Turkish Journal of Computer and Mathematics Education Vol.12 No.13 (2021), 7786 – 7806

Research Article

Investigating candlestick patterns using fuzzy logic in the stock trading system

Mojtaba Sadeghi[a], Dariush Farid[*b], Habibullah Ansari samani[c]

[a] master of financial management, yazd university, yazd, iran. email: **sadeghimojtaba2@gmail.com**
[b] associate professor of financial business management, faculty of economics, management and accounting - department of business management, yazd university, yazd, iran. email: fareed@**yazd.ac.ir**
[c] assistant professor of economics, faculty of economics, management and accounting - department of economic sciences - yazd university, yazd, iran. email: **h.samani@yazd.ac.ir**

Article History: Received: 14 July 2020; Accepted: 2 January 2021; Published online: 5 February 2021

Abstract: This research aims to design a stock market forecasting system based on candlestick patterns and use fuzzy logic to model market rules and candles. The present study investigates how to design an efficient trading algorithm using trading information analysis and signaling methods and combining them with the capabilities of fuzzy logic that have already been developed. The short- and medium-term benefits of the proposed method are proven in different markets. Furthermore, this study enables investors to use specialized knowledge so that they can invest more confidently. In this study, fuzzy logic is used to implement trading systems based on candlestick patterns. The implemented method achieved profitability and lower risk for two different markets without retraining the system and even for a different testing period.

Keywords: Stock trading, Candlestick patterns, Fuzzy logic

1.Introduction

Capital market investors were divided into two groups following the introduction of the capital market efficiency theory. People who believe in market efficiency favored long-term investments because they considered it impossible to make a profit through market forecasting, and so there is no opportunity to make abnormal profits from short-term buying and selling. The other group of investors does not believe in this theory and has some criticisms about it. They believed in capital market forecasting and therefore used different models for their forecasts. Aside from long-term investments, this category made short- and medium-term investments and, by continuously buying and selling, attempted to make abnormal profits. After assuming that the market is predictable, three questions regarding what share, what time frame, and what price must be answered.

Different models have been used in answering these questions. A classical prediction method such as econometrics and time series are used to investigate models that predict the desired share. Time-frame models look for a specific trading strategy and rely on technical analysis and forecasting models or AI models. To answer the question of what price, various models are used, including classic models, fundamental analyses, technical analysis, and artificial intelligence algorithms. We focus specifically on the third question, i.e. price forecasting since the greatest variation occurs in the forecasting area.

Also, studies have been done on this topic. The study by Chen et al. [1] used neural networks and genetic algorithms to design an intelligent decision support system for stock trading. This research was conducted on the Taiwan market, and its results are comparable with buying and holding, which shows favorable results. Letamendia [2] examined the effect of changes in genetic algorithm parameters on the design of the technical trading system and concluded that the results were sensitive to the parameter of the genetic algorithm. Caballero [3] used the relative strength index (RSI) indicator as a technical indicator in the neural network. The results of this research show great results on the IBEX index in Spain. A general regression neural network (GRNN) index used in this study predicted the future price of stocks and, in fact, the broad dimensions of future normal volume charts. The results provided by this paper are more useful than purchasing and holding strategies, simple moving averages, and indicators without neural networks. Aso et al. [4] examined candlestick chart technical instruments and proposed a new model for the leveling of the stock market based on recurrent networks and technical analysis of candlestick patterns. Using fuzzy logic, Hwang and Oh [5] predicted stock prices. In the proposed method by the researchers, the information on candlestick patterns is considered as an input to the fuzzy system, and the closing price of the share is considered the output. Sun et al. [6] investigated candlestick patterns for price forecasting in the context of technical analysis. The prediction efficiency of candlestick patterns was compared with technical analysis indicators and based on the obtained results, there were no significant differences between the two aforementioned methods.

The AL algorithms that are gaining popularity with investors are a combination of all forecasting methods with the ability to fit higher-order nonlinear curves. This type of algorithm can work with a large number of variables and find a suitable relationship between those variables. By combining the capabilities of fuzzy expert systems with candlestick patterns, we have tried to create an intelligent system for identifying patterns and signaling for buying and selling stocks. Fuzzy expert systems can make the pattern look flexible and in reality, this pattern can be recognized in more situations. Thus, this study is using this method to solve the problem of complexity of appearance and its adaptation to candlestick patterns.

Theoretical Foundations

Technical Methods

Because the subject of research is the use of candlestick patterns and their analysis using fuzzy logic, it is necessary to examine the basics of technical analysis more carefully. Candlestick patterns are a subset of technical analysis. To predict futures price movement, the technical analysis examines historical price movements and trading volume using charts and indicators. The study of investors is based on the assumption that price patterns will repeat in the future. Technical analysis is mainly used to identify trends in the early stages and to hold the investment until signs indicate a change in trend. Both of these approaches aim to predict stock movements from different perspectives. Typically, the technical analysis examines the reasons for market movement and their effects [7].

Technical analysis attempts to predict price trends by using price data and past trading volumes. This method's main disadvantage is its reliance on finding strong empirical rules in price and volume movements. In other words, supporters of this method are only interested in identifying the major turning points to assess price movements. In the real world, these rules are not always evident, often hidden by volatilities, and vary from share to share. Therefore, investors cannot consistently and accurately predict future prices using this method [8].

Technical analysis includes a broad range of methods, which we will discuss in general:

Methods based on chart shape: Technical patterns such as the head and shoulders pattern represent the specific types of price change charts that can forecast future price changes by identifying them for a particular stock. Elliott's wave analysis is one of the most famous patterns. Elliott's method asserts that all price movements in the long, medium, and short-run and even within a day are composed of five impulse waves and three corrective waves. By matching the shape of these waves on the price of each share in the sample, the start of the next wave and hence future price changes can be predicted.

Indicators-based methods: indicators are an empirical mathematical formula that uses different share prices throughout the day and trade volume to predict the future movement of the share. More than 50 technical indicators are known, so simultaneous analysis is impossible. Therefore, many researchers have used artificial intelligence and machine analysis methods to utilize indicators for stock filtering [9].

Candlestick patterns are one of the methods based on the shape which is as numerous as indicators. in contrast to indicators, these patterns have no quantifiable value and their appearance is the basis for judgment. As a result, there are no practical or qualitative ways of analyzing these all together. Therefore, in this paper, a method to use them in fuzzy logic has been proposed [10].

Artificial Intelligence-Technical Analysis

Technical tools provide valuable information about the market. It is possible to achieve much greater power when they are combined and simultaneously used. The most well-known hybrid technical analysis method is called CRISMA, which was developed by Pruitt and White in 1988. Based on what Pruitt and White proved between 1986 and 1990, CRISMA merges the relative strength index and moving average to predict the aggregate volume index buy and sell signals and ensures profits despite financial risks and trading costs. CRISMA employs a simple strategy to generate a signal, so that if the signal is generated from two rules, then the third rule signal should also be strong enough to take a position. Technical analysis systems have been profitable in the past, but not without problems. The criticisms about this method include the lack of attention to the trading costs, rate of return on capital, and the screening of the data in terms of the profitable aspects. As a result of future challenges as well as the opportunities for obtaining results from new AI methods, especially intelligent networks and metaheuristic algorithms for setting parameters and indicators of technical analysis, as well as receiving appropriate output from different indicators and converting them into a single signal, various hybrid models of technical analysis with mathematical, metaheuristic and artificial intelligence methods have been developed.

Stephanides and Papadamou [11] proposed improvements to the technical trading system using MATLAB software based on genetic algorithms in financial markets. This paper presents a new tool that is carried out under MATLAB software and is based on genetic algorithms, which specializes in optimized technical rule parameters and obtains satisfactory results. Different indicators have been investigated in this field due to the abundance of indicators and different attitudes.

To determine the medium base volume, Chavarnakul and Enke [12] selected two variables: VAMA volume adjustment and EMV moving ease. It is well known that trading volume can provide valuable information about stock price movements. Therefore, volume charts were developed to monitor stock movements. Volume charts were used to develop adjusted moving average volume and ease of movement indicators. Based on the neural networks and the indicators aforementioned, the researchers examined the profitability of stock trading.

In analyzing the stock trading solution, Yang et al. [13] used a new neural network model, Echo State, designed by Hess and Jagger [14], because it is simple and can solve problems. It is a storable recurrent network.

Research Methodology

The present study is considered applied research. Furthermore, the present study is a correlational study that investigates the trend of changes in different trading days and the issuance of related trading signals. All listed companies on the Tehran Stock Exchange make up the statistical population. We analyzed the results of investors' stock research from 2016 to 2016. This research is a type of technical and market forecasting research. In terms of analysis method, this research belongs to the category of artificial intelligence and intelligent systems research. The importance of various features of the input variables of the fuzzy system and widely used and highly reliable candlestick patterns in the Iranian capital market will be determined according to experts' opinions. We use both of these to design fuzzy expert systems. First, candlestick patterns are identified through a questionnaire, and then, when it comes to trading signals, the importance of multiple input variables considered for the fuzzy system is determined through a questionnaire.

The experts were chosen from the Iran Stock Exchange Brokerage Company. There are total of 53 experts of this brokerage, in the trading and analysis sections, according to the aforementioned filters, 35 people have qualified and the questionnaire was filled out based on their opinions. 211 questionnaires out of 378 sent to the research and development departments of the mentioned companies were returned. In the present study, information is collected in two general parts using a questionnaire. In the first part, experts were asked to identify the variables that are important to understanding candlestick patterns. This study considered 8 variables identified by previous research as selectable variables for experts. A questionnaire in the first part is as follows:

Table 1: the first part of the research questionnaire

Is the $\mathbf{L_{upper}(t)}$ variable used to identify candlestick patterns? often very **moderate** low negligible
Is the $\mathbf{L_{lower}(t)}$ variable used to identify candlestick patterns? often very **moderate** low negligible
Is the $\mathbf{0.5}$ variable used to identify candlestick patterns? often very **moderate** low negligible
Is the $\mathbf{L_{gap}(t)}$ variable used to identify candlestick patterns? often very **moderate** low negligible
Is the $\mathbf{L_{trend}(t)}$ variable used to identify candlestick patterns? often very **moderate** low negligible
Is the $\mathbf{L_{difopen}(t)}$ variable used to identify candlestick patterns? often very **moderate** low negligible
Is the $\mathbf{L_{difcentral}(t)}$ variable used to identify candlestick patterns? often very **moderate** low negligible

The second and third questionnaires based on the answers to the first questionnaire will be a permutation of the important variables already known from the current questionnaire. So, the first part of the questionnaire will be dependent on the results obtained from that part.

To identify candlestick patterns, all or a subset of these variables should be used. Using the following equation, we can calculate the first variable:

$$L_{upper}(t) = 100.\frac{high\ (t) - \max(open(t), close(t))}{open(t)}$$

(1)

The $L_{upper}(t)$ variable indicates the length of the top of the candle relative to the opening price. A higher value of this variable will occur the greater the difference in price between the high and low opening and closing price. The second variable is used to calculate the length of the candle's bottom:

$$L_{lower}(t) = 100.\frac{\min\left(open(t), close(t) - low\ (t)\right)}{open(t)}$$

(2)

By increasing this variable, the lower sequence of the candle will be longer on the relevant trading day. Finally, the candle body's length is measured with the following variable:

$$L_{body}(t) = 100.\frac{close(t) - open(t)}{close(t)}$$

(3)

The larger the candle's body length, the longer it is. Therefore, no matter if the price goes up or down during the day (white or black candle), this variable will indicate the length of the candle. The next variable indicates the price gap (if any) between the two candles at two consecutive day:

$$L_{gap}(t) = \begin{Bmatrix} 0 & \text{if } low(t) \leq high(t-1) \\ 100.\dfrac{low(t) - high(t-1)}{low(t)} & \text{in other case} \end{Bmatrix}$$

(4)

As a result of this, the value of the gap variable will be zero or positive, and the greater the distance between the lowest price today and the highest price yesterday, the higher the gap rate. next variable indicates the trend:

$$L_{trend}(t) = 100.\frac{close(t) - close(t-1)}{close(t)}$$

(5)

The calculated trend is positive if the price of today is higher than it was yesterday; otherwise it is negative. opening difference variable is shown in Equation (6):

$$L_{difopen}(t) = \begin{Bmatrix} 0 & \text{if } low(t-1) \leq open(t) \\ 100.\dfrac{low(t-1) - open(t)}{low(t-1)} & \text{in other case} \end{Bmatrix}$$

(6)

This variable can have a positive or negative value. Positive indicates that the opening price today was lower than yesterday's lowest price. The final variable is the centrality difference, which is shown in the following relation:

$$L_{difcentral}(t) = \begin{cases} 0 & \text{if } close(t) \leq \dfrac{open(t-1) + close(t-1)}{2} \\ 100.\dfrac{close(t) - \dfrac{open(t-1) + close(t-1)}{2}}{close(t)} & \text{in other case} \end{cases}$$

(7)

If the closing price today is higher than the average price yesterday, the centrality difference variable takes a positive value. Therefore, seven variables are calculated for each share in each day, based on the seven variables introduced in this section, which indicate the characteristics of the candle. Fuzzy sets transform these variables from quantitative values to verbal and qualitative values.

In order to convert quantity values L_{upper} and L_{lower} into fuzzy values, we will use trapezoidal fuzzy functions. Forecasting the future situation and signaling is the output of fuzzy systems. Quantitatively, this output is calculated using fuzzy rules, which will be presented in the next chapter. Based on these output states, the table below presents the probable outputs of the system under both ascending and descending trends.

Table 2: Convert Output Value To Trading Signals

Variable quantity value	upward trend	descending trend
$\mathbf{if\ x < 10}$	No action	No action
$\mathbf{if\ 0 < x < 30}$	No action	No action
$\mathbf{if\ 20 < x < 50}$	Getting ready to buy	Getting ready to sell
$\mathbf{if\ 40 < x < 70}$	Getting ready to buy	Getting ready to sell
$\mathbf{if\ 60 < x < 90}$	Buy if another pattern indicates the same amounts	Sale if another pattern indicates the same amounts
$\mathbf{if\ x > 80}$	Issuing of the purchase signal	Issuing of the sales signal

By using the above table, we can issue trading signals and design a trading system based on candlestick patterns.

The pattern that encourages traders to buy or sell in the traditional candlestick-based trading strategy is a prominent sign of market behavior. The following rules can be applied to a classic candlestick trading system based on the three patterns in Table 2-1:

1. reversal ascending

If

High(t-1)=Open(t-1) AND

Low(t-1)=Close(t-1) AND

High(t)=Close(t) AND

Low(t)=Open(t) AND

Low(t)>High(t-1)

Then the reversal is correct.

2. Hammer

If

Trend(t) <0 AND Trend(t-1)<0 AND

Trend(t-2)<0AND Low(t)< Low(t-1) AND

[High(t)=Max(Open(t), Close(t))< Body(t)/(5) AND

Min(Open(t),Clos(t))- Low(t)>2. |Open(t)-Clos(t)|

Then the reversal is correct.

3. Gap Cover

If

Trend(t) <0 AND Trend(t-1)<0 AND

Trend(t-2)<0AND Candlestick(t-1) is black AND

Candlestick(t) is white AND

Body(t-1)>2* Shadows(t-1) AND

Body(t)>2* Shadows(t) AND

Open(t)<Low(t-1) AND

Close(t)>Body(t-1)/2

Then the reversal is correct.

Conditions used in the purchase or sale order whereby a broker is instructed to complete the order or not to make any part of the order.

Findings

The researchers developed a questionnaire, which was reviewed and completed by 180 experts. In Table 4-1, we present data related to the fuzzy rules of the ascending reversal pattern, and in this table, we present a list of questionnaire items that indicate the variables in terms of importance.

Table 3: fuzzy rules for the ascending reversal pattern

$\mathbf{Lupper(t-1)}$	$\mathbf{Llower(t-1)}$	$\mathbf{Lupper(t}$	$\mathbf{Llower(t)}$	Lgap	Lbody (t-1)	Lbody (t)	Bullish
null	null	null	null	Very	high	Low	high

Very Low	null	null	null	Very	high	Low	high
null	null	null	null	Low	moder ate	Low	Very high
null	null	null	null	Very high	moder ate	moder ate	mode rate
Very Low	null	null	null	mod erate	Very high	Low	mode rate
null	null	null	Low	Very	Low	Low	mode rate
null	Very high	null	Low	Very	Very high	Very Low	high
null	Very high	null	null	Very Low	moder ate	moder ate	mode rate
null	high	null	null	null	high	moder ate	high

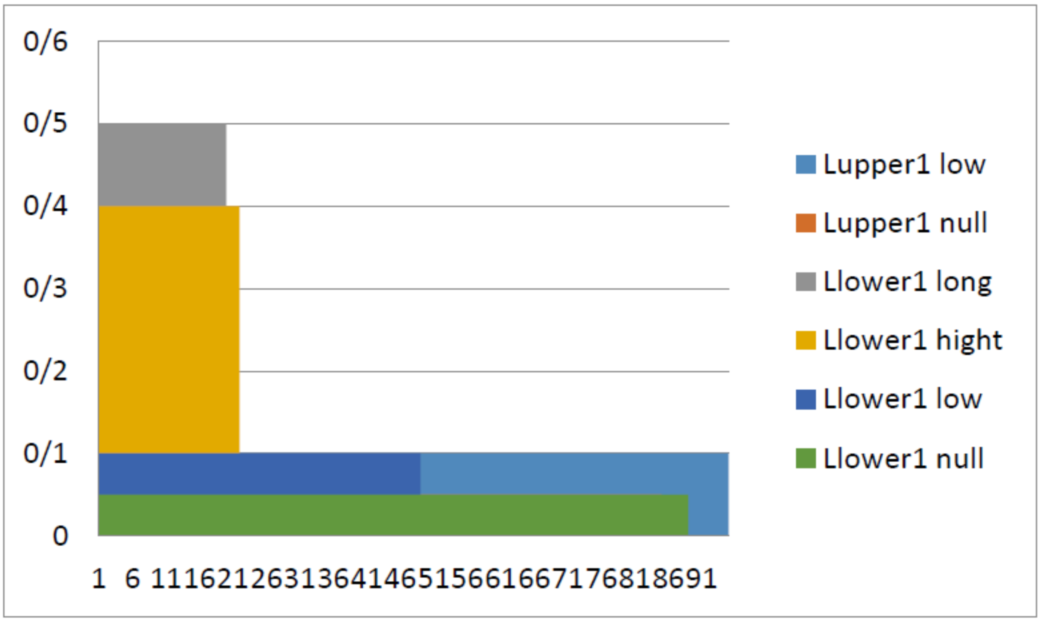

Figure 1: the significance of variables Lupper(t) and Llower(t)in the ascending reversal pattern

Figure (2) shows the significance of variables Lgap and Lbody(t-1) in reversal uptrend pattern. We can see in this Figure that these two variables are also of little importance in the ascending reversal pattern.

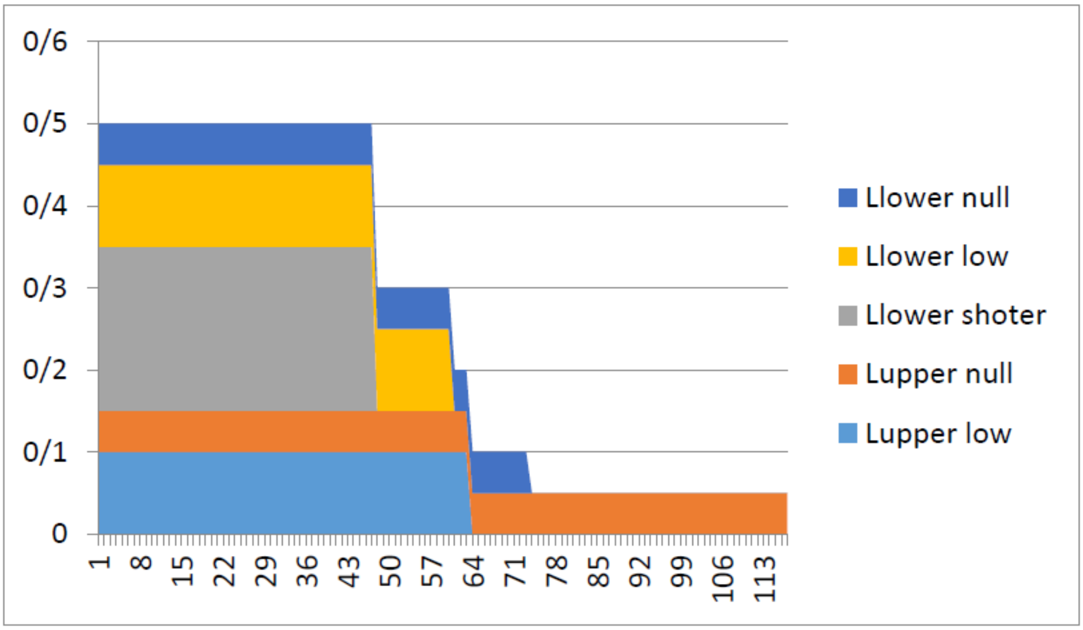

Figure 2: the significance of two variables lupper(t) and llower(t) in the ascending reversal pattern.

Figure (3) illustrates the significance of the two variables along with the reversal uptrend pattern. This Figure shows that these two variables play an extremely important role in the ascending reversal pattern.

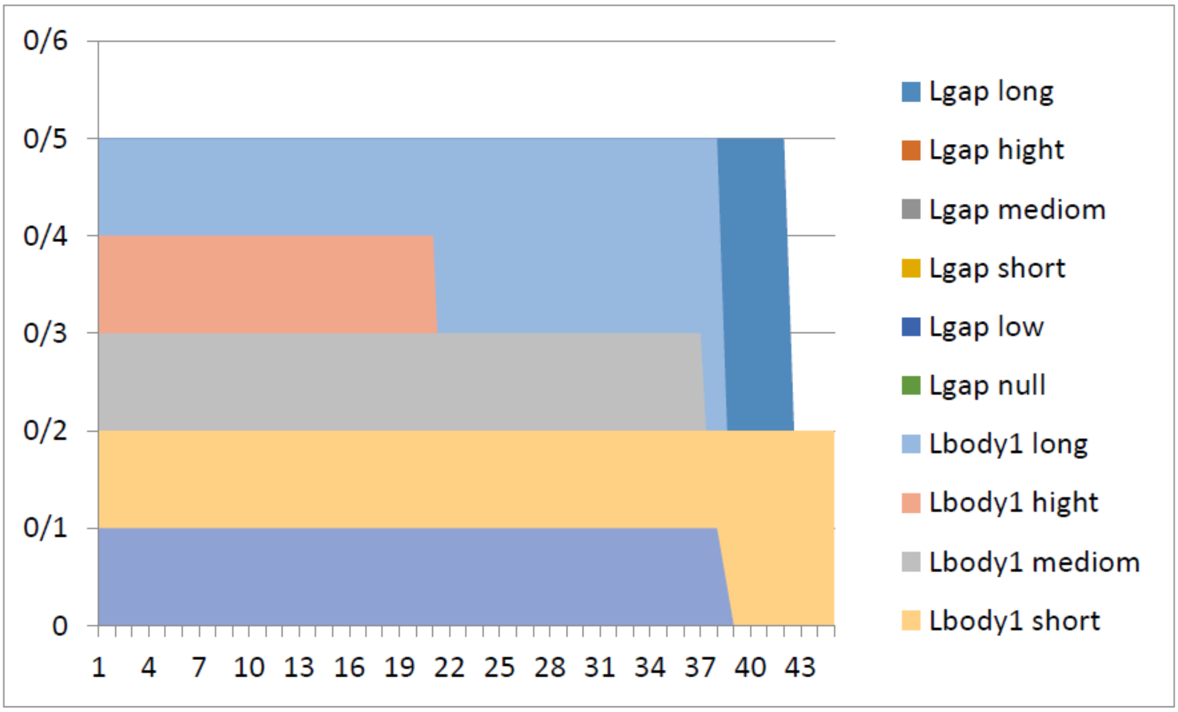

Figure 3: the significance of two variables lupper(t) and llower(t) in the ascending reversal pattern.

In Figure (4), we can see that the significance of the variables Lbody(t) and Bullish in the ascending reversal pattern is moderate.

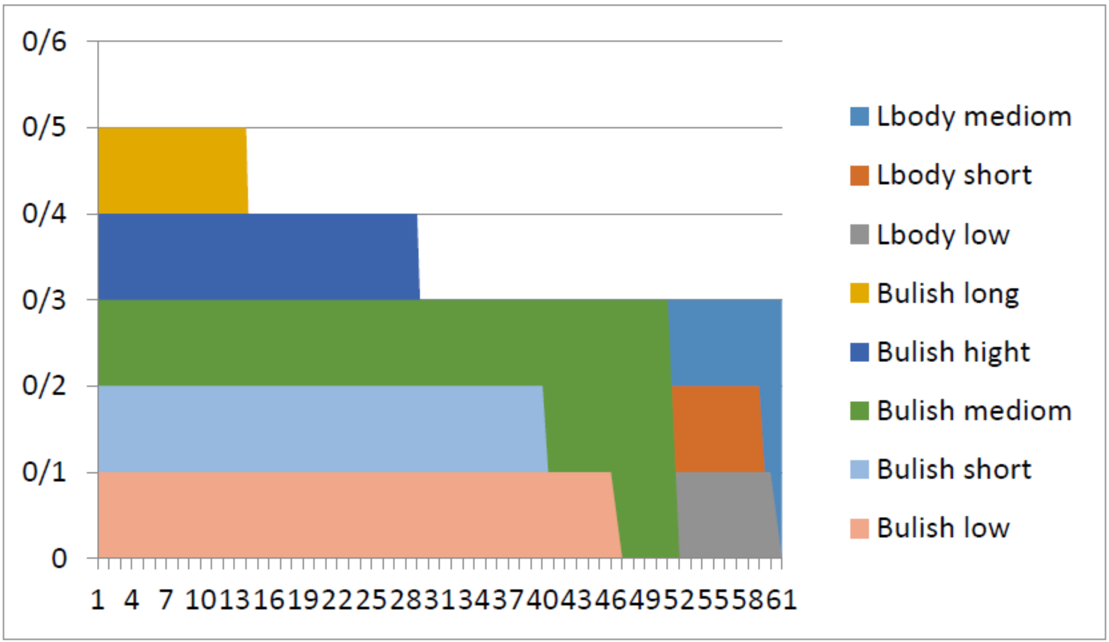

Figure 4: the significance of two variables lbody(t) and bullish in the ascending reversal pattern

Table 4: fuzzy rules for the hummer pattern

Lupper(t − 1)	**Llower(t − 1)**	**Trend(t − 2)**	**Trend(t − 1)**	Trend(t)	Lbody(t)	Bullish
null	Low	Low	Low	Low moderate	high high	Very high
null	Very high	Low	Low	moderate	high	high
null	high	Low	Low	moderate	high	moderate
null	Very high	Low	Very Low	Low	high	moderate
Low	high	Low	Very Low	Low	high	moderate
Very Low	moderate	moderate	Low	Low	high	Low
Low	Very high	Low	Low	high	high	Low

Low	Very high	Very Low	moderate	high	high	high
Very Low	moderate	Low	Low	Low	high	Very high

Figure (5) explores the significance of variables $\mathrm{Trend}(t-1)$ and $\mathrm{Trend}(t-2)$ in the Hummer model. This Figure shows that the variables have very little significance in the Hummer model.

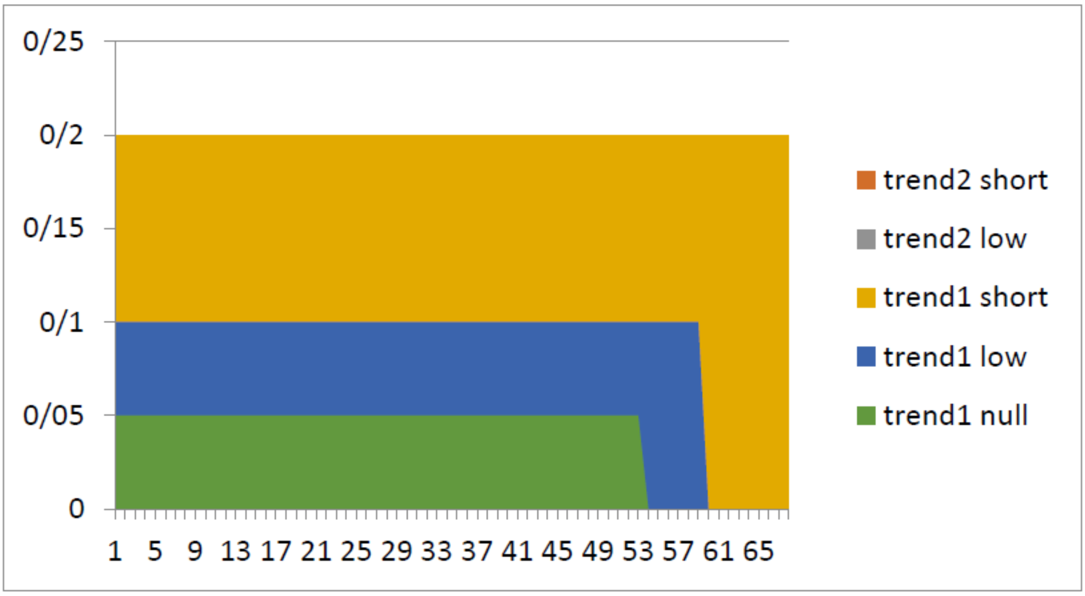

Figure 5: the significance of two variables $\mathrm{trend}(t-2)$ and $\mathrm{trend}(t-1)$ in the hummer pattern

Figure (6) examines the significance of two variables, $\mathrm{Llower}(t-1)$ and $\mathrm{Lupper}(t-1)$, in the Hummer model. As can be seen in this figure, in the Hummer model, the $\mathrm{Llower}(t-1)$ has very little importance and the $\mathrm{Lupper}(t-1)$ has very importance.

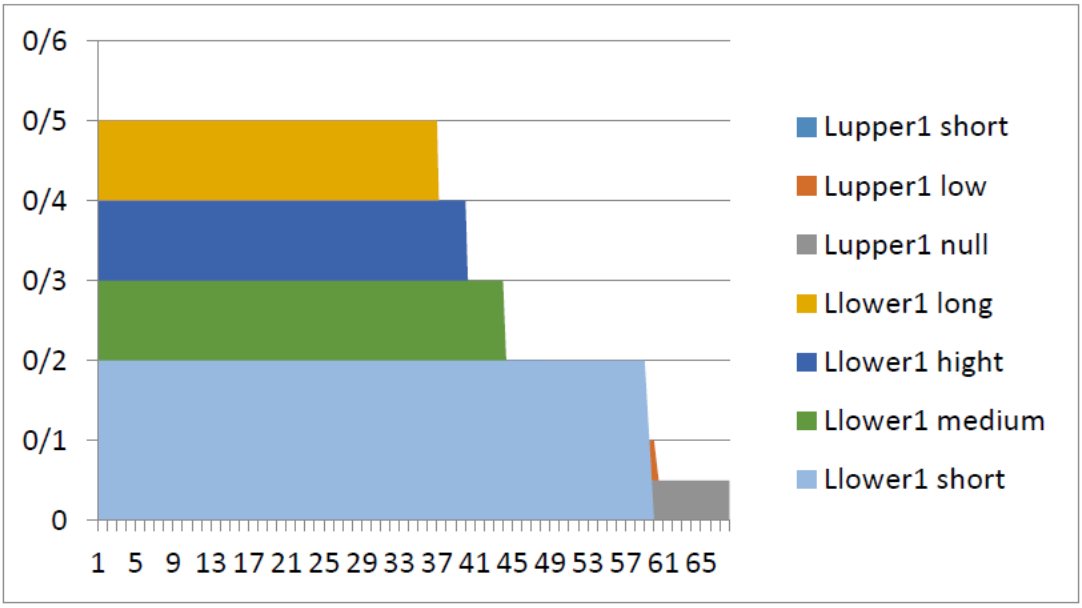

Figure 6: the significance of two variables $\mathrm{Lupper}(t-1)$ and $\mathrm{Llower}(t-1)$ in the hummer pattern

Figure (7) examines the significance of variables Trend(t) and Lbody(t) in the Hummer model. Here we can see that Lbody(t) and Trend(t) are of high and low importance in the Hummer pattern, respectively.

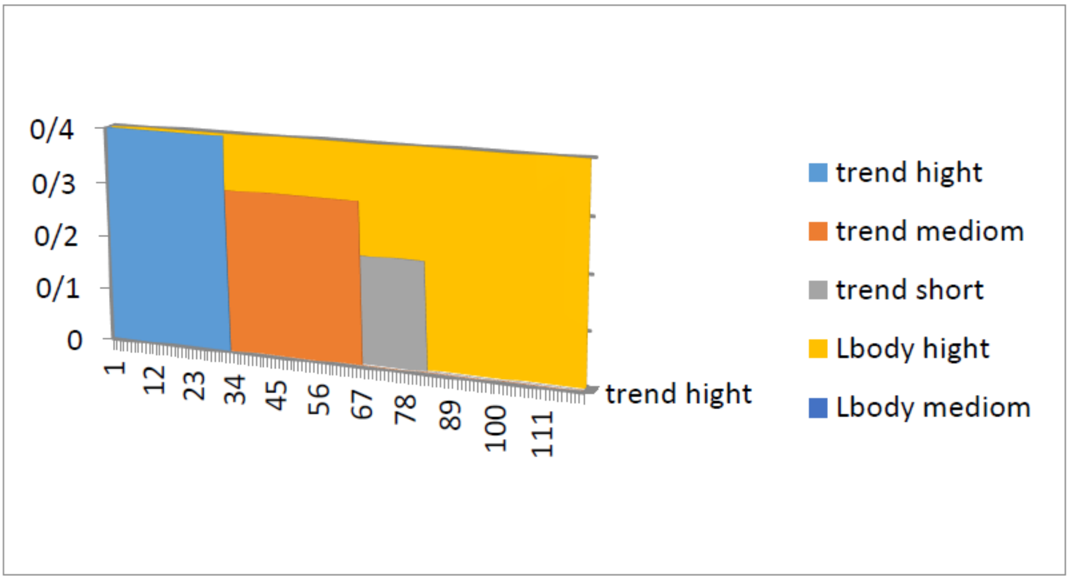

Figure 7: The significance of two variables $\mathrm{Trend}(t)$ and $\mathrm{Lbody}(t)$ in the Hummer pattern

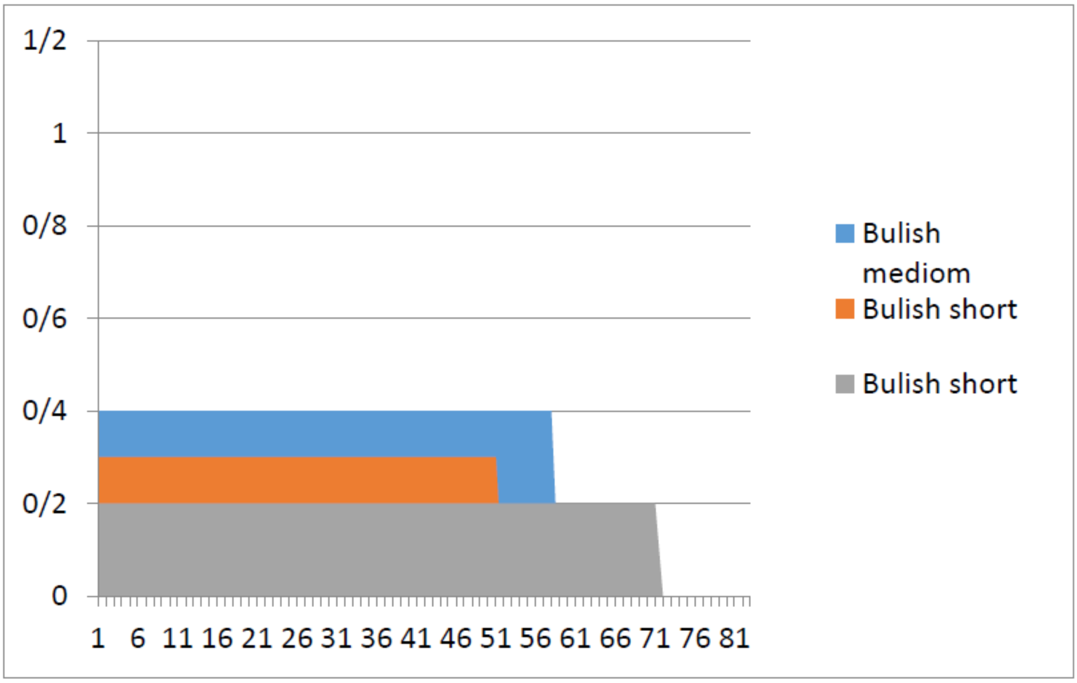

Figure 8: the significance of the bullish variable in the hummer model

Table 5: fuzzy results for the gap cover pattern

$\mathbf{Ldifopen(t)}$	$\mathbf{Ldifcentral(t)}$	$\mathbf{Trend(t-2)}$	$\mathbf{Trend(t-1)}$	Trend(t-1)	Trend(t)	Lbody(t-1)	Bullish
Low	Low	Low	Low	Low	Low	high	Very Low
Low	Very Low	Low	Low	null	Low	high	moderate
Low	Very high	Low	Low	Low	Low	high	moderate
Low	Very high	Low	Very Low	null	Low	moderate	moderate
Very high	moderate	Very Low	Very Low	null	Low	moderate	moderate
Very high	moderate	Low	Low	null	Low	high	high
Very high	Very high	Low	Low	Low	Low	high	moderate
high	Very high	Very Low	moderate	null	Low	moderate	high
high	high	Very Low	Low	Low	Very Low	high	moderate

Figure (9) examines the significance of the two variables $\mathrm{Trend}(t-1)$ and $\mathrm{Trend}(t-2)$ in the gap cover pattern. This diagram indicates that the variables in the gap cover pattern have little impact.

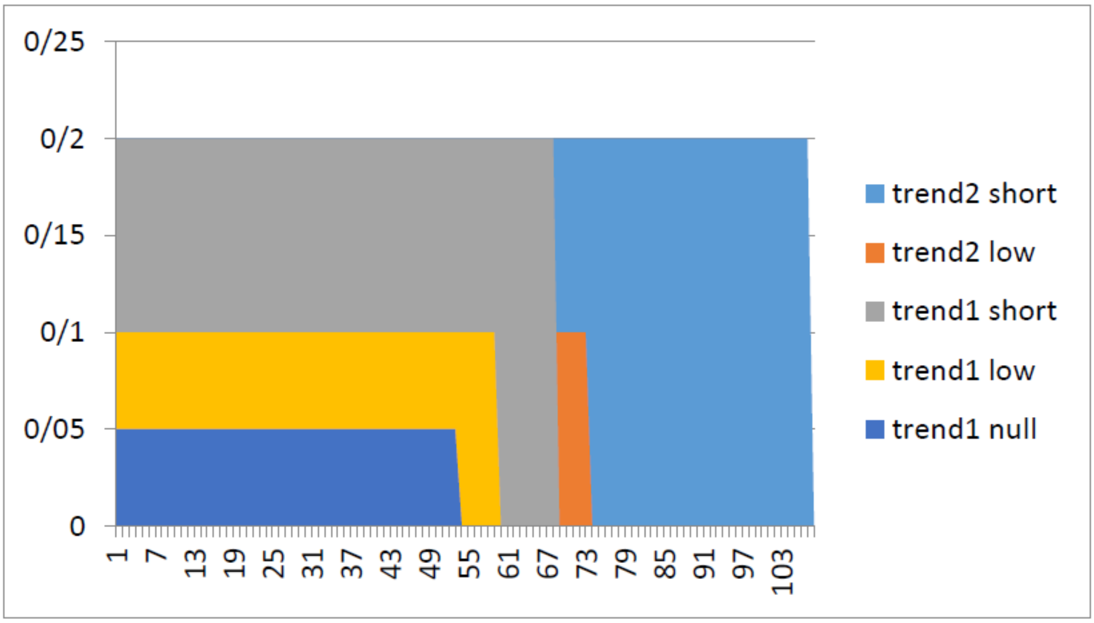

Figure 9: the significance of two variables, trend (t-1) and trend (t-2), in the gap cover pattern.

Figure (10) examines the importance of two variables $\mathrm{Ldifopen(t)}$ and $\mathrm{Ldifcentral(t)}$ in the gap cover pattern. These two variables are very important in the gap cover pattern, as can be seen in the diagram.

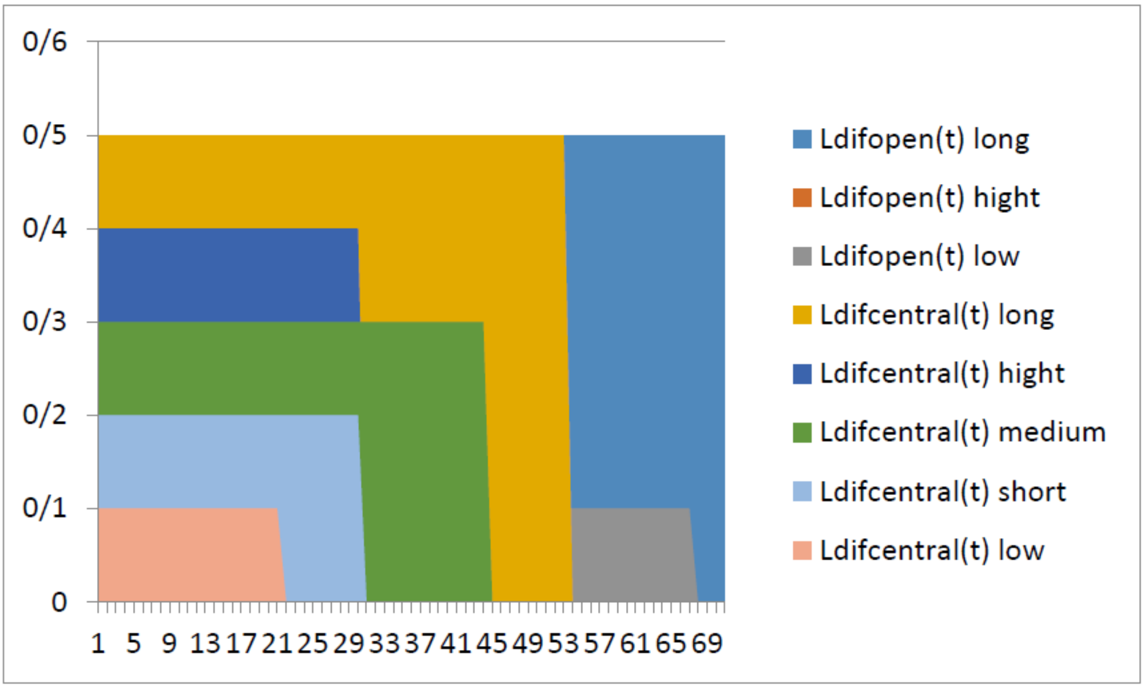

Figure 10: the significance of two variables, Ldifopen(t) and Ldifcentral(t), in the gap cover pattern

Figure (11) examines the importance of two variables Trend (t-1) and Lbody(t) in the gap cover pattern. Based on this diagram, it can be seen that the two variables Lbody(t) and Trend(t-1) have the greatest and least importance in the gap cover pattern.

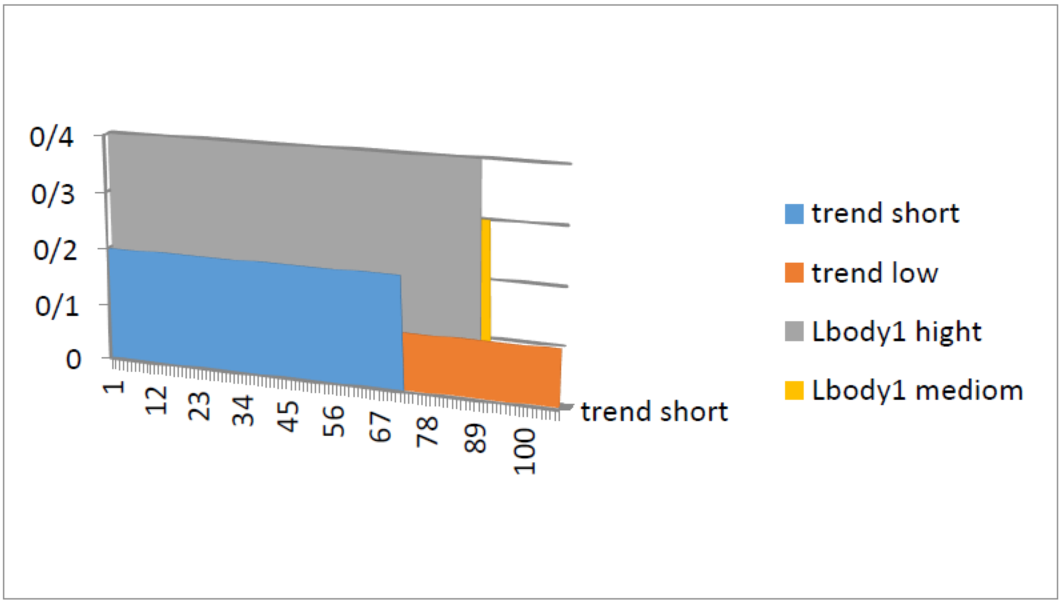

Figure 11: the significance of two variables, Ldifopen(t) and Ldifcentral(t) , in the gap cover pattern

In Figure 12, we see that the importance of the Bullish variable in the gap cover pattern is relatively small.

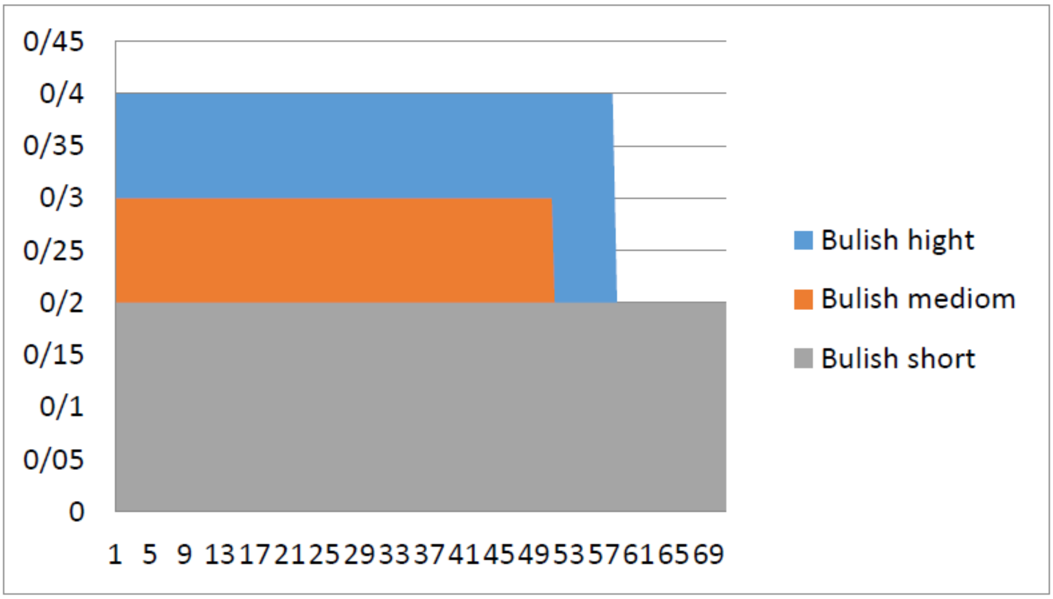

Figure 12: the significance of the bullish variable in the gap cover pattern

To test the fuzzy candlestick forecasting model, various scenarios were selected from Iranian stock markets. We used the same samples of securities. Naranjo et al.'s research was compared with candlestick intelligent decision-making systems. the 17 securities that are intended for the Iranian stock market include: Motogen, Kable Alborz, Iran Tire, Derakhshan Tehran, Niroo Moharekeh, Daropakhsh, Lastic Sahand, Siman Tehran, Saipa, Siman Sepahan, Siman Fars and Khuzestan, Iran Carbon, kaaf, Ama Sanat, Absal, Pars Electric and Iran Khodro.

Training and validating the fuzzy model, as well as evaluating its performance, has been accomplished using two different capital management strategies. Experiment 1 employs an "all or nothing" strategy, that is, enters the market with all available resources at the time. The information provided by the fuzzy output was then used in Experiment 2 to determine the desired amount for the investment. For the second case, the entry is determined by the percent of available capital, which is determined by the variable (ascending 0-100). Investment portfolios have a total value of 5,000,000 Tomans for each security in Iran.

Table 6: training results for the fuzzy trading system (experiment 1)

corporation	Net profit	Max DD(%)	Total Trades	+ trade	- trade	The average trade	Average profit	Average loss	Average loss/ Average profit
Energy 3	742.000	–3.57	41	28	13	1.07	5.24	–0.41	1.34
Kable Alborz	150.000	–6.52	24	18	6	0.51	1.76	–0.51	1.26
Iran Tire	230.000	–8.3	28	19	9	0.07	2.12	–0.65	1.75

Derakhshan Tehran	352.000	–3.49	16	10	6	0.42	0.58	–0.54	1.41
Niroo Moharekeh	221.000	–2.45	17	9	8	0.24	1.79	–1.23	0.89
Daropakhsh	310.000	–8.26	38	30	8	0.36	2.35	–1.76	1.85
Lastic Sahand	590.000	–11.14	41	25	16	1.21	3.45	–2.76	1.71
Siman Tehran	621.000	–2.15	43	32	11	1.28	1.89	–0.78	1.21
Saipa	321.000	–5.3	29	22	7	1.21	2.23	–0.23	1.36
Siman Sepahan	815.000	–3.81	51	45	6	0.85	3.74	–0.43	1.17
Siman Fars and Khuzestan	840.000	–5.22	27	21	6	0.86	3.85	–0.67	0.79
Carbon Iran	-4.000	–1.23	25	21	4	0.02	4.52	–0.90	1.65
Kaaf	115.000	–4.61	10	4	6	0.52	0.83	–0.78	1.04
Ama Sanat	20.000	–2.39	15	9	6	1.21	1.78	–0.62	0.99
Absal	257.000	–4.1	19	12	7	0.47	0.37	–3.67	1.39
Pars Electric	341.000	–10.36	27	18	9	0.41	6.45	–4.76	1.25
Iran Khodro	1.225.000	–3.20	89	50	39	1.13	10.85	–0.54	1.64
Total	7.146.000	–86.1	540	364	176				

Table 7: Training results for the fuzzy trading system (Experiment 2)

corporation	Net profit	Max DD (%)	Total Trades	+ trade	- trade	The average trade	Average profit	Average loss	Average loss/ Average profit
Energy 3	600.000	–3.2	22	18	4	0.07	4.02	–0.15	1.2
Kable Alborz	110.000	–4.2	15	10	5	0.10	0.96	–1.23	0.87
Iran Tire	280.000	–2.2	16	10	6	0.18	1.42	–0.45	1.01
Derakhshan Tehran	200.000	–1.9	12	7	5	0.14	1.02	–.52	1.23
Niroo Moharekeh	150.000	–5.8	11	8	4	0.04	0.78	–1.2	1.54
Daropakhsh	346.000	–7.6	26	15	11	0.16	1.28	–0.79	1.76
Lastic Sahand	375.000	–3.4	33	25	8	0.21	1.20	–0.65	1.21
Siman Tehran	540.000	–1.45	31	21	10	0.14	2.3	–0.48	1.32
Saipa	500.000	–4.6	23	18	5	0.15	1.87	–0.58	1.14

Siman Sepahan	751.000	–2.45	35	28	7	0.18	2.42	–0.25	1.65
Siman Fars and Khuzestan	862.000	–6.8	18	11	7	0.13	3.14	–0.18	1.32
Carbon Iran	–86.000	–1.3	13	2	12	–0.18	0.15	–2.2	0.58
Kaaf	–10.000	–5.1	5	1	4	0.10	0.23	–0.97	0.80
Ama Sanat	100.000	–3.7	8	6	2	0.16	0.88	–0.65	1.01
Absal	114.000	–1.5	19	12	7	0.23	0.94	–0.44	1.28
Pars Electric	285.000	–7.3	24	20	4	0.17	2.89	–0.64	1.79
Iran Khodro	950.000	–4.65	37	31	6	0.33	0.6.23	–0.23	2.50
Total	5,967,000	–67.15	348	243	107				

Table 8: results of standard business system training

corporation	Net profit	Max DD (%)	Total Trades	+ trade	- trade	The average trade	Average profit	Average loss	Average loss/ Average profit
Energy 3	300.000	-1.23	6	4	2	0.47	4.02	–0.15	1.2
Kable Alborz	60.000	–1.48	9	7	2	0.59	0.96	–1.23	0.87
Iran Tire	120.000	–0.23	7	3	4	–0.45	1.42	–0.45	1.01
Derakhshan Tehran	53.000	–0.58	5	3	2	1.20	1.02	–.52	1.23
Niroo Moharekeh	–2.000	–2.2	6	3	3	1.22	0.78	–1.2	1.54
Daropakhsh	250.000	–3.82	12	7	5	–0.28	1.28	–0.79	1.76
Lastic Sahand	150.000	–1.21	18	12	6	1.67	1.20	–0.65	1.21
Siman Tehran	330.000	–0.21	14	8	6	1.62	2.3	–0.48	1.32
Saipa	287.000	–1.28	11	8	3	1.52	1.87	–0.58	1.14
Siman Sepahan	552.000	–0.67	21	11	10	–0.51	2.42	–0.25	1.65
Siman Fars and Khuzestan	680.000	–3.40	9	7	2	0.78	3.14	–0.18	1.32
Carbon Iran	–6.000	0.00	7	5	2	–0.02	0.15	–2.2	0.58
Kaaf	–96.000	–2.34	3	1	2	0.35	0.23	–0.97	0.80
Ama Sanat	14.000	–0.78	5	3	2	0.90	0.88	–0.65	1.01
Absal	28.000	0.00	10	5	5	1.83	0.94	–0.44	1.28

Pars Electric	157.000	–1.54	12	4	8	1.42	2.89	–0.64	1.79
Iran Khodro	723.000	–1.92	16	20	11	1.67	0.6.23	–0.23	2.50
Total	3.600.000	–22.89	171	111	60				

On Figure (13) we see that the fuzzy strategy in Experiment 1 has better growth than the fuzzy strategy in Experiment 2, and both fuzzy modes in Experiment 1 and 2 have a higher profitability in the stock market than the standard mode.

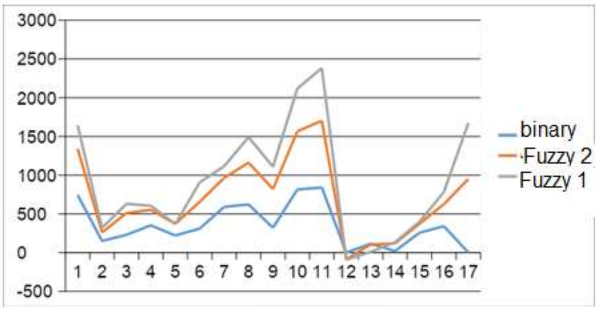

Figure 13: training course for three strategies

From the results of the training phase (Tables 6, 7, and 8), the following observations can be drawn. At the first stage, based on the advantages, the fuzzy system 1 is the best one, earning 7.146.000 Tomans or 5.51%.

With 5,967,000 Tomans, the fuzzy 2 educational system earns a profit of 3.14%. Finally, the standard system earns a profit of 3,600,000 Tomans or 1.2%. According to the maximum DD, the classical system obtained the lowest value (-1.5%), followed by fuzzy test system 2 (-3.76%) and fuzzy test system 1 (- 6.80%). The above three values are assumed to be low and can be assumed by investors. However, such a low profit for a standard system does not justify its low profit. Success rates are similar for all three systems, although both fuzzy systems (60.23%) have a higher success rate than the classical system (65.36%). Since the standard system has stricter regulations for securities identification, it should be more successful due to its fuzzy features but at the expense of having fewer identified patterns.

However, fuzzy systems have better beats and detect more objects, so combining both leads to better results. For all systems, the maximum DD is low as well. The Fuzzy 2 test system achieves a 41.42% reduction compared to the Fuzzy 1 test system. Profits dropped 35.48% due to its conservative strategy. Although both Max DD values can be tolerated by traders, they depend on the investment strategy. To make more profit, they must choose an aggressive strategy (fuzzy experiment 1) or a conservative strategy (fuzzy experiment 1) that could result in a decrease in profits. Nevertheless, the reduction of Max DD in the classical system, as previously mentioned, does not necessarily justify the reduction in profit.

Figure 4-13 shows the capital principle as a function of time for the three systems. You can see the upward trend in the diagrams, which is similar to the fuzzy systems in Experiment 1 and Experiment 2 while the standard system does not appear to have acquired this characteristic during its training period. Moreover, we can observe a difference between Experiment 1 and

Experiment 2 fuzzy systems. In Fuzzy Experiment 2, the line is smoother, implying that the capital drop is smaller and, as a result, the emerging peaks are smaller.

Conclusion

Based on fuzzy logic, the present study examines candlestick patterns in a stock trading system. Based on candlestick patterns, this study proposes a method for implementing trading systems using fuzzy logic. We observed that the system implemented using the proposed method was able to achieve profitability and lower risk for two different markets without retraining the system and even for a different testing period.

In addition, these results are interesting to investors since they suggest that this fuzzy approach can be used to implement stable trading systems. Investors also have an advantage since it is not a black box system. The system is mainly devised as a result of the rules that they set up using their expert knowledge. It allows them to set the rules and reverse them when the rules become ineffective. As far as we know, our work is similar to the expert system provided by Lee and Jo [15].

Even though the output of the intelligent system may not be very predictable (Kamo and Dagli [16]), it can suggest the best time to buy or sell in a particular market, as well as the likely amount of investment in the portfolio. So, an expert system provides a simple, yet practical, capital management strategy.

The main issue with our system is that it requires experts with expertise in fuzzy logic to define membership tasks and rules, or guide them in the process. Lee et al. [17] and Camus and Dagli [16] found that this problem occurs in other intelligent systems. There are several candlestick patterns applied in this study, both ascending and descending. This will allow the system to profit in ascending or descending markets. Furthermore, it would be interesting to implement a more advanced capital management strategy, such as the one proposed by Naranjo et al. [18]. As expected, we tested the profitability of this model and its level of risk.

In addition, we would like to test our system in the foreign exchange market, the world's largest financial market where other interesting fuzzy approaches have been successfully explored. Dymova, Sevastjanov, and Kaczmarek [19] presented an expert system based on new technical characteristics and explicit-rule reasoning, namely, a combination of fuzzy sets and Dempster-Schaefer theory. One interesting development in our work is the development of a trading system for candlesticks per day, and through that, we can assess whether candlestick patterns are useful at higher frequencies.

Our system was tested using a stock portfolio. However, it would be interesting to create a portfolio smartly. In this context, we could use the results of studies like Al-Mahdi and Yang's suggestion [22], which used repetition reinforcement learning (RRL) to build the comparative work sample using the maximum possible weakness.

As a result, it is recommended that in evaluating forecasting models, along with statistical errors, we pay particular attention to the new criteria of the accuracy of forecasts, and use models both in assessing forecasting results and choosing the most predictably profitable share.

References

1. R. J. Kuo, C. H. Chen, and Y. C. Hwang, “An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network,” Fuzzy sets Syst., vol. 118, no. 1, pp. 21–45, 2001.

2. L. Nunez-Letamendia, “Fitting the control parameters of a genetic algorithm: An application to technical trading systems design,” Eur. J. Oper. Res., vol. 179, no. 3, pp. 847–868, 2007.
3. J. L. Jiménez Caballero and R. J. Ruiz Martínez, “Las redes neuronales en su aplicación a las finanzas,” Banca Finanz. 54, 19-26, 2000.
    A. Bahrami et al. Hamekhani, "Using Neural Networks to Predict Stock Price Trends," Quarterly Journal of Management and Accounting Studies, vol. 2, no. 3, 1395.
4. H. Hwang and J. Oh, “Fuzzy models for predicting time series stock price index,” Int. J. Control. Autom. Syst., vol. 8, no. 3, pp. 702–706, 2010.
5. N. T. Son, L. Van Thanh, T. Q. Ban, D. X. Hoa, and B. N. Anh, “An analyze on effectiveness of candlestick reversal patterns for Vietnamese stock market,” in Proceedings of the 2018 International Conference on Information Management & Management Science, 2018, pp. 89–93.
6. M. Moradzadeh Fard, R. Darabi, and r. Shah Alizadeh, "Integration of Artificial Intelligence Techniques for Provide Stock Price Prediction Model", Financial Accounting and Auditing Research (Journal of Financial Accounting and Auditing), vol. 6, no. 24, pp. 89–101, 1393.
7. K. Kim and I. Han, “Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index,” Expert Syst. Appl., vol. 19, no. 2, pp. 125–132, 2000.
    A. Taftian, F. Abui Mehrizi, and F. Hirani, "Study of the Relationship between Capital Structure, Operating Cycle, and Inflation at the Tehran Stock Exchange", the first national conference on overcoming the economic recession; challenges and solutions. Islamic Azad University, Yazd Branch, Yazd, 2015.
8. Kh. Nasrallah, S. Samadi, and M. Vaez Barzani, "Assessing the usefulness of Japanese candlestick patterns in the Tehran Stock Exchange", Financial Accounting Research, Vol. 5, No. 3, pp. 59–72, 2013.
9. S. Papadamou and G. Stephanides, “Improving technical trading systems by using a new MATLAB-based genetic algorithm procedure,” Math. Comput. Model., vol. 46, no. 1–2, pp. 189–197, 2007.
10. T. Chavarnakul and D. Enke, “Intelligent technical analysis based equivolume charting for stock trading using neural networks,” Expert Syst. Appl., vol. 34, no. 2, pp. 1004–1017, 2008.
11. X. Lin, Z. Yang, and Y. Song, “Intelligent stock trading system based on improved technical analysis and Echo State Network,” Expert Syst. Appl., vol. 38, no. 9, pp. 11347–11354, 2011.
12. H. Jaeger and H. Haas, “Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication,” Science (80)., vol. 304, no. 5667, pp. 78–80, 2004.
13. K. H. Lee and G. S. Jo, “Expert system for predicting stock market timing using a candlestick chart,” Expert Syst. Appl., vol. 16, no. 4, pp. 357–364, 1999.
14. T. Kamo and C. Dagli, “Hybrid approach to the Japanese candlestick method for financial forecasting,” Expert Syst. Appl., vol. 36, no. 3, pp. 5023–5030, 2009.
15. C.-H. L. Lee, A. Liu, and W.-S. Chen, “Pattern discovery of fuzzy time series for financial prediction,” IEEE Trans. Knowl. Data Eng., vol. 18, no. 5, pp. 613–625, 2006.

16. R. Naranjo, A. Meco, J. Arroyo, and M. Santos, “An intelligent trading system with fuzzy rules and fuzzy capital management,” Int. J. Intell. Syst., vol. 30, no. 8, pp. 963–983, 2015.
17. L. Dymova, P. Sevastjanov, and K. Kaczmarek, “A Forex trading expert system based on a new approach to the rule-base evidential reasoning,” Expert Syst. Appl., vol. 51, pp. 1–13, 2016.
18. J. H. Fock, C. Klein, and B. Zwergel, “Performance of candlestick analysis on intraday futures data,” J. Deriv., vol. 13, no. 1, pp. 28–40, 2005.
19. Aguilar-Rivera and M. Valenzuela-Rendón, “A new multi-period investment strategies method based on evolutionary algorithms,” Neural Comput. Appl., vol. 31, no. 3, pp. 923–937, 2019.
20. S. Almahdi and S. Y. Yang, “An adaptive portfolio trading system: A risk-return portfolio optimization using recurrent reinforcement learning with expected maximum drawdown,” Expert Syst. Appl., vol. 87, pp. 267–279, 2017.