [3]. In this research, by integrating various analytical strategies and leveraging artificial intelligence, the goal is to find an intelligent method for entering trades with minimal error. The variables used in this study will focus on technical indicators, complemented by two tape-reading variables. The scope of this research will include data from the years 2017 to 2020, and the accuracy of the proposed method will be evaluated within this timeframe. Accordingly, a fuzzy system with 5 inputs will be developed, consisting of 3 technical inputs and 2 tape-reading inputs, to determine the likelihood of the current point being a reversal. What is crucial in this context is the sensitivity of fuzzy systems to accurately and optimally determining membership functions. In this research, cumulative intelligence algorithms will be used to optimize the membership functions for the system in question. Ultimately, the goal of implementing this system is to reduce trading errors and alleviate the complexities of fundamental analysis and other aspects, thereby facilitating easier profit-making in financial markets.

Therefore, this research aims to present a new tool that can generate accurate trading signals at reversal points using the proposed technical analysis tools. Based on what has been discussed, the proposed technical analysis will operate using a set of technical analysis rules. Thus, investors in financial markets, with the support of this system, will be able to make timely and accurate decisions in their trades and maximize their investment returns.

2 Research background

Sadighi et al. [21] presented a hybrid metaheuristic model for optimizing investment strategies based on market trend predictions in the Forex market. Data for the Rial to Dollar currency pair, spanning from 2013 to 2019, was used for training and testing. The proposed architecture for machine learning, as well as the implementation and study of the proposed trading system, is thoroughly described. The research shows promising results during the testing period, with an investment return of 129%.

Hervani and Khalili Iraqi [10] proposed a design based on an algorithmic trading strategy. The results indicate that the algorithmic trading strategy using the Adaptive Moving Average (AMA) indicator can be utilized to predict future stock price movements in the Iranian capital market. The study found that using a strategy based on the Adaptive Moving Average (AMA) algorithm yields better returns compared to a buy-and-hold strategy. Additionally, with the assumption of transaction costs, the AMA-based strategy achieved higher returns in 23 out of 30 scenarios, and without transaction costs, it achieved higher returns in 27 out of 30 scenarios compared to the buy-and-hold strategy.

Raisi and Beheshti [20] focused on predicting the trends of the Tehran Stock Exchange based on technical analysis and optimizing a multilayer perceptron neural network using a differential evolution algorithm. The results indicate that trading using the proposed system is much more efficient compared to methods such as low-risk investments (e.g., bank deposits) and even buying and selling based solely on technical analysis results.

Afshari Rad et al. [2] developed an intelligent model for predicting stock trends using technical analysis methods. The results showed that the proposed method has an average accuracy rate of 97% in predictions.

Khanjarpanah et al. [16] investigated the application of technical methods for stock price prediction using nonlinear probability models and artificial neural networks. The results indicated that nonlinear probability models had a better predictive performance with a 92.76% accuracy rate compared to neural networks. However, when comparing the models' ability to predict price increases, there was no statistically significant difference between them. Similarly, no significant statistical difference was found between the models' predicted values for price increases and the actual values. In terms of error measurement criteria, the nonlinear probability model was found to have superior performance compared to other models.

Asghara Tabar and Jafari Samimi [4] explored and optimized moving averages of stock prices on the Tehran Stock Exchange using a genetic algorithm-based metaheuristic approach. In the first part of the study, the adaptive genetic algorithm was employed to optimize parameters such as population size, final generation, chromosome selection type, rates of crossover and mutation operators, and the formulation of initial generation functions, crossover, mutation, and especially the fitness function. Ultimately, the algorithm identified an optimal set of time periods for each stock. The genetic algorithm enhanced and optimized technical trading rules. In the second part, two moving averages were calculated based on these optimal periods using Excel (these periods are parameters for the two-cross-line method). The study used Adaptive Moving Averages (AMA) because AMA allows analysts greater control over market trends. By applying two moving averages to recent stock prices, future trends can be determined, enabling traders to make informed trading decisions.

Memarzadeh et al. [19] presented a method based on deep learning networks for predicting prices in financial markets. After implementing the mentioned techniques, results for each technique and their evaluation parameters were obtained. Comparing the results of various techniques, the LSTM (Long Short-Term Memory) method achieved the highest accuracy among all the techniques. Conversely, the decision tree method showed the lowest accuracy.

Lee et al. [17] focused on predicting global markets based on price chart images using deep Q-networks. The study found that, with sufficient data for smaller financial markets, this method could yield better results and greater profits in smaller financial markets.

Jadhav et al. [13] investigated and predicted stock market indices using artificial neural networks with forecasting algorithms. Predicting stock prices is a crucial financial topic due to the variability and complexity of stock price data. Investors face a decision-making process when buying stocks, aiming to select stocks that provide maximum benefits. Success and profit in investing are not possible without accurate analysis and understanding of stock and market conditions; thus, investors should buy and sell stocks based on thorough analysis. In this research, stock purchasing methods using various strategies were examined compared to the buy-and-hold approach. The proposed algorithm offers buy/sell/hold recommendations to investors and was tested in the Bombay stock market, demonstrating good performance of the proposed model.

Lin [18] examined and analyzed technical analysis and stock return forecasting using an aligned approach. The analysis of stock returns based on vector autoregression indicates that the economic source of predictive power mainly comes from temporal changes in future cash flows (i.e., the cash flow channel).

Ijegwa et al. [12] explored and forecasted stock markets using technical analysis with fuzzy logic. The stock trading decision-making process is complex, resulting in recommendations for buying, selling, or holding. Data from two Nigerian banks were collected to test and evaluate the system. Technical indicators were calculated for each data point, and testing was conducted over a two-month period using these indicators. When the system's output was compared with actual data collected from the Nigerian Stock Exchange, it provided recommendations on when to buy, sell, or hold. Therefore, when combined with individual trading skills, the system can function effectively as a model in the stock market.

Hui and Chan [11] investigated whether trading strategies can outperform buy-and-hold strategies in unique markets. Their research indicated that the three trading strategies used performed better during unfavorable periods compared to favorable times. Specifically, their trading strategies proved useful in protecting investors from significant losses during bearish markets and economic downturns.

3 Research methodology

This research is applied in nature, meaning it aims to acquire the necessary knowledge to develop a tool that addresses key needs of shareholders, such as identifying reversal points crucial for buying and selling decisions. Additionally, since the research seeks to uncover relationships between variables to identify reversal points and evaluate the impact of these changes on overall results, it is considered a causal or experimental study in terms of methodology. It also involves quantitative data and is cross-sectional with a forward-looking perspective. The study covers the period from 2017 to 2022.

The variables used in this research will be a combination of technical indicators and market sentiment variables, which will be input into a fuzzy system. Three technical indicators and two market sentiment variables will serve as independent variables, while one output indicating the probability of the current point being a reversal point will be considered the dependent variable. The variables will be examined in detail.

- Independent Variables

The independent variables in this research will actually be the inputs to the fuzzy system, which are three technical indicators.

- RSI Indicator: Also known as the Relative Strength Index, this indicator belongs to the family of oscillators and involves moving averages in its calculations. Essentially, it is a tool for assessing market trends and the strength of price movements. The Relative Strength Index examines a specified period, typically 14 days, to evaluate the buying and selling strength of a trading option and displays it on a chart with three different ranges. The oscillation range of this oscillator spans from 0 to 100, with levels 0 to 30 considered as the oversold zone and levels 70 to 100 as the overbought zone [22].
- CCI Indicator: Also known as the Commodity Channel Index, this indicator is an oscillator that defines a range between two upper and lower bounds and then creates a trend indicator oscillating between these limits. This indicator also pays significant attention to the strength of the recent price trend, as momentum indicators show the acceleration of the trend. The CCI indicator is used to alert traders to overbought or oversold conditions of an asset. It essentially informs when the price of an asset is significantly higher than its intrinsic value or lower than its original price [5].
- MFI Indicator: The Money Flow Index is constructed using both price and trading volume and oscillates between 0 and 100. It indicates bullish trends when money flows into a stock and the price increases, and bearish trends when money flows out and the price decreases. The overbought threshold for this indicator is 80-100, while the oversold threshold is below 20 [15].
- Increase in Buyer Strength Relative to the 10-Day Average: The relative strength of buyers compared to sellers in trading symbols is a crucial decision-making factor for traders when deciding to enter or exit a stock. In this research, since we are focused on identifying reversal points, it is necessary for a point to be considered a reversal if there is a significant increase in buyer strength relative to sellers on that day compared to previous days. Therefore, the difference between the buyer strength of the current trading day and the average buyer strength over the past 10 days is also considered one of the independent variables.
- Trading Volume to Monthly Average Ratio: One of the indicators that can reveal characteristics of reversal points in stock histories is an increase in trading volume as the stock approaches these points. Therefore, the ratio of trading volume to the monthly average is included as one of the independent variables in the research.

- Dependent Variable
  - Reversal Point Probability: The output of the fuzzy system used in this research will indicate the probability that the price chart has the potential to reverse direction from the current range upwards. This probability will be represented by a value between 0 and 1. Naturally, the closer this value is to 1, the higher the likelihood of a reversal from the current range.

$$\mu_{Prob}(y) = \begin{cases} Low & \text{if } 0 \leq y \leq 0.33 \\ Medium & \text{if } 0.33 < y \leq 0.67 \\ High & \text{if } 0.67 < y \leq 1 \end{cases}$$

The research population consists of the price information of symbols listed on the Tehran Stock Exchange. The sample of the study includes 5 stocks from each trading board of the stock exchange and the over-the-counter (OTC) market. The proposed model for identifying reversal points will be applied to each of these stocks.

4 Findings

In this section, as previously mentioned, the optimized membership functions for the inputs will be determined using a genetic algorithm. Subsequently, the optimized fuzzy system will be validated. Once the results from the validation phase of the proposed FIS (Fuzzy Inference System) are confirmed, the performance of the system will be assessed based on real data, and the results will be reported.

- Optimization of fuzzy system membership functions

  In this section, the optimization of fuzzy membership functions will be carried out based on the genetic algorithm. For this purpose, it is necessary to define a fitness function for the genetic algorithm. The inputs and outputs of the fuzzy system, as described in section 3, are as follows:

– RSI Indicator

$$\mu_{RSI}(x) = \begin{cases} Low(RSI), & \text{if } 0 \leq x \leq 30 \\ Medium(RSI), & \text{if } 30 < x \leq 70 \\ High(RSI), & \text{if } 70 < x \leq 100 \end{cases}$$

– CCI Indicator

$$\mu_{CCI}(x) = \begin{cases} Low(CCI), & \text{if } -100 \leq x \leq 0 \\ Medium(CCI), & \text{if } 0 < x \leq 100 \\ High(CCI), & \text{if } x > 100 \end{cases}$$

– MFI Indicator

$$\mu_{MFI}(x) = \begin{cases} Low(MFI), & \text{if } 0 \leq x \leq 20 \\ Medium(MFI), & \text{if } 20 < x \leq 80 \\ High(MFI), & \text{if } 80 < x \leq 100 \end{cases}$$

– Ratio of daily trading volume to monthly average

$$\mu_{VolumeRatio}(x) = \begin{cases} Low & \text{if } x < 1.5 \\ High & \text{if } x \geq 1.5 \end{cases}$$

– Difference between current buyer strength and 10-day average

$$\mu_{PowerDifference}(x) = \begin{cases} Low & \text{if } x < 1.2 \\ High & \text{if } x \geq 1.2 \end{cases}$$

Given the above criteria, the task is to determine the optimal membership functions for the fuzzy system. To optimize the membership functions using the genetic algorithm, we will first define the parameters of the indicators based on the type of reversal point, whether the trend changes from bearish to bullish or vice versa. For trading panel parameters, higher ratios and differences in buyer strength indicate a higher likelihood of a reversal point. Next, we will consider the optimal scenarios for the maximum and minimum values of these indicators and extract several sample reversal points from the financial market. Based on these samples and the ideal conditions of the indicators at reversal points, we will perform fuzzy membership function optimization. The objective function for the genetic algorithm will consider the deviation of the indicators from the ideal state. In other words, the algorithm will try to minimize the distance and discrepancy between the ideal and current states by adjusting the membership functions of the fuzzy system inputs. Therefore, the objective function for the genetic algorithm will be defined as follows:

$$Minimize\ f = D_{indicators} = IdealStatus - CurrentStatus$$

in the above relationship, $CurrentStatus$ refers to the current values of the indicators and other inputs of the fuzzy system. Specifically, the average values of the indicators at more than 100 reversal points are measured, and the discrepancy between the current status of the indicators and these ideal values is evaluated. Based on these evaluations, optimal membership functions are determined using the genetic algorithm. The results from the optimization process will be reviewed subsequently.

Table 1 displays the parameters of the genetic algorithm used in this study for optimizing membership functions:

Table 1: Genetic Algorithm Parameters

Parameters	**Value**
Number of Generations	20
Number of Iterations	50
Crossover Rate	80
Mutation Rate	0.2
Mutation Percentage	10

Based on the table above and after implementing the genetic algorithm, the convergence trend of the genetic algorithm for optimizing the membership functions is shown in Figure 1.

As shown, the algorithm converged at the 36th iteration with a value of 0.08 for the objective function. The next steps involve examining the optimized membership functions and validating the FIS system based on these membership functions. Figure 2 displays the optimized membership functions for the first input, which is the RSI indicator.

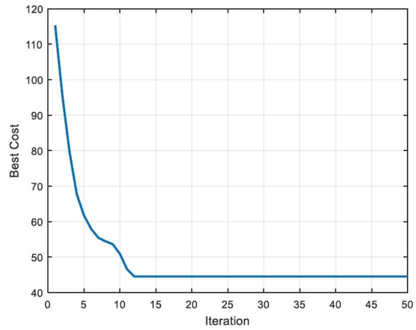

Figure 1: Convergence Trend of the Genetic Algorithm

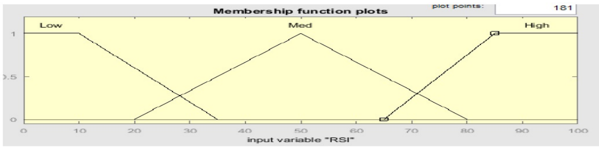

Figure 2: Optimized Membership Functions for the RSI Indicator

As shown in the figure above, for the RSI indicator, three membership functions with levels Low, Med, and High have been defined. The genetic algorithm has determined the optimal starting, central, and ending values for each membership function. Next, in Figure 3, the optimized membership functions for the second input, which is the CCI indicator, can be seen:

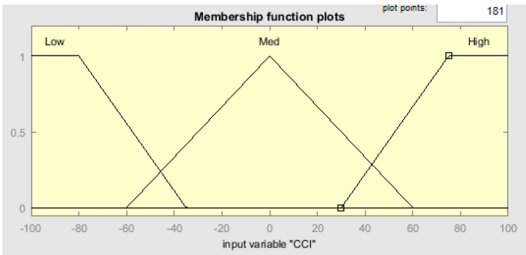

Figure 3: Optimized Membership Functions for the CCI Input

Similar to the first input, three membership functions with the levels Low, Med, and High have been defined for this input as well. The optimization algorithm has determined the optimal values for the start, center, and end of each membership function. It is worth noting that three levels of membership functions are considered for indicators, while two levels are set for tabular variables. In the following, Figure 4 shows the optimized membership functions for the third input, which is the MFI indicator:

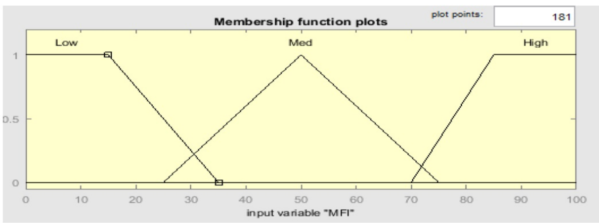

Figure 4: Optimized Membership Functions for MFI Input

Figures 5 and 6 also show the optimized membership functions related to the two board parameters:

As shown in the two figures above, for these two inputs, two levels are considered: Low and High. For the volume-to-monthly-average ratio, a ratio less than 1.5 is considered Low, while a ratio greater than this value is considered High. For the difference in buyers' power compared to the 10-day average, values higher than 1.2 are considered High, and values lower than 1.2 are considered Low.

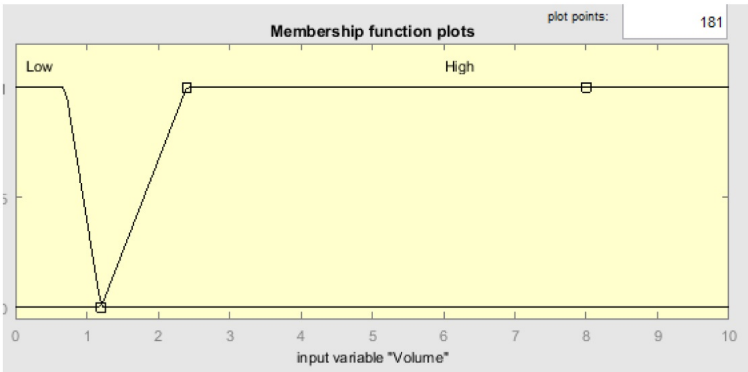

Figure 5: Optimized membership functions for the ratio of daily trading volume to the monthly average

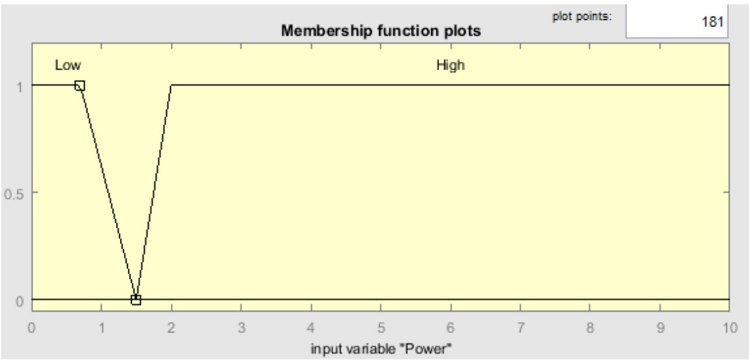

Figure 6: Optimized membership functions for the difference in buyers' power compared to the 10-day average

After optimizing the membership functions for the inputs, the next step is to address the membership functions for the output parameter, or Prob, which represents the probability of the trading day being a reversal point. Considering the membership functions introduced for the system under review, the number of output membership functions are displayed after optimization in Figure 7.

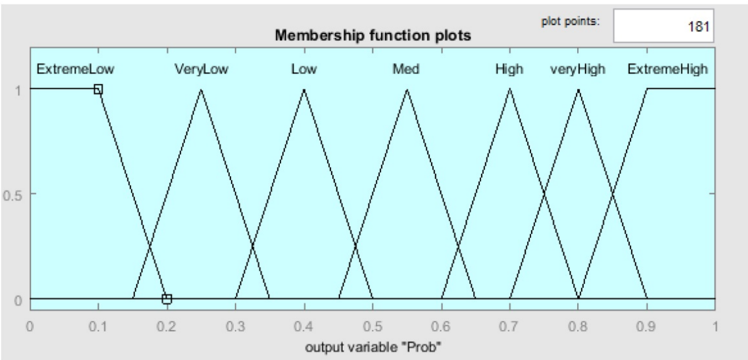

Figure 7: Optimized Membership Functions for Output Prob

Now, after optimizing the membership functions for inputs and outputs, the definition of fuzzy rules based on the logical relationship between inputs and outputs will be performed. The table based on which the fuzzy rules for reversal from the Trough are defined is Table 2.

It should be noted that, in the last row, for the remaining cases, the output value of Prob is considered as the Medium state. In Table 3, the fuzzy rules for the membership functions of reversals from the top are also presented:

Similar to the previous case, for the remaining membership function states, the output is considered as Medium. In Figure 8, the list of fuzzy rules defined in MATLAB software is displayed:

Table 2: Fuzzy Rules for Reversals from the Trough

RSI	**CCI**	**MFI**	**PowerDiff**	**VolRatio**	**Prob**
Low	Low	Low	High	High	Extreme High
Low	Low	Low	High	Low	Very High
Low	Low	Med	High	Low	High
Low	Med	Low	High	Low	High
Med	Low	Low	High	Low	High
Med	Med	Med	Low	Low	Extreme Low
Med	Med	Med	Low	High	Very Low
Med	Med	Low	Low	High	Low
Med	Low	Med	Low	High	Low
Low	Med	Med	Low	High	Low
Others	*	*	*	*	Med

Table 3: The fuzzy rule table for reversals from the top

RSI	**CCI**	**MFI**	**PowerDiff**	**VolRatio**	**Prob**
High	High	High	Low	Low	Extreme High
High	High	High	Low	High	Very High
High	High	Med	Low	High	High
High	Med	High	Low	High	High
Med	High	High	Low	High	High
Med	Med	Med	High	High	Extreme Low
Med	Med	Med	High	Low	Very Low
Med	Med	High	High	Low	Low
Med	High	Med	High	Low	Low
High	Med	Med	High	Low	Low
Others	*	*	*	*	Med

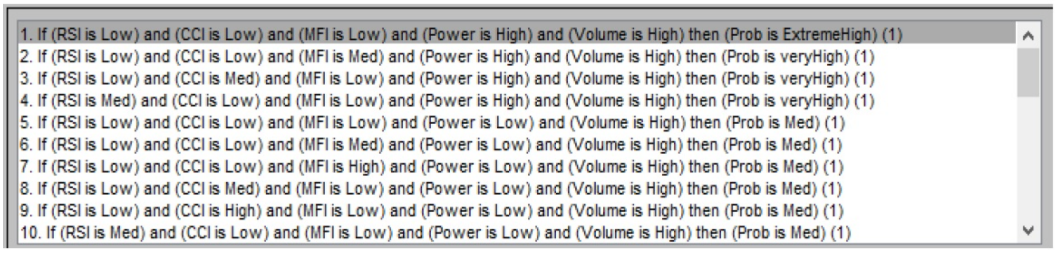
1. If (RSI is Low) and (CCI is Low) and (MFI is Low) and (Power is High) and (Volume is High) then (Prob is ExtremeHigh) (1)
2. If (RSI is Low) and (CCI is Low) and (MFI is Med) and (Power is High) and (Volume is High) then (Prob is veryHigh) (1)
3. If (RSI is Low) and (CCI is Med) and (MFI is Low) and (Power is High) and (Volume is High) then (Prob is veryHigh) (1)
4. If (RSI is Med) and (CCI is Low) and (MFI is Low) and (Power is High) and (Volume is High) then (Prob is veryHigh) (1)
5. If (RSI is Low) and (CCI is Low) and (MFI is Low) and (Power is Low) and (Volume is High) then (Prob is Med) (1)
6. If (RSI is Low) and (CCI is Low) and (MFI is Med) and (Power is Low) and (Volume is High) then (Prob is Med) (1)
7. If (RSI is Low) and (CCI is Low) and (MFI is High) and (Power is Low) and (Volume is High) then (Prob is Med) (1)
8. If (RSI is Low) and (CCI is Med) and (MFI is Low) and (Power is Low) and (Volume is High) then (Prob is Med) (1)
9. If (RSI is Low) and (CCI is High) and (MFI is Low) and (Power is Low) and (Volume is High) then (Prob is Med) (1)
10. If (RSI is Med) and (CCI is Low) and (MFI is Low) and (Power is Low) and (Volume is High) then (Prob is Med) (1)

Figure 8: Fuzzy rules defined in MATLAB software

More than 50 fuzzy rules have been defined based on the specified inputs and outputs, which are optimized according to the membership functions.

- Validation of the Fuzzy System

  In this section, the validation of the optimized model is conducted. For this purpose, values are assigned to the membership functions, and the output is examined. Naturally, the overall relationship between these membership functions must be maintained during this assignment. In this way, by changing the range of each membership function, what is observed in the above tables should also occur for the Prob value in practice. If this happens, it can be concluded that the proposed model possesses the necessary validity for identifying reversal points. Next, in Figure 9, all indicators are set to the "Med" state, and the output is shown.

  As shown, the output in this state is 0.5, which is reasonable given the state of the indicators. Further validation for two cases of trend changes from peaks and troughs is displayed, and the results of the Prob output are evaluated. In Figure 10, the values of buyer strength and the RSI indicator are altered, and the result of the validation is shown:

  As observed, the probability of reversal increased with the increase in the board parameters. Next, while keeping the two parameters that were changed in the first validation constant, three other parameters were adjusted, and the output result is shown in Figure 11:

  It can be observed that with changes to the indicators and their increased values, the probability of a reversal has increased again. It should be noted that due to limitations in the display of fuzzy rules in the Fuzzy Toolbox of MATLAB, 30 fuzzy rules have been validated and the results are mentioned. The confirmation of these rules will

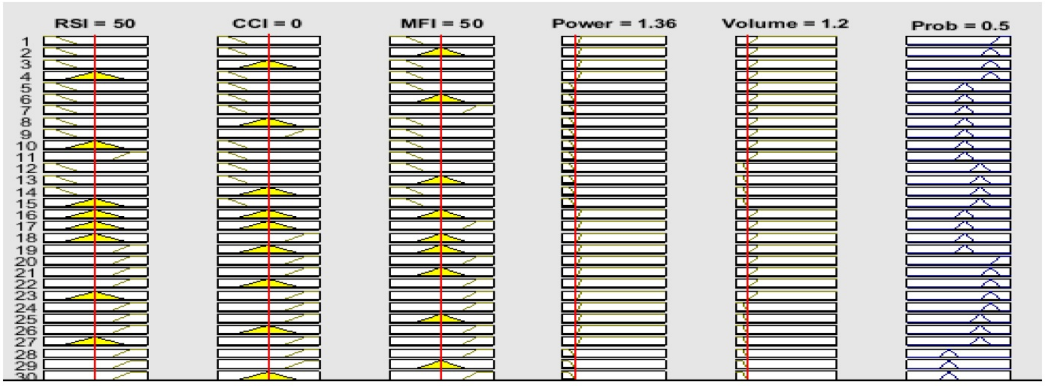

Figure 9: Output Status in the 'Med' State of the Indicators

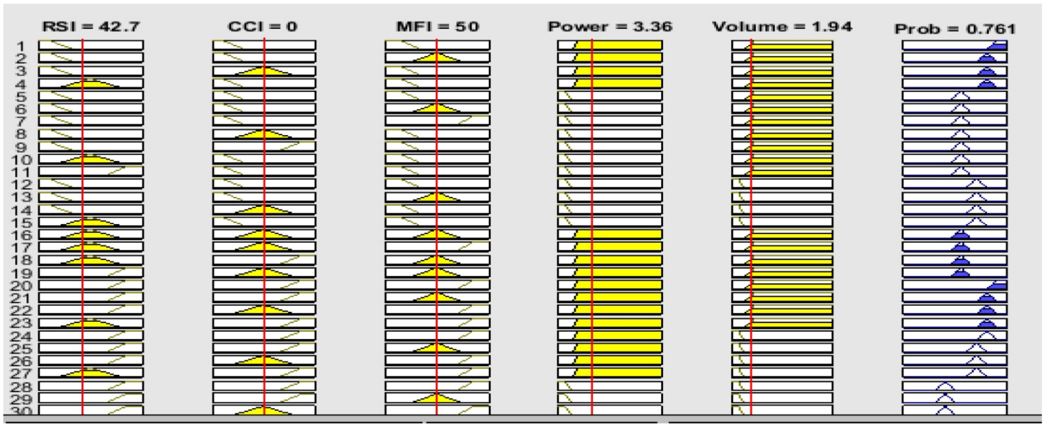

Figure 10: First Validation Result for Trough Reversal

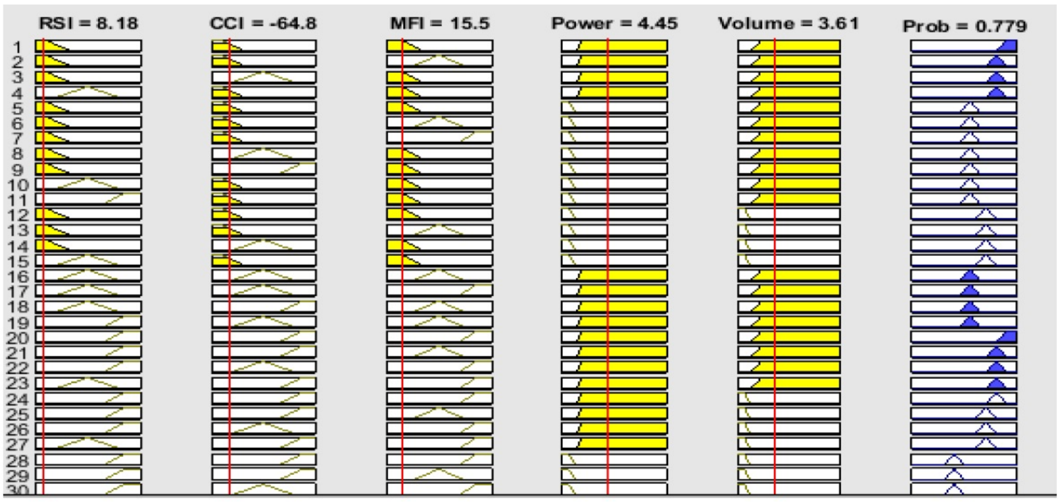

Figure 11: Second Validation Result for Trough Reversal

imply the validity of the remaining rules as well, since the logic of the rules is entirely the same. Additionally, the results of two validations for reversals from the top have also been reviewed. In this context, Figure 12 shows changes in the two input parameters, Buyer Strength and RSI, compared to the base case, and the resulting output is displayed.

It is observed that with indicators increasing into the overbought zone and a decrease in the power compared to the 10-day average, the likelihood of a reversal point has increased to over 90%. As in the previous section, for

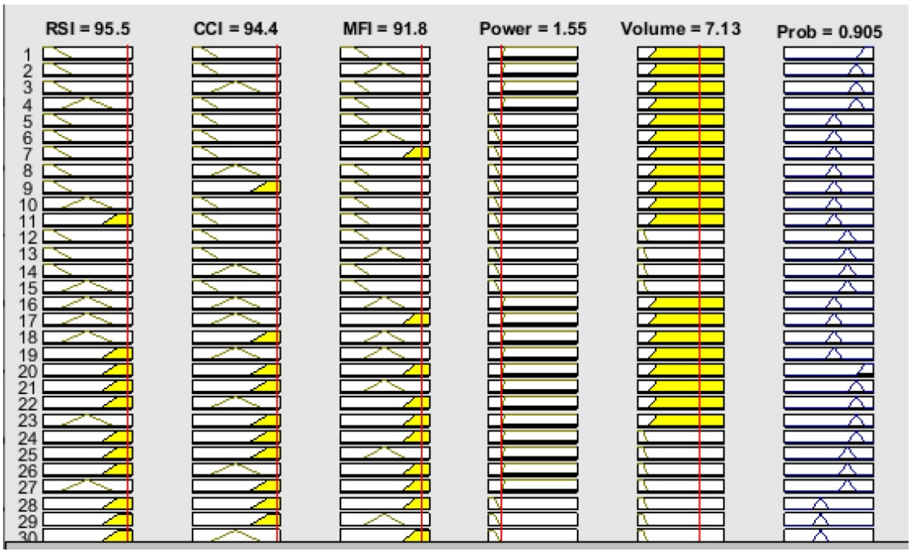

Figure 12: First Validation Result for Reversal from the Top

validating the fuzzy system for detecting reversals from the top, two parameters (buyer power and RSI) were kept constant while the other three inputs were varied. The results are shown in Figure 13.

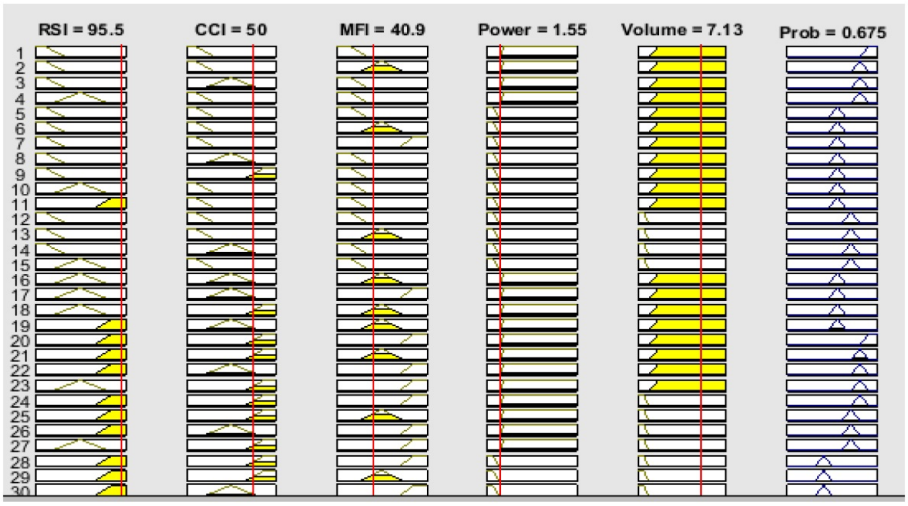

Figure 13: Second Validation Result for Reversal from the Top

As observed, a decrease in indicator values led to a reduction in the likelihood of a reversal point, which indicates that the fuzzy rules defined and aligned with the optimized membership functions are logically correct. After completing the validation, the three-dimensional and two-dimensional surfaces based on the fuzzy rules, as well as the membership functions for inputs and outputs, which also depict the relationships among them, are drawn and presented. Figure 14 shows the three-dimensional surface among the RSI indicator, Power, and the output.

As observed, changes in the inputs also lead to changes in the output. The logic of these output changes is exactly in accordance with the fuzzy rule tables. Additionally, Figure 15 shows the three-dimensional surface of the board parameters and the Prob output.

As can be observed, as the values of the board parameters increase, the Prob also shows an increase, which confirms the contents of the tables related to the fuzzy rules. In addition, Figures 16 and 17 show two examples of the two-dimensional surfaces of the board parameters and the Prob output, illustrating the relationship between the two parameters and the output on the xy plane.

It is worth noting that for combining other input parameters and the Prob output, all three-dimensional and two-dimensional surfaces can also be displayed. After examining these surfaces, the relationships between them

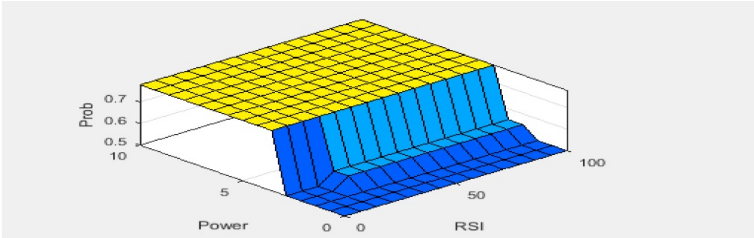

Figure 14: Three-dimensional surface of the RSI, Power, and Prob output parameters.

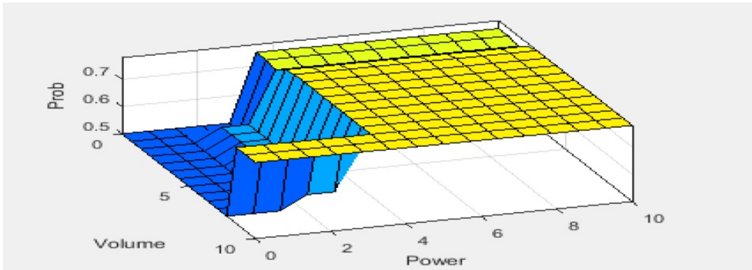

Figure 15: Three-Dimensional Surface of Board Parameters and Prob Output

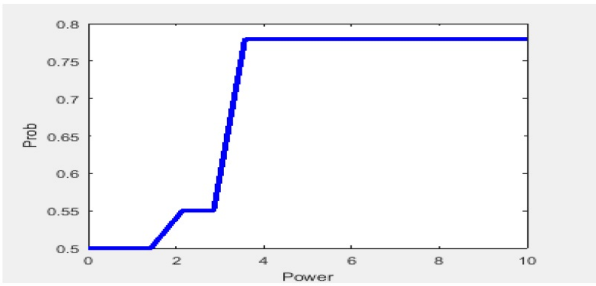

Figure 16: The relationship between the buyer power difference with the 10-day average and the Prob output

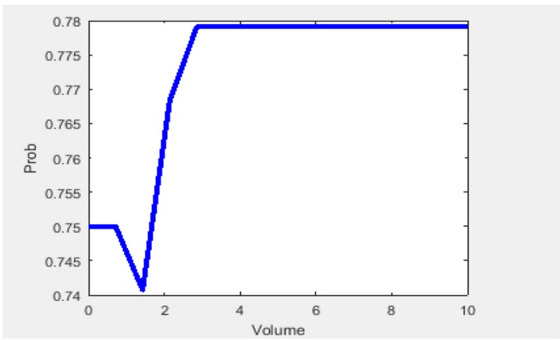

Figure 17: The relationship between the trading volume ratio to the monthly average and the Prob output

were confirmed with the fuzzy rule tables.

After validating the proposed model in the validation phase, it is time to use the proposed system in practice. Next, practical examples in the financial market will be examined.

Based on the previous discussion, here are formulas and concepts that are used in this research:

Objective Function for Genetic Algorithm:

$$\text{Objective Function} = \sum_{i=1}^{n} |\text{IdealValue}_i - \text{CurrentValue}_i|$$

where IdealValue_i represents the ideal value for the i-th indicator, and CurrentValue_i is the current value of the i-th indicator.

Membership Function for RSI Indicator:

$$\text{Membership Function}_{Low}(x) = \max\left(0, \min\left(1, \frac{30-x}{30-0}\right)\right)$$

$$\text{Membership Function}_{Medium}(x) = \max\left(0, \min\left(1, \frac{x-30}{70-30}\right)\right) \quad \text{for} \quad 30 \leq x \leq 70$$

$$\text{Membership Function}_{High}(x) = \max\left(0, \min\left(1, \frac{x-70}{100-70}\right)\right)$$

Membership Function for CCI Indicator:

$$\text{Membership Function}_{Low}(x) = \max\left(0, \min\left(1, \frac{100-x}{100-(-100)}\right)\right)$$

$$\text{Membership Function}_{Medium}(x) = \max\left(0, \min\left(1, \frac{x-30}{70-30}\right)\right) \quad \text{for} \quad -100 \leq x \leq 100$$

$$\text{Membership Function}_{High}(x) = \max\left(0, \min\left(1, \frac{x-100}{200-100}\right)\right)$$

Membership Function for MFI Indicator:

$$\text{Membership Function}_{Low}(x) = \max\left(0, \min\left(1, \frac{20-x}{20-0}\right)\right)$$

$$\text{Membership Function}_{Medium}(x) = \max\left(0, \min\left(1, \frac{x-20}{80-20}\right)\right) \quad \text{for} \quad 20 \leq x \leq 80$$

$$\text{Membership Function}_{High}(x) = \max\left(0, \min\left(1, \frac{x-80}{100-80}\right)\right)$$

Membership Function for Trading Volume Ratio:

$$\text{Membership Function}_{Low}(x) = \max\left(0, \min\left(1, \frac{1.5-x}{1.5-1}\right)\right)$$

$$\text{Membership Function}_{High}(x) = \max\left(0, \min\left(1, \frac{x-1.5}{2-1.5}\right)\right)$$

Membership Function for Buyer Power Difference:

$$\text{Membership Function}_{Low}(x) = \max\left(0, \min\left(1, \frac{1.2-x}{1.2-0}\right)\right)$$

$$\text{Membership Function}_{High}(x) = \max\left(0, \min\left(1, \frac{x-1.2}{2-1.2}\right)\right)$$

- Practical Implementation and Simulation Results

  In this section, based on what was previously mentioned, the research results from the years 2017 to 2021 will be evaluated, and several examples of reversal points under the specified conditions will be examined. In this context, a few examples (from different years) will be evaluated in detail, and the remaining cases will be summarized in a results table. Finally, the simulation results will be assessed, and the effectiveness of the proposed method will be reviewed. Initially, the price chart of the Khesapa symbol from the year 2017 will be analyzed, and the performance of the proposed method will be evaluated on it. Figure 18 shows the price chart of this symbol for the year 2017.

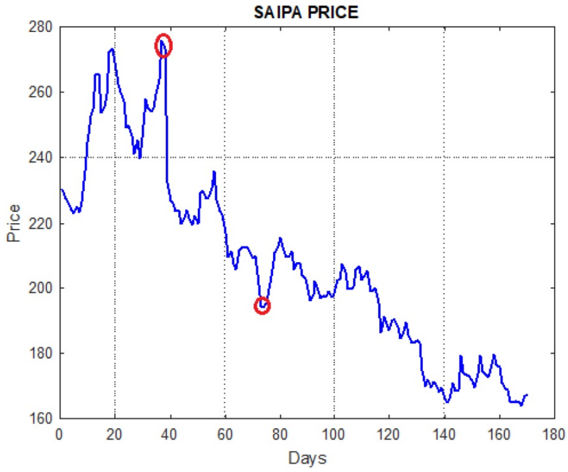

Figure 18: The price chart of Khesapa for the year 2017

Figure 19: Price Chart and Indicators for Khesapa Symbol on the Dates Under Review

As shown in the above figure, several examples of reversal points are visible in the chart, which can be used to evaluate the proposed method. The marked examples will be evaluated here. Additionally, in Figure 19, the values of the indicators used in the chart are displayed:

It is worth noting that the historical indicator charts were extracted from the Rahavard365 website. The red horizontal lines correspond to reversal points from the peak, and the green lines correspond to reversals from the trough. Additionally, in the three indicator charts, the graphs from peak to trough are RSI, CCI, and MFI, respectively. The table below displays the input and output values of the fuzzy system for the first reversal point:

As observed, based on the input values, the fuzzy system provides a probability of 91% for the considered point being a reversal point. This output means there is a 91% chance that the current point is a reversal point (in this case, from a peak). Therefore, traders should consider exiting the position on this day. The input and output

Table 4: Input and Output Values of the Fuzzy System for Khesapa

Parameter	**Value**
RSI	71
CCI	117
MFI	86
Power	0.89
Volume	2.3
Prob	0.91

values for a reversal point from the trough are also shown below:

Table 5: Input and Output Values of the Fuzzy System for Khesapa

Parameter	**Value**
RSI	29.8
CCI	166
MFI	29
Power	1.6
Volume	1.8
Prob	0.74

As observed, in this case, the probability of a reversal point from the trough is given as 0.74, which falls into the medium probability range according to the qualitative ranking. As the trend continues, it is noted that after a period of growth, the price chart eventually followed a downward trend. Next, Figure 20 shows the price chart of the Khodro symbol for the year 1997:

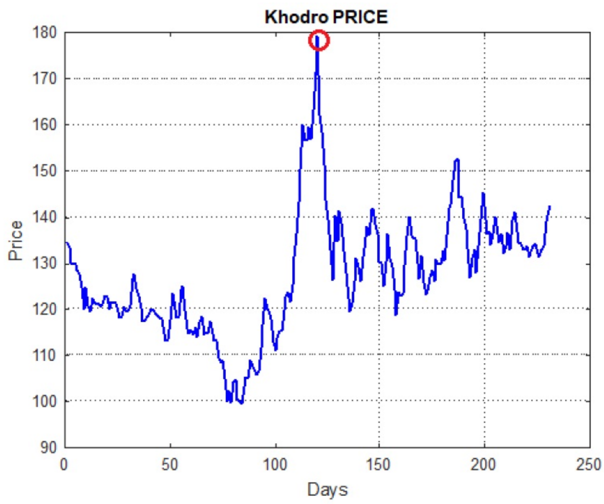

Figure 20: Price Chart of the Khodro Symbol and the Reversal Point Under Review

As shown in the chart above, the price chart from the marked reversal point has experienced a significant decline. The chart of the indicators for the mentioned symbol on the specified date is also shown in Figure 21:

In the table below, the input and output values of the fuzzy system for the examined reversal point are listed:

Table 6: Input and Output Values of the Fuzzy System for Khesapa

Parameter	**Value**
RSI	78.8
CCI	128
MFI	74
Power	-1.8
Volume	5.4
Prob	0.93

As can be observed from the table above, for the given inputs at this point, the probability of a reversal point is stated to be 93%, which is a significant value. Therefore, at this point, the intelligent model suggests traders exit

Figure 21: Indicator charts for the symbol "Khodro" at the used reversal point

the stock. One price chart sample from 2020 during the deep decline of the stock market is also reviewed, and afterward, a table will be provided with more sample cases, including their input and output values, followed by a detailed explanation of the results. Figure 22 shows the price chart of 'Hekashti' in 2020.

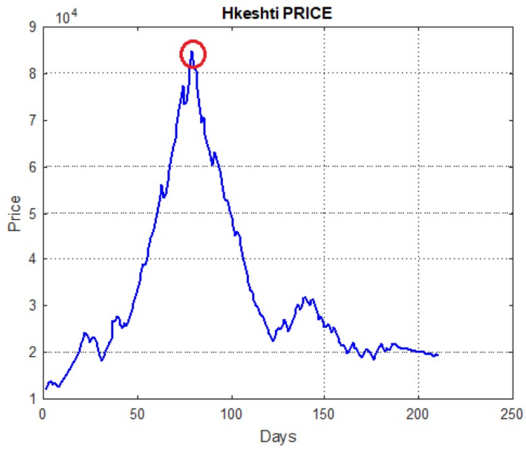

Figure 22: Price chart of Hekashti in 2020 and the reversal point under review

As can be observed, this chart, at its peak price in 2020, experienced an unprecedented decline, which is followed by Figure 23, showing the input indicator values for that year.

As can be seen, in addition to the high values of the indicators, divergence is also noticeable in all three cases. The input values are shown in the following table.

As observed, the probability of this being a reversal point is also reported to be 96%, indicating a very high risk for the stock at this point. In the following Table 8, several examples have been examined in terms of inputs and outputs.

As seen in the above table, for the examined reversal points (in addition to the detailed cases that were previously analyzed graphically), the proposed model has provided high-probability alerts for reversals from peaks and troughs. Another observation from the analysis was that alerts for peaks had higher accuracy and reliability compared to troughs. The analysis of over 50 reversal points showed that the proposed system issued alerts with

Figure 23: Indicator values at the reversal point under review

Table 7: Input and output values of the fuzzy system for Khesapa

Parameter	Value
RSI	88.4
CCI	134
MFI	81
Power	-2.8
Volume	5.1
Prob	0.96

Table 8: Examples of reversal points and the output values of the proposed fuzzy system for these points.

Symbol	Date	Type of reversal	RSI	CCI	MFI	Power	Volume	Prob
Khesapa	2020.08.03	from the peak	83	166	50	0.24	6.4	0.9
Khodro	2020.07.28	from the peak	81	180	73	0.26	5.8	0.93
Foolad	2020.05.26	from the peak	51	-71	34	2.4	3.1	0.84
Famelli	2020.05.26	from the peak	46	-89	30	2.7	3.4	0.87
Vatejarat	2020.09.29	from the peak	30	-195	44	2.8	2.4	0.88

a high probability of return (over 85%) for more than 95% of the reversal points. What is important is that the examined points were those where the price chart had experienced at least a 37% increase or decrease after the reversal.

Considering what was proposed in the first hypothesis of the research and according to the findings in section 4, the proposed method has improved trading returns due to its high accuracy in identifying reversal points. Specifically, if users act on high-probability alerts (above 85%) by entering or exiting trades according to the type of reversal point, they will be in a suitable position for approximately 94% of their trades, as seen in Table 9. This will significantly contribute to increasing trading returns.

- Hypothesis Testing of the Research

First Hypothesis of the Research: The proposed method can enhance the trading returns of users from various sectors by identifying reversal points.

As observed from the research findings, warnings above 85% were issued at reversal points in over 94% of the samples examined. As previously mentioned, the reversal points considered in this study involve a 37% decline or increase after the reversal point. It is evident that the accuracy of the predictions will be affected if this range is reduced. The 37% benchmark is based on the definitions of minor and major points, which are criteria used by market participants to determine new peak and trough points.

Hypothesis 2: The proposed method will significantly reduce users' reliance on technical and fundamental analyses, which can sometimes be a source of error.

Technical and fundamental analyses are widely used methods among investors. Technical analysis is more common among short-term and medium-term investors, while fundamental analysis is generally preferred by long-term investors. Therefore, Hypothesis 2 of this research suggests that the proposed method can serve as an alternative to technical analysis for investors. This approach could be particularly useful in preventing losses, especially given the large influx of ordinary people into the stock market, as seen in previous years. Additionally, since technical and fundamental analyses are produced by human sources, errors in these analyses are inevitable. Given the breadth of analyses and the number of securities, the amount of error is likely to be significant. Thus, from this perspective, the need to reduce errors through the use of artificial intelligence tools becomes evident. The increasing prevalence of smart trading systems, as seen in cryptocurrency exchanges, also indicates a necessary shift towards systems similar to the one presented in this research.

Based on the research findings, out of 60 points analyzed, 4 points had alerts below 85. Among these, 2 points were subsequently flagged with alerts above 80%, and only 1 point had an alert below 80%. This indicates the effectiveness of the proposed system. The reason for considering points with alerts above 85 in the system's accuracy is that the optimized membership functions, developed using genetic algorithms, have categorized points with a return probability above 85% into the highest probability group.

Hypothesis 3 of the Research: The proposed method in this study will yield better and higher returns compared to the returns obtained from a buy-and-hold strategy.

As mentioned, even among long-term investors who adhere to a buy-and-hold strategy, the proposed method can perform better. According to Hypothesis 3 of the research, the proposed method, by providing specific days for entering and exiting trades, performs better than the buy-and-hold approach for several reasons. For example: In the buy-and-hold method, there is a need to continuously assess market conditions over extended periods and determine the precise timing for entering and exiting trades, which can lead to a higher margin of error due to its human origin. In contrast, the proposed method, by establishing a defined mechanism, significantly reduces this margin of error.

5 Discussion and conclusion

What was presented and examined in this research was an optimized fuzzy system using a genetic algorithm, based on 5 inputs and 1 output. The inputs used included 3 technical indicators and 2 tape reading indicators, which are among the most commonly used by traders. The total number of samples examined was 60 return points, of which 35 were peak return points and 25 were trough return points. The overall results are summarized in the table below:

Table 9: Overall Results of the Proposed Method

Type of Points	Total Number	Alert Above 85	Alert under 85
Return from Peak	35	33	2
Return from Trough	25	23	23

Considering what was proposed in the first hypothesis of the research and according to the findings in section 4, the proposed method has increased trading returns due to its high accuracy in identifying reversal points. Specifically, if users enter or exit trades based on the high-probability alerts (above 85%), as shown in Table 9, they will be positioned correctly in approximately 94% of their trades, which significantly enhances trading returns.

As noted in the table above, over 94% of the examined samples generated alerts with probabilities above 85% at the reversal points. As previously mentioned, the reversal points considered in this study are defined by a 37% increase or decrease after the reversal point. It is clear that reducing this range will affect the stated accuracy. The 37% threshold is based on the definition of minor and major points, which is a criterion for determining new peak and trough points among market participants.

Technical and fundamental analysis are two commonly used methods among market participants. Technical analysis is more prevalent among short-term and medium-term investors, while fundamental analysis is more suited for long-term buyers. Consequently, the second hypothesis of this research suggests that the proposed method can be used as an alternative to technical analysis for investors. This could be particularly effective given the influx of ordinary people into the stock market, similar to what has been observed in previous years, to help prevent losses.

Furthermore, since technical and fundamental analyses are produced by human sources, errors are inevitable. Given the broad scope of analyses and the numerous symbols, these errors can be substantial. Thus, there is a need to reduce errors through the use of artificial intelligence tools. The growing trend of intelligent trading systems, as seen in cryptocurrency exchanges, also necessitates a shift towards systems similar to the one proposed in this research.

According to Table 9, out of the 60 points examined, 4 points had alerts below 85%. Among these, 2 points had alerts above 80% again, and only 1 point had an alert below 80%. This indicates the effectiveness of the proposed system. The reason for the accuracy of the system, which shows alerts above 85%, is that the membership functions optimized by the genetic algorithm classify points with over 85% likelihood of reversal as those with the highest probability.

As mentioned, even among long-term investors who believe in buying and holding stocks, the proposed method can offer better performance. According to what is stated in the third hypothesis of the research, the proposed method provides a more precise approach to entry and exit timings compared to the buy-and-hold strategy for several reasons. For instance, in the buy-and-hold method, there is a need to continuously assess market conditions over extended periods to determine the exact timing of entry and exit. This process, being human-driven, can lead to higher error rates. In contrast, the proposed method offers a more accurate approach due to its defined mechanism, resulting in a significantly lower error rate.

Additionally, the disparity in analyses among market participants, especially for newcomers to the field, can lead to confusion and potentially substantial financial losses. The proposed method aims to alleviate the need for detailed analyses from various individuals, some of whom might lack sufficient expertise or deliberately disseminate incorrect analyses to manipulate others into investing in their preferred stocks. Systems like the one presented in this research can play a leading role in preventing such issues and protecting the public from significant financial losses. In the following, a comparison of the results obtained from the proposed method with existing strategies commonly used among market participants will be discussed.

Table 10: Comparison of Detection Accuracy and Error Rates for Reversal Points

Strategy	Percentage of Correct Detection	Percentage of Incorrect Detection	Detection Difference
Proposed Method	86	14	72
MACD strategy	79	21	58
RSI strategy	77	23	54
EMA20	82	18	64
EMA80	83	17	66

Regarding the above table and its difference from Table 9, it is essential to note that in Table 9, all the points examined were reversal points, and for these reversal points, the proposed method issued alerts above 85% in more than 94% of the cases studied. However, this table considers the entire trend and price chart. To explain the results of this examination, for the proposed method, in the price trend of a symbol, and according to the above table, out of every 100 alerts issued as reversal points, 86 were correctly identified as reversal points, while 14 were erroneous. This means that although a reversal alert was issued, the alerted point was not a reversal point. Therefore, as stated, the higher the difference in detection between the two strategies, the better the performance of the method. As observed in the above table, the proposed method has shown better performance with a considerable difference compared to the strategies used by market participants.

Based on the hypotheses presented in the research, this section will provide suggestions. To increase trading performance (as outlined in Hypothesis 1 of the research), the proposed method could be complemented with signals from strategies such as moving averages. Additionally, two of the five inputs in the proposed fuzzy system are composed of board components. Furthermore, the effectiveness of metaheuristic algorithms in dealing with uncertainty and finding optimal values has led to their increasing use. Therefore, to find optimal values for these board components, which are used as thresholds for identifying reversal points, optimization algorithms can be employed. Determining these values should be directly related to the total number of shares and the free float of the symbol, considering the significance of the total trading volume and the symbol's volume base. For example, the 10-day buyer strength in a symbol like "Vatejarat" cannot be equal to that of a small food industry symbol. Therefore, it is suggested to use metaheuristic algorithms to find optimal parameters for each symbol's board components based on the history of each stock, specifically for that symbol.

In line with Hypothesis 2 of the research, considering what was found in section 4 and the limitations of human analysis mentioned in the conclusions of this chapter, it is suggested that the presented system and similar ones should initially be evaluated by expert teams to identify their strengths and weaknesses. For example, in addition to the aspects discussed in this research, combining moving average strategies with what is proposed in this research could be explored.

Finally, based on Hypothesis 3 of the research, since errors in determining entry points by long-term investors using a buy-and-hold strategy can lead to a lack of capital return over a significant period and result in minimal profits, it is suggested that incorporating fundamental analysis parameters into the long-term analysis of the proposed system be explored. This would help analysts and long-term investors in accurately determining entry points.

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