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The Effectiveness of the Automatic System of Fuzzy Logic-Based Technical Patterns Recognition: Evidence from Tehran Stock Exchange

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ABSTRACT

The present research proposes an automatic system based on moving average (MA) and fuzzy logic to recognize technical analysis patterns including head and shoulder patterns, triangle patterns and broadening patterns in the Tehran Stock Exchange. The automatic system was used on 38 indicators of Tehran Stock Exchange within the period 2014-2017 to evaluate the effectiveness of technical patterns. Having compared the conditional distribution of daily returns under the condition of the discovered patterns and the unconditional distribution of returns at various levels of confidence driven from fuzzy logic with the mean returns of all normalized market indicators, we observed that in the desired period, after recognizing the pattern, all patterns investigated at the confidence level 0.95 with a fuzzy point 0.5 contained useful information, practically leading to abnormal returns.

1 Introduction

The stock market is one of the most attractive places for investment, especially for traders because it provides a good market place for both long and short term investment to increase their profit. It is also highly important for companies because it is one of their primary sources to raise money. However, stock trading is very risky and the decision-making process in stock trading is a very critical and important process that must be taken correctly and at the right time [9]. Stock markets are complex systems within which a high number of participants converge, interacting with each other to maximize their profits using trading stocks [11, 15]. Even though the supporting principle in stock markets is a sample (to buy low and sell high) the decision concerning when and how much to buy or sell is not that simple.

To overcome this difficulty, a set of techniques have been emerged such as speculative analysis which can be thought of as the study of market information to predict rise and fall trends. A particular case of this analysis is a technical analysis which is one of the most widely used mechanisms in decision making support. This technique has been used widely because of its effectiveness and relative simplicity. Applying investment strategies with technical analysis requires us to make use of indicators

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that use mathematical and statistical models calculated from historical data of stock prices and volumes [1]. Investment in the capital market as a means of earning money has been of special importance to investors, thus, they began developing different analyses and methods to predict and increase the return on their investments. The decision-making process in stock trading is complex. There are large numbers of technical indicators that are used by traders to study the trends of the market. The traders decide on buying and selling stocks based on their observations[5]. Investors in recent decades invented and developed various tools and analyses, which fall into two general classifications of technical analysis and fundamental analysis. Even though the supporting principle for stock markets is really simple: to buy low and sell high; the decision of when and how much to buy or sell is not that simple. To overcome this difficulty, a set of techniques have emerged: speculative analysis, which can be thought of as the study of market information to predict rise and fall trends [6]. A particular case of this analysis is technical analysis, which is one of the most widely used mechanisms in decision making support due to its effectiveness and relative simplicity.

Applying investment strategies with technical analysis requires making use of indicators which are mathematical and statistical models, calculated from historical data of stock prices and volumes [8]. Investors consider technical analysis more than fundamental analysis due to its simplicity. Based on recent research, technical analysis enjoys high efficiency in predicting the onset of uptrend and downtrend in the market. The technical analysis comprises two spheres of indicators and patterns. The patterns of technical analysis are a series of geometric shapes, through the finding of which, analysts predict the next movement of the market. Patterns fall into two categories, namely, continuation and reversal patterns. Continuation patterns are, with their completion, a set of patterns that continue their path in their previous movement direction (before entering the pattern), which include patterns such as triangles. After completing the pattern, in reversal patterns, the price continues in the opposite direction. The head and shoulder pattern is among the most significant patterns in this regard. Researchers disregard such pattern in academic research because patterns are recognized through the eye and brain analysis, their recognition varies from person to person and has an intuitive nature, therefore, using automatic pattern recognition systems and providing a scientific look to the category of patterns in technical analysis is a solution to this problem.

In the meantime, using fuzzy logic can draw the system's mechanism closer to individual decisions. In contrast to conventional indicators, the fuzzy logic-based technical analysis indicators rely on subjective analyses of investors, such as risk-taking, rather than relying on logical analyses. The fuzzy technical analysis deals with how the decision is made and how non-professional investors react in the market. They use the general market information, such as profitability and fluctuations in stock prices as an input and provide sale and purchase signals as an output [4].

The present study seeks an answer to the following questions:

1. How can we design a technical analysis pattern recognition system using the moving average and fuzzy logic?

2. Do the methods used in the research have proper performance and efficiency in systematically recognizing the technical analysis patterns?

3. Do the patterns discovered by the system provide investors with useful information?

2 Theoretical Foundations and Research Literature

Forecasting financial market indices have become a necessary operation for investors' decisions to maximize the return of their investments. The complex behaviour of the stock market requires us to develop forecasting systems. To outperform the stock market index, a stock portfolio must be actively managed by periodically buying and selling a selected group of stocks. The technical analysis is concerned with the price movements in the market. Technical analysts attempt to use tools such as technical indicators, oscillators, and charts to recognize patterns that can estimate future movement[25]. The technical analysis is conducted through studying the behaviour and price and stock movements in the past and determining the price and future trend of the stock. Changes in stock prices are analyzed based on historical background and chart by a technical analyst. Mostly stock-jobbers practice this method and thus aim at increasing their desired returns when stock prices rise. Having examined the past prices and the volume of future movement transactions, the technical analysis predicts the price. These analyses focus on using a chart and mathematical and geometric relationships to discover small and large trends, where purchasing or selling opportunities are determined by estimating the market fluctuations range. The price changes and the trend of change in certain periods form the basis for prediction in the technical analysis, and traders analyze the market by observing price charts and using the necessary indicators for their strategy. The basis of this investment method is determining the market entry and exit points, where the transactor himself finds them or uses the findings of others. The technical analysts principally hold that whatever they are, the events affect the price and ultimately the chart. Thus, those who regardless of news and events correctly analyze the chart can lay the groundwork for the transaction. In public opinion, technical analysis is a simple method of market analysis and investment, which uses simple instruments such as a chart to study the price or rate variations. Charles Henry Dow's findings and research were the roots of technical analysis. Dow's theory is based on a philosophy that says the price or market indicators adsorb every significant factor and reflects it explicitly, similar to the moonshine that reflects sunlight. Supply and demand, the volume of transactions, price fluctuations, goods rates, interest rates, and all other things can be seen through the reaction of investors and market players on price chart, and all of these factors can be seen by studying the price changes or market indicators [13]. Dow's theory generally aims at determining the change of direction in the main trends or the market movement.

In technical analysis, analysts interpret price charts to study the price behaviour and movement (rate) in the past, based on which they can predict the future trend. In the present study, the only way to achieve market expectations is historical background and price variations. According to some investors, this analysis method relies on trends and is only in favour of speculators and those who benefit from price fluctuations. It falls into two general categories, namely, the use of indicators such as MACD, RSI, OBV, etc., and the use of cognitive patterns, most notably the rectangle or twin pattern, the triangle or flag pattern, broadening pattern and the head and shoulder pattern [10]. From the perspective of market infrastructures, technical analysis can be beneficial when expert transactors do systematical mistakes or unaware transactors leave predictable effects on prices. Moreover, technical analysts face a high degree of uncertainty in transactions, because technical analysis indicators, namely, weighted mean, lack sufficient filters when facing sudden changes [19], i.e. its logic is applied in almost stable conditions that are far from uncertainty. Therefore, applying fuzzy logic, along with MACD indicators, relative strength indicator (RSI), Stochastic Oscillator, and on-balance volume (OBV) can enhance individual capabilities in presenting purchasing and selling signals and maintenance [11].

Regarding the technical recognition patterns, Kamijo and Tanigawa [12] used a self- referential neural network to recognize the triangle patterns in technical analysis. They used 16 patterns for the network training stage, and using the three-year data on the Tokyo Stock Exchange of Japan, quite accurately reported the results of the correct pattern recognition. Using an automatic pattern recognition system, Lo et al.[16] developed a system for recognizing technical analysis patterns. They investigated 8 technical analysis patterns, such as head and shoulder and triangle patterns. Their method included using the flattened chart extrema and adjusting parameters in line with the geometric proportion of the patterns. Their results on a large number of stocks during the period 1962-1996 indicated that several patterns contained useful information. In 2001, Anand et al. [2] proposed a recognition language called chart-pattern language (CPL) to recognize patterns in charts using fuzzy limitations, which allowed the recognition of complex patterns made up of simple patterns. Dong and Zhou [29] utilized fuzzy logic to investigate the technical analysis patterns. The first flattened the stock price chart with the aid of Gauss kernel to discover the head and shoulder, triangle and rectangle patterns and then used the maximum and minimum of the flattened charts to recognize patterns. They defined fuzzy parameters and valued them by the Trapezoidal Fuzzy Number for each pattern and developing proportionality in the dimensions. Their results on the stock of the NASDAQ and S & P indicators subset indicate that the system designed to discover the technical analysis patterns would be profitable by adjusting the parameters of trapezoidal fuzzy numbers.Alejandro et al. [1] proposed an indicator for technical analysis based on fuzzy logic. Unlike traditional technical indicators, it is not an objective mathematical model. It incorporates subjective investor features such as the risk tendency into consideration. The fuzzy logic approach allows us to represent a more "human" action in decision-making reasoning that a non-expert investor might have in a real market. in this research paper, the use of a multi-agent-based simulation platform has been used. This allows us to incorporate the behavior and profits obtained by agents in the traditional technical indicators such as MA, RSI, and MACD into consideration and compared them with data obtained by agents that use the fuzzy indicator for the decision making process. Tealab et al. [25] proposed a short-term stock fuzzy decision system using a novel trading strategy based on a mixture of technical indicators at the Athens Stock Exchange. Fuzzy logic is applied for both trading rules definition and portfolio management. The selected stock market technical indicators for designing trading rules consist of commonly used indicators and newly developed ones. The results are compared to classical non-fuzzy systems in addition to the latest fuzzy approaches. The proposal's performance produced fewer losses and better profits. The results demonstrate that fuzzy logic is promising in portfolio management with a steady upward profit and low losses. García et al. [5] by using a hybrid fuzzy neural network, predicted the one-day direction of the German DAX-30 stock index. They implement different models depending on whether all the indicators and oscillators are used as inputs, or if a linear combination of them obtained through a factor analysis is used instead. To guarantee the robustness of the results, they train and apply the HyFIS models on randomly selected subsamples 10,000 times that The results show that the reduction of the dimension through the factorial analysis generates more profitable and less risky strategies.Peykani et al. [21] presented a new approach for efficiency measurement and ranking of stocks. They proposed a model to measure the efficiencies of stocks in the presence of negative data and uncertainty with input/output parameters. By using the data from the insurance industry, this model is also implemented for a real case study of Tehran stock exchange (TSE). To analyze the performance of the proposed method several Fuzzy Data Envelopment Analysis Models (RFDEA) have been proposed. This has been done by using various fuzzy measurements such as probability, necessity, and validation by Peykani et al. Despite the regular fuzzy DEA methods. The proposed models can endogenously adjust the confidence level of each constraint and produce both conservative and non-conservative methods based on various fuzzy measures. Then, the developed RFDEA models are linearized and compared to regular fuzzy DEA models numerically. Illustrative results in all of the FDEA and RFDEA models show that maximum efficiency is obtained for possibility, credibility and necessity-based models respectively [22]. Taherinia and Rashidi Baghi [24] predicted stock return by using financial variables with an artificial neural network approach at TSE. The results indicated that there is a meaningful relationship between the associated variables and return.Peykani et al. [20] presented a model to deal with confusing and unclear data in Possibilistic Data Envelopment Analysis (PDEA). In this model, three measures took into account; namely, possibility, necessity and credibility measures to form the Fuzzy DEA (FDEA) models. This model considered the tendency of decision-maker (DM) to taking an optimistic, pessimistic, and compromise attitude. However, decision-makers might have different preference and so it is necessary to customize fuzzy DEA models according to the properties of DMUs. This paper proposes a novel fuzzy DEA model based on the general fuzzy measure in which the attitude of DMUs could be determined by the optimistic-pessimistic parameters. As a result, the proposed FDEA model is general, applicable, flexible, and adjustable based on each DMUs. A numerical example is used to explain the proposed approach while the usefulness and applicability of this approach have been illustrated by using a real data set to measure the efficiency of 38 hospitals in the United States.

Leigh et al. [14] presented a pattern recognition model using the pattern adaptation method for sudden and abnormal market changes in the New York Stock Exchange during the period 1981-1999. Recognizing these changes can serve as a signal for investors to change the opposite of the market direction after an abnormal change and predict the next direction of the market. By predicting stock prices using Elliott waves, Volna et al.[26] proposed a neural network for finding the pattern of the most common and significant patterns of Elliott waves. To train the neural network, they used 10 patterns and by daily, hourly, 10-minute and one-minute investigations on the several price stocks evaluated the result quite reliable. Zapranis and Tsinaslanidis [28] presented a new way to recognize one of the technical analysis models called the Saucer pattern. In this method, the stock movement in the space of two concentric circles was used, and the environment of two circles was considered as resistance lines and support. To evaluate the usefulness of the designed system, it was implemented in seven stocks and implemented on seven subsets. The result of the research indicated that the higher market return is generated by the pattern recognition system only in the first period, and the return declines as we get closer to the present time. Volna et al. [27] designed multiple neural networks based on the Elliott wave pattern recognition to introduce a multiple neural network system, where the first neural network recognizes the pattern and the second predicts the market movement direction. They used 12 widely used patterns of Elliott waves to train the neural network, and finally investigated the result of their work on the time series of several stocks and positively evaluated the result. Using fuzzy logic, Gradojevic and Gençay [7] introduced a method to reduce the uncertainty of technical trading strategies in the field of market timing and order size. Based on the results of their research, the fuzzy indicators of the technical analysis dominate the moving average, especially in periods with high fluctuation.

Ehteshami et al.[3] applied the data mining algorithm at TSE to predict stock price trends. They found that those algorithms can forecast negative stock returns. However, the random forest algorithm is more powerful than decision tree algorithms. Also, stock return from the last three years and selling growth are the main variables of negative stock return forecasting. Based on Fuzzy Knowledge-Based Systems, Nakano et al.[17] presented a framework for technical transactions, including a module for investment proposals and a module for evaluating and developing high-performance portfolios. In the out of sample test of the designed system, he proposed a set of investment portfolios that presented satisfactory results during periods of decline in the capital market of Japan. Naranjo et al.[18] presented a methodology for discovering candlestick patterns in a fuzzy logic-based trading system. The fuzzy rules paved the way for adding uncertainty to the decision-making system on the decision-making time and the investment value. Using two portfolios of the NASDAQ-100 and Eurostoxx markets and the traditional purchase and maintenance strategy they investigated the function of this smart trading system. Based on the findings, this trading system proposes more returns with less risk compared to non-fuzzy trading systems. Radfar et al. [23] presented a decision-making model for selecting venture capital investment in emerging companies by using the qualitative method. By collecting qualitative data through literature reviews and conducting an in-depth interview with experts and venture capital firms, they presented a native decision-making model for selecting venture capital in emerging companies that included16 main themes and 86 sub-themes.

3 Research Methodology

The present research used the daily time series of the returns and price of companies listed in Tehran Stock Exchange during the period 2014-2017 to discover the technical patterns. The research aims to design and evaluate the efficiency of a technical analysis pattern recognition system in the Tehran Stock Exchange. The study used Rahavard Novin Software to provide the data required and used MATLAB software environment and coding in it for studying and implementing the models. The present study provided a technical pattern recognition system. These patterns include the normal triangle continuation patterns and the broadening triangle and the reversal patterns of an inverse head and shoulder patterns, which uses the moving average method and fuzzy logic. First, the researcher defines patterns investigated by the system based on the behaviour of several points of sequential extremum. Then, he uses a normal 9-day moving average to smooth and identify the maximum and minimum points of the price chart, and to reach high-quality patterns defines variables in terms of the geometric behaviour of the patterns, where changing the value of these variables will change the shape of the pattern. The values of these variables are placed in fuzzy sets so that by adjusting the parameters of the fuzzy number, higher-quality patterns are identified. After designing the pattern recognition system, the key issue is whether the discovered patterns are fruitful and contain useful information or not. More precisely, is the calculated returns in the periods after the completion of the pattern had a significant difference with the total indicator return?

Generally, the research has the following stages: 1- normalizing the price chart and the chart of all indicators and developing cumulative charts of the indicators; 2- smoothing the price chart using the normal 9-day moving average method (to avoid possible errors and to recognize the main extremum points); 3 - Proposing an initial definition for the studied patterns in terms of maximum and minimum points; 4. Determining the maximum and minimum points of the price chart, with the aid of smoothed price chart extremum using moving average filter; 5. Introducing fuzzy variables to geometrically control the patterns and simulate them based on fuzzy numbers; 6. Comparing the conditional distribution of daily returns on the condition of the patterns and non-conditional distribution at different levels of confidence driven from fuzzy logic and the statistical assumption test of the difference between the mean returns of the patterns and the return on the market indicator. All the indicators investigated are considered as a time series considering that several research patterns do not occur frequently. To this aim, the time series of the return of each indicator is normalized in terms of its mean and standard deviation, and their connection leads to a time series, i.e. it $\{x_t^1\}_{t=1}^T, \{x_t^2\}_{t=1}^T, \ldots, \{x_t^{38}\}_{t=1}^T$ is the time series of the daily return of the desired indicators, first these series are normalized as follows, and connected to each other to form a single time series(1) & figure1:

$$y_t^1 = \{\frac{x_t^1 - \mu_1}{\sigma_1}\}_{t=1}^T, y_t^2 = \{\frac{x_t^2 - \mu_2}{\sigma_2}\}_{t=1}^T, \ldots, y_t^{38} = \{\frac{x_t^{38} - \mu_{38}}{\sigma_{38}}\}_{t=1}^T \qquad (1)$$

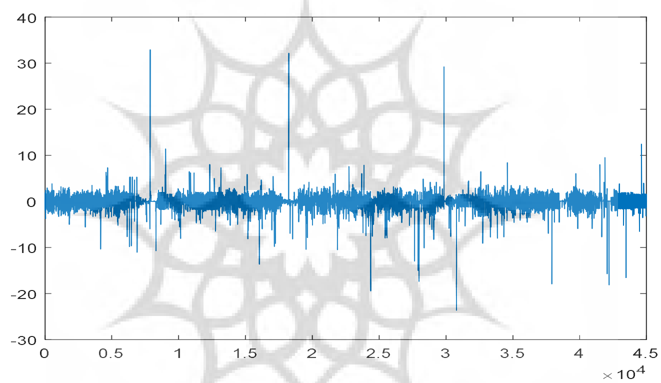


Fig. 1: The Cumulative Chart of Normalized Indicators

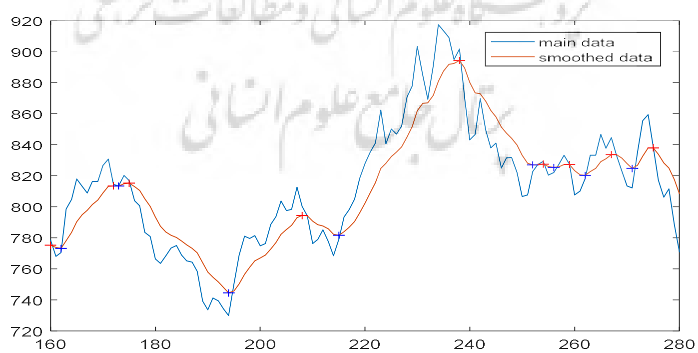
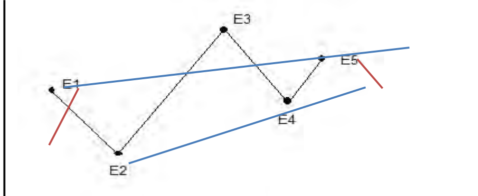
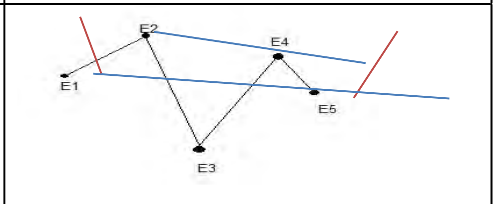
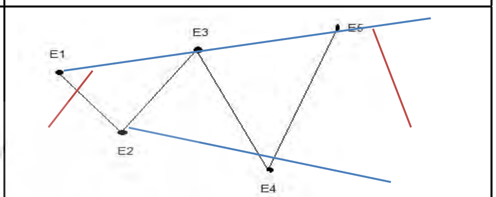
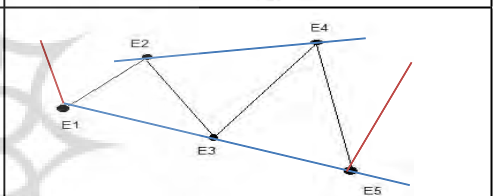
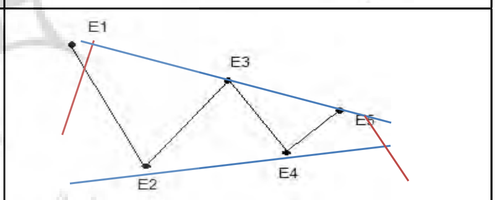
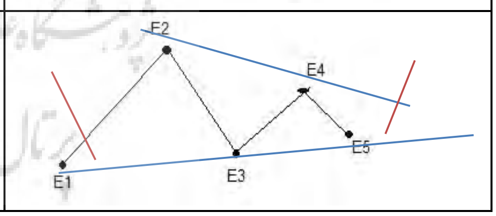


Fig. 2: A Sample of the Extrema Obtained by Smoothing

Table 1: Initial Limitations of Pattern Recognition for the Obtained Extrema Sequences

Pattern	Chart
Head and shoulder (HS) pattern: In this pattern, the following relationship should exist between the extrema. $E_3 > E_1 \quad AND \quad E_3 > E_5$ $E_4 > E_2$	
Inverse Head and shoulder (IHS) pattern: As seen in this chart, in this pattern the following relationships should exist between the extrema. $E_3 < E_1 \quad AND \quad E_3 < E_5$ $E_4 < E_2$	
Broadening top (BTOP) pattern: In this pattern, the first point of pattern extremum is the maximum type. $E_1 < E_3 < E_5$ $E_2 > E_4$	
Broadening bottom (BBOT) pattern: In this pattern, the first point of pattern extremum is the minimum type. $E_1 > E_3 > E_5$ $E_2 < E_4$	
Triangle top (TTOP) pattern $E_1 > E_3 > E_5$ $E_4 < E_2$	
Triangle bottom (TBOT) pattern $E_1 < E_3 < E_5$ $E_4 < E_2$	

Assume that $\{x_t\}$ is the price time series of stock. To remove the noise effect and outliers, using the 9-day moving average, the author smoothed stock price. All-time series are smoothed using a normal moving average, and the extrema[1] of moving average chart is known as time series extrema. (Fig.2)

[1] Maximum and minimum of a function in one period refer to the largest value and smallest value of the function in that period.

The study then determined the maximum and minimum points of the smoothed series $\{y_t\}$. Such that the time t^* is a local minimum point for $\{y_t\}$, when $y(t^*) < y(t^*-1)$ and $y(t^*) < y(t^*+1)$, and time t^* is a local maximum for $\{y_t\}$ when $y(t^*) > y(t^*-1)$ and $y(t^*) > y(t^*+1)$ the extreme point of price series $\{x_t\}$ are considered equal to extreme points $\{y_t\}$. Then, the series values $\{x_t\}$ for the five successive extremes are considered E_1, E_2, E_3, E_4, E_5. Calculating the five successive extrema based on the conditions indicated in Table 1 may be indicative of one of the technical analysis patterns.

After the sequence of the extrema found passes the initial limitations of the extrema, and the system recognized that this sequence may be one of the desired patterns, fuzzy logic recognition system is used to ensure precise recognition of the pattern, which comes in several types in the present research and the adjustment of variables mentioned were conducted using the trapezoidal fuzzy number.
This state has four main points a, b, c, d. Before pointing a and after point d equal 0, between point a to b, the point with a positive gradient of 1 / (b-a) is on the rise up to reaching a perfect point, the pattern has the best state between point b to c and obtains the full point, and from point c to d, with a negative gradient of 1 / (d-c), the pattern credibility declines (figure 3) & (Table 2), so that at point d the pattern with zero points will not be accepted. Table2 shows Parameters used by the fuzzy system to control the credibility of the recognized extrema sequence for valid pattern recognition

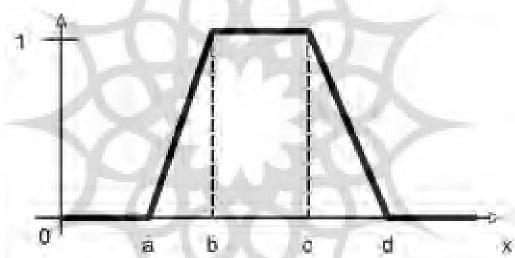


Fig. 3: Trapezoidal Fuzzy Number

Considering the initial conditions, which were solely about comparing extremum points, patterns were shapeable in quite different forms. For instance, in the head and shoulders, the head point can take distance from the shoulders, or a shoulder position very high or very low relative to the other. Thus, the variables must be somehow defined such that by controlling them the pattern does not lose its standard state accepted by technical analysts. These variables which are used as parameters of the fuzzy logic system for recognition are defined based on Table 3. As stated, this study uses trapezoidal fuzzy numbers. Therefore, the parameters used for adjusting the trapezoidal numbers will be considered by the [19].

Table 2: Pattern Recognition

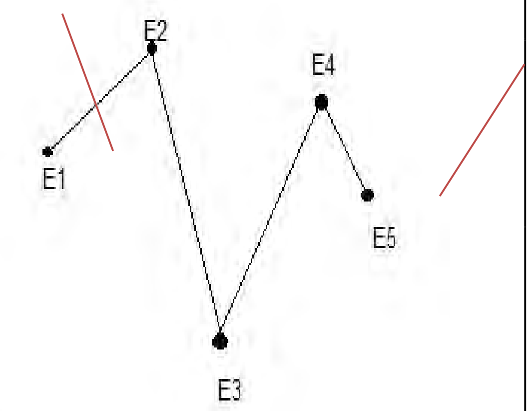
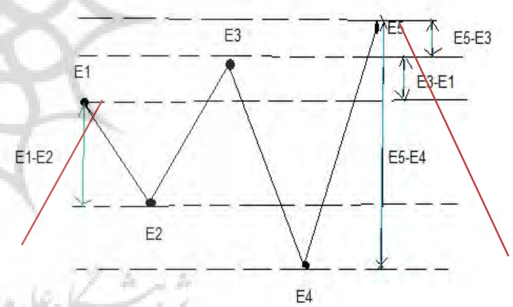
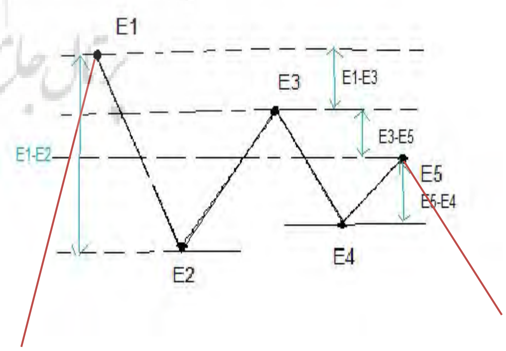
Description	The function of the fuzzy parameter	
Description of the parameters stated in conditions 1-3 related to HS and IHS	*HS / IHS*	
Condition 1: It is about the head and shoulder pattern (both normal and inverse) and the variable introduced is about the head height of the pattern relative to the shoulders.	$\frac{2E_3 - E_1 - E_5}{E_1 + E_5 - E_2 - E_4}$	
Condition 2: It is about the head and shoulder pattern (both normal and inverse) and the variable introduced is about the center of gravity of the shoulders pattern	$0.5\lvert E_5 - E_1\rvert$	
Condition 3: It is about the head and shoulder pattern (both normal and inverse) and the variable introduced is about the center of gravity of the neck-line.	$0.5\lvert E_4 - E_2\rvert$	
Description of the parameters stated in conditions 4 and 5 related to BTOP And BBOT	BTOP / BBOT	
Conditions 4 and 5: It is about the broadening triangle pattern (whether top or bottom), and the variable introduced is as the following figure regarding the degree of broadening (top) and aggregation (bottom) of the broadening triangle.	$\frac{E_5 - E_3}{E_3 - E_1}$ $\frac{E_5 - E_4}{E_1 - E_2}$	
The description of the parameters expressed in conditions 6 and 7 related to TTOP and TBOT	TTOP / TBOT	
Conditions 6 and 7: It is about the triangle pattern (whether top or bottom) and the variable introduced conforms the following chart and about the degree of broadening (top) and aggregation (bottom) of the broadening triangle.	$\frac{E_5 - E_3}{E_3 - E_1}$ $\frac{E_1 - E_2}{E_5 - E_4}$	

Table 3: Trapezoidal Number Parameters

pattern / condition	a	b	c	d
HS / IHS				
*condition*1	0.1	1	5	40
*condition*2	$-\infty$	$-\infty$	$0.005(\frac{E_1+E_5}{2})$	$0.04(\frac{E_1+E_5}{2})$
*condition*3	$-\infty$	$-\infty$	$0.005(\frac{E_1+E_4}{2})$	$0.04(\frac{E_1+E_4}{2})$
BTOP / BBOT				
*condition*1	0.1	0.8	1.2	10
*condition*2	1.2	2	4	15
TTOP / TBOT				
*condition*1	0.1	0.8	1.2	10
*condition*2	1.2	2	4	15

After the initial pattern recognition by the relationship between the extrema, the study calculated the rate of the conditions met for that pattern. For instance, a pattern with the following initial conditions is the head and shoulder pattern. $E_3 > E_1$ AND $E_3 > E_5$, $E_4 > E_2$

The standard rate of extrema is calculated to develop a head and shoulder pattern in conditions 1, 2, and 3, and their average was calculated as the point of that pattern. Obviously, higher points of a pattern make it closer to the standard level. Thus, the point for each pattern paves the way for selecting patterns with better quality, which explains how the pattern recognition phase ends. Having recognized the patterns based on the desired fuzzy point, the researchers investigated whether the patterns found contain useful information for investment. Technicality believes that the period investigated after pattern discovery was as long as the period needed for the formation of the pattern. In order to identify the useful information content of the recognized patterns, after finding the pattern with the desired fuzzy point level, the period $[t_0, t_1]$taken to form the pattern was considered, then the price series are considered at the end of the pattern as much as the calculated time, and this period is divided into four equal periods. The stock returns are calculated from the end of the pattern to the first quarter (r_1), from the end of the pattern to the second quarter or median (r_2), the end of the pattern to the third quarter (r_3) and from the end of the pattern to the final quarter (r_4), and the daily return equivalent is calculated for the returns obtained at each stage. If the return obtained during t days is equal to r, then the daily equivalent return would be:

$$rd - (1+r)^{1/t} - 1 \quad (1)$$

Then, the mean comparison test is conducted for each time series and daily return series of the total indicator. If we observe a significant difference between the mean of that series and the daily return series of the stock indicator at least in one of the series, then it is concluded that the pattern found contains useful information to gain abnormal returns. (Figure 4)

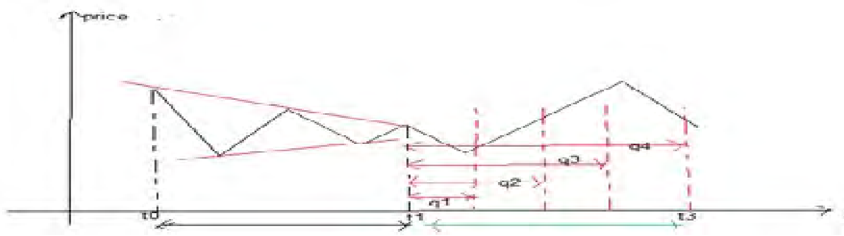


Fig. 4: Quarters after Pattern Recognition

4. Research Findings

After smoothing the chart and extracting the extrema points smoothed, the position of the points found in the main chart is measured relative to each other. Only through considering the initial conditions of the extrema to recognize a special type of pattern is obtained by measuring the position of the points discovered relative to each other based on Table 1 (regardless of the pattern point obtained based on fuzzy criteria). The number of patterns is as table 4:

Table 4: Number of Discovered Patterns

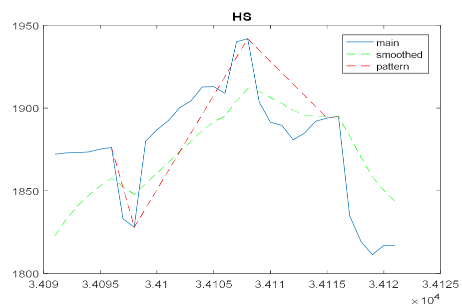
Based on the initial extremum limitations (regardless of the fuzzy logic)			**Based on the minimum point 0.5 in the fuzzy logic system**
Pattern	**name**	**Number of discovered patterns**	**Number of patterns discovered**
Head and shoulder	HS	445	238
Inverse Head and shoulder	IHS	405	209
Broadening top	BTOP	71	17
Broadening bottom	BBOT	103	38
Triangle top	TTOP	75	39
Triangle bottom	TBOT	82	47

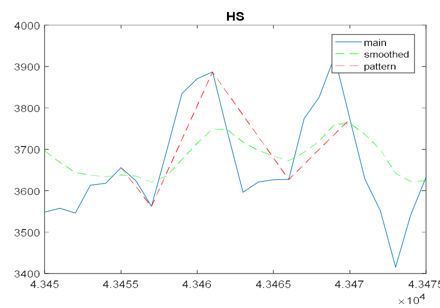
Table 5 presents a sample of the patterns recognized by the system and the degree of conforming to the requirements of Table 3. In each chart, the price is displayed with a continuous blue line and the smoothed chart with a green dotted line, and the pattern that the system was discovered based on the maximum and minimum points of the smoothed chart was displayed with a red dotted line. In the first chart, the head and shoulder pattern has a fuzzy point 1. The highest peaks representing the head and the other two peaks smoothed by the chart (9-day moving average) represent the shoulders of the patterns which are easily identified. In the second chart, the head and shoulder did not achieve the full fuzzy point and gained the point 0.7678, the head of the pattern 4.345 of the horizontal axis and the two maximum points on the left and right of the pattern head represent the shoulders of the pattern. The technical analysts consider this pattern closer to the twin pattern than the head and shoulder pattern, and based on the technical principles of the fuzzy recognition system, this pattern was given a point of 0.7678. Similarly, you can see how other patterns were obtained. Table 5 shows a sample of patterns that they have identified by the pattern recognition system along with the fuzzy point of for pattern

Table 5: Pattern Rcognition

Head and Shoulder

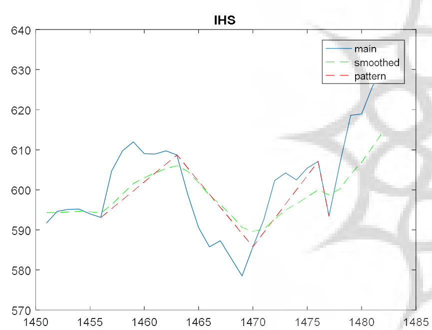
Points	Membership degree Condition 3	Membership degree Condition 2	Membership degree Condition 1	Point	Membership degree Condition 3	Membership degree Condition 2	Membership degree Condition 1
1	1	1	1	0.7678	1	0.99	0.3136

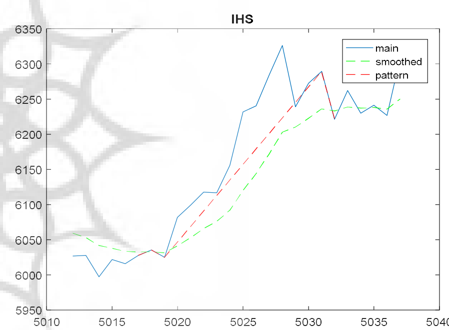




Inverse Head and shoulder

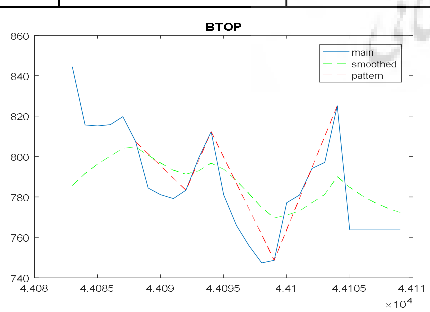
0.9853	1	0.956	1	0.8416	1	0.752	0.5250





Broadening top

Point	Membership degree condition 2	Membership degree condition 1	Point	Membership degree condition 2	Membership degree condition 1
0.813	1	0.6227	0.9319	0.9514	0.9124



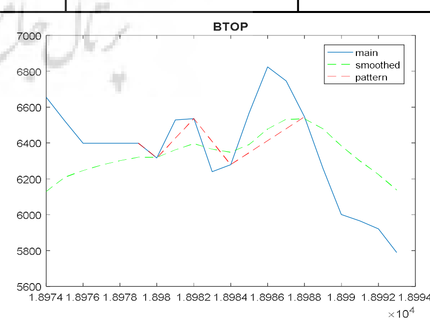
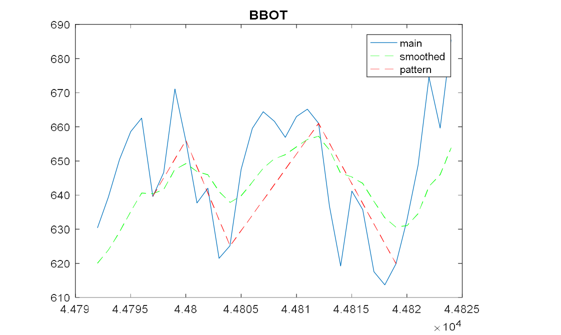
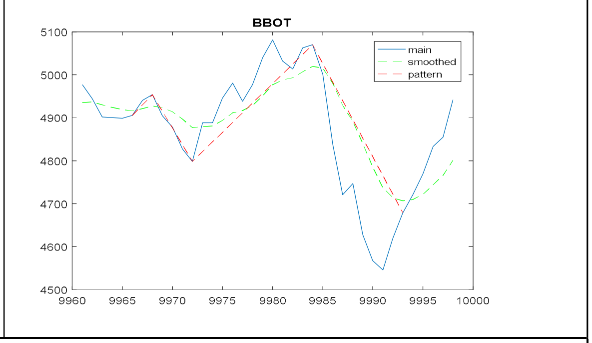


Table 5: Continue

Broadening bottom

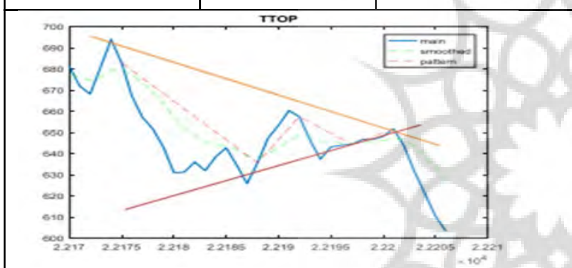
Point	Membership degree Condition 2	Membership degree Condition 1	Point	Membership degree Condition 2	Membership degree Condition 1
1	1	1	0.8957	0.95	0.8415

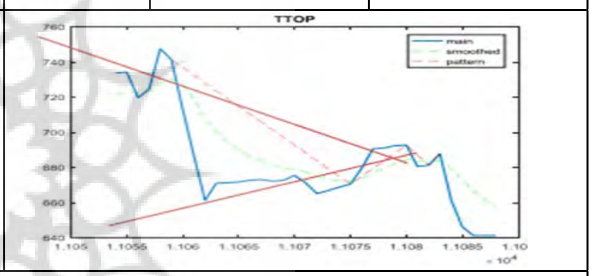




Triangle top

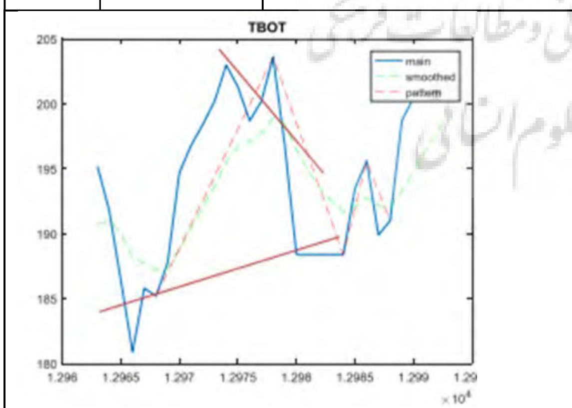
Point	Membership degree Condition 2	Membership degree Condition 1	Point	Membership degree Condition 2	Membership degree Condition 1
0.4641	0.4127	0.5155	0.9505	0.9011	1

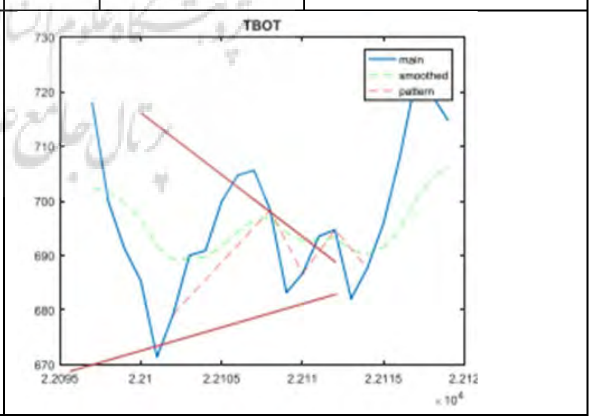




Triangle bottom

Point	Membership degree Condition 2	Membership degree Condition 1	Point	Membership degree Condition 2	Membership degree Condition 1
0.3262	0.4224	0.23	0.7705	1	0.541





In the first step, we measure the results to determine the efficiency of the designed fuzzy logic system and validating the research and responding the second question of the research to conduct the comparison test between the returns of the normalized cumulative indicator and the returns of the quarters of the patterns which were extracted regardless of fuzzy logic and only with the initial limitations of the extrema and based on the Table 1. The following table indicates the results of this test. Table 6 shows the probability value of the comparison test of the quarter's means and the total cumulative return indicator based on the discovered patterns by considering the initial limitations of the extrema and regardless of the fuzzy logic

Table 6: Pattern Recognition

IHS	Probability value	HS	Probability value
First quartile	0.0003	First quartile	0.0728
Second quartile	0.0000	Second quartile	0.3766
Third quartile	0.0313	Third quartile	0.8648
Forth quartile	0.0137	Forth quartile	0.3284
BBOT	Probability value	BTOP	Probability value
First quartile	0.1710	First quartile	0. 0005
Second quartile	0.6640	Second quartile	0.0201
Third quartile	0.5031	Third quartile	0.2445
Forth quartile	0.7231	Forth quartile	0.8362
TBOT	Probability value	TTOP	Probability value
First quartile	0.0055	First quartile	0.0971
Second quartile	0.0494	Second quartile	0.9340
Third quartile	0.1834	Third quartile	0.9508
Forth quartile	0.0240	Forth quartile	0.9622

Considering that the probability less than 0.05 is only observed in the IHS, BTOP, and TBOT patterns, it can be concluded that only based on the extrema points and regardless of fuzzy logic, the patterns obtained by fuzzy logic without refinement contain useful information only in the three mentioned patterns.

In the second step, we used the main feature of the designed system, i.e. determining the pattern points based on fuzzy logic. The higher points of a pattern lead to more geometric pattern credibility and the extracted pattern is closer to the pattern desired by the technical analysts. In this step, the minimum point in fuzzy logic is considered equal to 0.5. obtained based on the following results. Considering fuzzy logic and comparing the number of patterns based on the fuzzy system with the number of extracted patterns, regardless of the fuzzy system indicates a significant difference in the reduction of the number of patterns, which indicates the increase of the discovered pattern credibility based on the technical principles. Having discovered the patterns using the mean comparison test, the daily returns of the quarters were compared with the daily returns of all the normalized cumulative indicators, and if only one of the quarters is less than 0.05, it indicates the usefulness of the pattern for gaining profit.

Table 7 presents the results of a comparison test of the mean of indicator returns of the total normalized cumulative indicator and the returns of the quarters after discovering the pattern (considering the fuzzy conditions and the minimum fuzzy point 0.5). Table 7 shows the probability value of a comparison test of the mean quarter of the total normalized cumulative return indicator based on patterns discovered considering the minimum level of point 0.5 in a fuzzy logic system.

Table 7: pattern recognition

IHS	Probability value	HS	Probability value
First quartile	0.0000	First quartile	0.0433
Second quartile	0.0146	Second quartile	0.0867
Third quartile	0.3417	Third quartile	0.5266
Forth quartile	0.1353	Forth quartile	0.3831
BBOT	Probability value	BTOP	Probability value
First quartile	0.0000	First quartile	0.0203
Second quartile	0.0015	Second quartile	0.0000
Third quartile	0.0011	Third quartile	0.0000
Forth quartile	0.0190	Forth quartile	0.0021
TBOT	Probability value	TTOP	Probability value
First quartile	0.0083	First quartile	0.0217
Second quartile	0.0274	Second quartile	0.7908
Third quartile	0.1173	Third quartile	0.8444
Forth quartile	0.0025	Forth quartile	0.8800

Considering that at least one quarter is observed in all patterns with the test probability value less than 0.05, it can be concluded that at the minimum level 0.5, all patterns contain useful information for the fuzzy logic system, and can provide the investor to a return above the mean of the total indicator return, which indicates the usefulness of the technical analysis patterns.

5 Conclusion and Discussion

Aimed at determining the usefulness of head and shoulder, triangle and broadening triangle patterns in Tehran stock exchanges, this research confirmed the presence of useful information in these patterns and indicated that statistically at 95% confidence level, these patterns yield higher return compared to the mean returns of the total cumulative indicators. In the first step, after finding the patterns, regardless of the limitations and conditions of fuzzy logic, a significant number of patterns were obtained with the initial conditions of the extremum points of the patterns, and in fact, when the fuzzy logic conditions were not used to extract the pattern, there was a significant difference between the number of patterns obtained compared to the terms of the fuzzy logic condition, which is indicative of the refinement characteristic of fuzzy logic, used in the second step for patterns exceeding the extrema limit. By placing discovered patterns in the fuzzy logic conditions and increasing points from 0 to 0.5 to investigate fuzzy logic function, a significant reduction was observed in the number of patterns, which indicates the efficiency of the designed limits and conditions of fuzzy logic, and expresses an increase in the credibility of the pattern extracted by fuzzy logic. The reason beyond such inference is the difference between the results of the mean comparison test in two states, namely, considering or disregarding fuzzy logic. When considering fuzzy logic conditions, all patterns contain useful information, while only IHS, BTOP, and TBOT patterns have useful information, if we disregard these conditions. Thus, we can conclude that by correctly determining the fuzzy logic criteria and conditions, a high step can be taken for systematic pattern recognition. Fuzzy logic empowers the system to move from the state of absolute decision-making to relative decision-making and recognize technical

patterns that have relative characteristics. We can also conclude that a higher minimum fuzzy point for pattern recognition yields better patterns for recognition, which, according to technicians, the patterns have higher credibility, also, a higher fuzzy point leads to a decrease in the number of recognized patterns. This result is consistent with Zhou and Dong [34] findings regarding the ability of algorithms in discovering patterns differences and achieving abnormal returns based on fuzzy patterns. Ijegwa et al. [9] also emphasized the enhancing effectiveness of technical indicators based on fuzzy logic. Naranjo et al. [18] also held that the candlestick pattern in a fuzzy logic-based trading system was associated with more return and less risk compared to conventional techniques. Gradojevic and Gençay [7] also suggested using fuzzy logic to reduce the uncertainty of technical trading strategies in market timing and order size, especially in volatile periods. On this basis, the study suggested comparing the adjustable parameters of the recognition system, i.e. the coordinates of the fuzzy numbers used, taking into account the historical data of optimization and the results of profitability.
Finally, the implementation of these studies for analyzing short and long term content can examine the effectiveness of technical tools. Besides, those who research on content analysis can examine the effectiveness of bid and ask Quotes signals based on technical signals. Moreover, Researchers can compare the results of investment strategies based on technical signals and fundamental analysis.

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