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Designing and Investigating the Profitability of Fuzzy Inference Trading System based on Technical Signals and Corrective Property

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Abstract

Technical analysis is constituted as an approach in the market analysis which is based on the study of pricing behavior and shares size in the past and price determination and its procedure in the future. Algorithmic transactions are growing rapidly in order to automate business strategies, given the arrival of computer-based technologies and the rapid processing of bulky information. Trading systems combine input information and ultimately identify the time of purchase and sale by forming one signal. In this paper, the training system is a kind of fuzzy inference system that combines fuzzified RSI and SO signals from technical analysis. The system's trade rules database (selling, buying, and holding) would be calculated based on an optimization process using PSO. This optimization process should be repeated at certain intervals to keep the system up to date. This process is called the corrective property of systems. The findings on the overall index in the period 2001/3/21-2019/3/20 indicate that the system having optimized training on training data has an average daily return of /0027, risk-taking of /0065 and the daily sharp ratio of /42. Concerning the index of return and sharp ratio, the findings reveal that the system outperforms the signals and the market performance.

Keywords: Corrective property, Fuzzy inference system, Oscillators, PSO.

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Introduction

Shareholders typically would confront a plethora of information in the stock market. This sort of information should be combined if it aspires to persuade an investor to open, retain or terminate a trade event. Today, transaction systems whose objects are to optimize the information and extract selling and buying signals in the data mining domain have developed extensively. The cumulative diversity of these systems results from diversity in models and input information including paired trading systems and momentum systems (Wang, et al, 2016).

Technical analysis is perceived as a market analysis approach prevalent among stock exchange actors. This analysis is based on the description of behavioral pricing and trading volume using technical tools (graphs and oscillators). There are a lot of trading strategies in technical analysis; a trading system would be developed based on a technical tool. The study aims at introducing a corrective and generalizable trading system (keeping system parameters up to date through time) according to fuzzy inference systems. The purpose behind the above-mentioned trading system is to combine individual trading strategies in technical analysis to achieve a mixed strategy. The correctness of the trading system helps the system to retain its efficiency and process new information properly. This holds a special feature for our study's trading system. In what follows the study is composed of the theoretical framework, literature review, methodology, statistics, recommendations, and the concluding section.

Theoretical framework and literature review

Technical analysis is constituted as an approach in the market analysis which is based on the study of pricing behavior and shares size in the past and price determination and its procedure in the future. The alterations in stock prices would be analyzed using historical records and different graphs and oscillators. This method is extensively utilized by speculators in a short period of determining to increase their return when the stock price is high (Murphy, 1999). One of the tools used in technical analysis is an oscillator which is a function of the size and price of the trade and which fluctuates between two levels. RSI is one oscillator that is highly applied and famous. The default setting for the RSI is 14 days and it is based on losses and gains (in the last 14 days). To calculate this oscillator, the formula is as indicated in (1):

$$RSI = 100 - \frac{100}{1 + RS} \tag{1}$$

$RS = Average\,Gain\ /\ Average\,Loss$

In RS formula, the numerator equals the average of the whole increase in prices and the denominator equals the absolute value of the total of the whole decrease in prices in the last 14 days. Since RS is always positive, it is crystal clear that RSI is a digit between 0 and 100. Typically and empirically two key points 30 and 70 or 20 and 80 would be chosen as saturation point of sales (the dominance of losses over gains and getting ready to buy) and saturation point of buying (the dominance of gains over losses and getting ready to sell) respectively.

SO or stochastic oscillator fluctuates between 0 and 100. To calculate this oscillator, the values of %k and %D would be computed as indicated in (2).

$$\%K = \frac{(Current\ Close - Lowest\ Low)}{(Highest\ High - Lowest\ Low)} \times 100 \tag{2}$$

In this formula, %D stands as the 3 days simple moving average for %K. In the above calculation, the most and the least price would always be calculated at certain intervals. Generally speaking, this period takes 14 days. The concept of this oscillator is such that the magnitude of the price would always be calculated in terms of the most and the least distance in the period (14 days). Thus, the extent the value %k becomes larger and its closeness to 100 indicates the shares more potential for reductions in prices. On the other hand, the extent the value %k becomes smaller and its closeness to 0 indicates the shares more potential for an increase in prices. Often two thresholds of overbought and oversold would be taken into account for this oscillator; typically, these two lines would be lines 80 and 20 respectively (Ijegwal et al, 2014).

Concerning the stipulated concepts, each of them would be utilized in determining a trading strategy and via some computer programs, turned into an automated and algorithmic transaction. Algorithmic trading in financial markets means utilizing computer programs to introduce trading orders. To select and implement these orders from various aspects like timing, price or size, one or more algorithms would be decided and run without human intervention.

Many pieces of researches have been undertaken to investigate the profitability of trading strategies based on technical signals. Tadi and Motahari Nia (2018) utilized paired strategy and the post-test revealed that assuming the existence of a short-selling system and in the desired threshold domain, the paired trading returns would be more than buying and holding strategy. Fallahpour and Hakimian (2017) calculating and investigating Sortino ratio and return revealed that paired trading system performance as a neutral trading system compared to market’s alterations and procedures holds a considerable return in comparison to normal stock return in the same period. Molaee et al (1396) evaluated the profitability of the price momentum strategy (prices move toward the last procedure and a concept from technical analysis) in Iran’s stock market exchange. The findings indicated that considering the risk the strategy had excess return. Abbasi et al (2015) introduced an automated trading system that combines technical analysis with an adaptive neuro-fuzzy inference system to predict the process of stock prices and an increase in returns. The results revealed that through regulating technical oscillators' parameters stock price alterations could be predicted more efficiently. Nasrollahi et al (1382) evaluated the profitability of Japanese candlestick patterns. The results indicated that most patterns (18 patterns) once not considering transaction fees acquired more significant interests than holding and buying methods. Nabavi and Hassan Zade (1390) argued that the exponential moving average method is more reliable in predicting stock prices in terms of reliability measures (average absolute value of error and tracker indicator).

Sherbibi (2018) investigated the profitability of market cycle oscillators like simple harmonic oscillator and wave period oscillator in America’s stock market exchange from 2000 to 2015. The results revealed that both oscillators had a better performance in sharp ratio measures compared to market performance. Brown (2018) investigated the profitability of the divergence trading system in America’s stock market. The relative strengths index and Mckay index were used in this study. Brown concluded that the profitability of the divergence system based on the Mckay index is considered to be higher than the relative strengths index. Lim et al (2016) investigated the profitability of the Ichimoku cloud in America and Japan’s stock market exchange from 2005 to 2014. They chose conservative and aggressive strategies for their transactions and indicated that the frequency diagram for the profitability of the selected stocks in the sample is positively skewed with a small tail. Volna et al (2013) introduced a multiple neural network system the first of which is used for pattern recognition and the second neural network is used for predicting market movement direction. They utilized 12 patterns of Elliott waves to teach neural networks and checked the results on the time-series data for some stock prices and evaluated their findings positively.

Each indicator or oscillator by itself conveys special information and illuminates one aspect of markets. The appropriate combination of such oscillators would be able to present better information to investors. Many types of researches revealed that concurrent uses of a group of oscillators' information result in higher profitability than individual uses of them. For instance, Wang et al (2016) introduced a trading system for a linear combination of technical analysis signals. In this system, two thresholds for stocks selling and buying and periods for calculating portfolio efficiency and review are taken into consideration. The results revealed that the designed trading system has higher profitability compared to individual applicability of signals and passive strategy of holding and buying. Magda et al (2013) using multi-purpose planning including two purposes of annual return and sharp ratio tried to optimize and combine four technical measures (a convergence-divergence index version and two RSI versions) and revealed that combined systems have higher returns compared to individual systems. Theodorus and Dimitrus (2013) designed a virtual fuzzy neural network using technical input for short-term forecasting of exchange rate Euro to the US dollar. The results indicated that neural networks with a number of inputs of technical indices resulted in a better conclusion than using an individual index. Hirabayashi et al (2009) tried to optimize the combination of business rules based on technical analysis indices in the currency market (Dollar-Euro). They used a genetic algorithm to optimize and combine three technical indices of the simple moving average, exponential moving average, and relative strengths index and revealed that the combined optimized system has a higher return compared to holding and buying strategies, unoptimized systems, and individual systems.

As indicated earlier, a lot of research has shown that collective uses of oscillators would be able to enhance the profitability of trading systems. For instance, regression models, neural networks, decision trees models and, etc … introduced methods for combining different signals. One of these approaches which have been utilized in the present paper is fuzzy inference systems with the corrective property. Suppose a driver perceives two signals indicating the distance to the car ahead and his/her speed in each time and categorize them with language concepts such as short, high or too high. Then, he/she ranks the existing standards in his/her conceptual schema database. For instance, one such rule indicates that when speed is high and the distance to the car ahead is short, the driver must regulate the speed to control the car. The final reaction of the driver is to set the car’s speed through gear and brake. Simply put, this study concentrates on an investor instead of the driver and focuses on SO and RSI instead of speed and distance. As a consequence, the driving rules would be displaced by trading rules and the system output includes buying, holding or selling. Many kinds of research have used fuzzy systems to design trading systems.

Naranjo and Santos (2017) introduced a new method for prediction based on the Japanese candlestick system and the fuzzy inference system. They classified two features of the Japanese candlestick system including the body position to the whole candle and body size as fuzzy numbers and named them as a fuzzy inference system output. The system input consists of three fuzzy variables which would be defined as stocks low-high-close-open prices. In the end, a proposed combined algorithm has been implemented on 15 stocks. Ijegwal et al (2014) designed a fuzzy inference system using three technical oscillators of RSI, stochastic RSI and balance volume. They used ten combined rules stipulated in terms of these four indices in the stock exchange market to design a trading system. The results revealed that this method had a higher return compared to the applicability of trading rules for each of these indices by themselves. Alejandro et al (2013) designed a fuzzy inference system using four indices of moving average, RSI, convergence-divergence, and risk-taking and investigated the findings on the stock index of five European cities including Madrid and Frankfurt. Zhou and Don (2005) used a fuzzy inference system to find Figure patterns in technical researches. For instance, they designed a fuzzy neural system to predict head and shoulders patterns. Simutis (2000) designed a fuzzy inference system using four technical indices of RSI, moving average, money flow, and Bollinger bands. Simutis used twenty trading rules to predict trading (buying and selling) time. The results revealed that the proposed system compared to the passive strategy of holding and buying acquired a higher sharp ratio. Thus, this study aims at investigating the following questions:

1. How can a trading system with corrective property be introduced by combining fuzzy inference system and technical indicators?

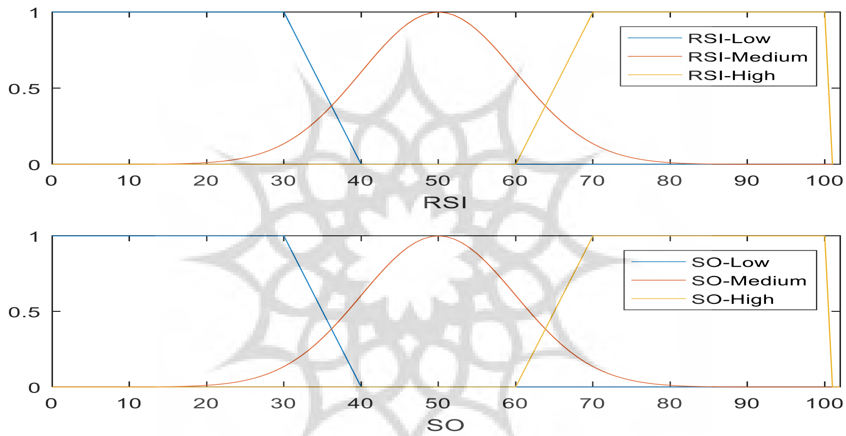
2. How is the profitability of the trading system designed in indicators such as daily return average and Sharp ratio?

3. Is the profitability of the combined system better than the trading systems formed on the basis of individual technical indicators?

The innovation of the trading system used in the present paper is its corrective property and would be able to adapt itself to new conditions just like a driver making appropriate decisions and using proper rules (updating his/her rues database) when riding in different conditions.

Methodology

In classical logics set membership is taken as zero (no membership) and one (membership). Thus, membership is a function in which its domain is the member of the set {0, 1}. But, fuzzy logic extends the concept of membership degree in a cluster into span [0, 1]. The philosophy behind fuzzy logic is that in the real world most of the human's arguments and reasons are relative and uncertain. Fuzzy numbers are a special kind of fuzzy clusters that are characterized by an interval of normal, convex and limited support. Various types of fuzzy numbers such as a triangle, a trapezoid, etc… have been introduced and utilized. In the present paper the system input- RSI and SO oscillators- would be classified into three levels of low, average and high with



the help of fuzzy numbers. The numbers used in the research are presented in the Figures. As it is clear, trapezoid numbers are used to indicate low and high states while Gauss numbers are used to show average state.

Figure 1. Fuzzy numbers describing inputs

Thus, on a specific day and if SO and RSI values are indicated, the membership degrees of the stipulated fuzzy numbers in Figure (1) would be identified. After a fuzzy description of input variables, a database must be introduced to infer trading situations. For this reason, 27 rules according to Table (1) could be designed.

Table 1. All extractable rules in the model

IF	RSI low	&&	SO low	THEN	Buy or Hold or Sale
IF	RSI low	&&	SO medium	THEN	Buy or Hold or Sale
IF	RSI low	&&	SO high	THEN	Buy or Hold or Sale
IF	RSI medium	&&	SO low	THEN	Buy or Hold or Sale

IF	RSI medium	&&	SO medium	THEN	Buy or Hold or Sale
IF	RSI medium	&&	SO high	THEN	Buy or Hold or Sale
IF	RSI high	&&	SO low	THEN	Buy or Hold or Sale
IF	RS high	&&	SO medium	THEN	Buy or Hold or Sale
IF	RSI high	&&	SO high	THEN	Buy or Hold or Sale

Rules compose of one LHS including two separate constituents about SO and RSI language situations and multiplication rule could be used for its valuation. Thus, the values of LHS are presented in table (2).

Table 2. The values of nine existing LHS in the rules database

Rule(1)=RSI_Low(RSI(i))*SO_Low(SO(i));
Rule(2)=RSI_Low(RSI(i))*SO_Medium(SO(i));
Rule(3)=RSI_Low(RSI(i))*SO_High(SO(i));
Rule(4)=RSI_Medium(RSI(i))*SO_Low(SO(i));
Rule(5)=RSI_Medium(RSI(i))*SO_Medium(SO(i));
Rule(6)=RSI_Medium(RSI(i))*SO_High(SO(i));
Rule(7)=RSI_High(RSI(i))*SO_Low(SO(i));
Rule(8)=RSI_High(RSI(i))*SO_Medium(SO(i));
Rule(9)=RSI_High(RSI(i))*SO_High(SO(i));

The rules RHS are unknown to investors and the investors would not be able to recognize that the first rule in an optimized state would be relevant to what situation (buying, holding or selling). If RHS were known, the multiplying value in LHS would be deemed the rules points for that position. For instance, if the rule number (1) mandates to buy something and the multiplying value in LHS equals /8, the output point of this rule equals /8. Since the rules RHS in Table (3) are unknown, all possible combinations would be scrutinized through an optimizing process to select the best RHSs in such a way that the trading system profits would be maximized. If -in an optimized condition- in a trading day some rules vote for buying, some vote for holding and some vote for selling, the points for buying, selling and holding equal to the average points of voting rules for buying, selling and holding respectively. As stated earlier, the trading system in this paper holds corrective property and this means that the extracted rules are not permanently stable. These rules often would become up to date based on the RHS data. For this purpose, besides the unknown RHS of (rules) trading system, two parameters θ_1 and $\theta_2$would be added to the model unknowns. θ_1 stands for the inspection period and indicates how often the rules must be up to date.θ_2 indicates that upon updating time, the information about several periods ago must be utilized to recalculate parameters' optimization. The maximized objective function which identifies trading system variables equals to the maximization of daily return average of trading situations by the system.

Statistics

This paper investigated the profitability of the trading system on the Tehran Stock Exchange TEPIX (Tehran Price Index) as the market representative. The Figure for Tehran Stock Exchange TEPIX from 2001/3/21 to 2019/3/20 is given in Figure (2) which includes 4398 daily data. Descriptive statistics for the daily return of TEPIX is also presented in Table (3).

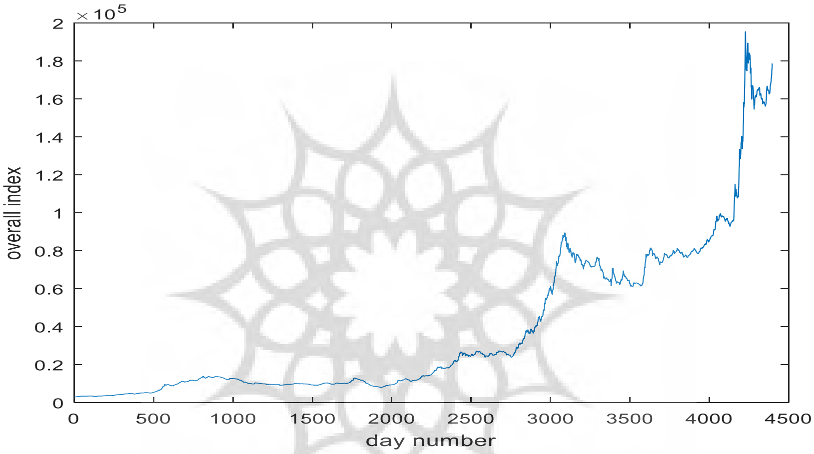


Figure 2. TEPIX index from 2001/3/21 to 2019/3/20

Table 3. The statistical description of TEPIX return

Statistical feature	**Value**
Daily return average	0/000955
median	0/000406
Maximum	0/07217
Minimum	-0/055125
Standard deviation	0/006943
Skewness	0/423926
Kurtosis	8/419673

The combined trading system

To design and optimize the fuzzy trading system with corrective property MATLAB programming has been utilized. To optimize the unknown parameters of the system on the first 2398 data as training data PSO with 200 repetitions and 100 particles has been used. Concerning optimization, trading expenses have been taken into consideration and in the sum of buying and selling %15 (according to Tehran Stock Exchange) as trading expenses have been subtracted from the return of discovered position trading. The system's objective function was defined as the maximization of the average daily return resulted from trading positions. The limitations used in the optimization of the system's parameters form relation (3):

$$150<\theta_1<300 \quad 20<\theta_2<120 \tag{3}$$

Having finished the optimization process, the optimized values of two general corrective parameters were estimated as θ_1=181,θ_2=54, this means that the rules database is optimal for the 181 days and it has to be re-optimized every 181 days using 54 previous daily data. For instance, the first set of buying and selling rules is indicated in Table (4).

Table 4. The first rules database

Mandate	Rule number
Buying	6
Maintaining	1,2,4,5,8
Selling	3,7,9

Table (4) stipulates that for the first 181 days of test data, the sixth rule mandates to buy, the first, second, fourth, fifth and eighth rules mandate to maintain the previous situation and the third, seventh, and ninth rules mandate to sell. The final points for selling, holding and buying in a day equal to the average points of selling, holding and buying which have been presented in Figure (3) for the first 181 days of test data.

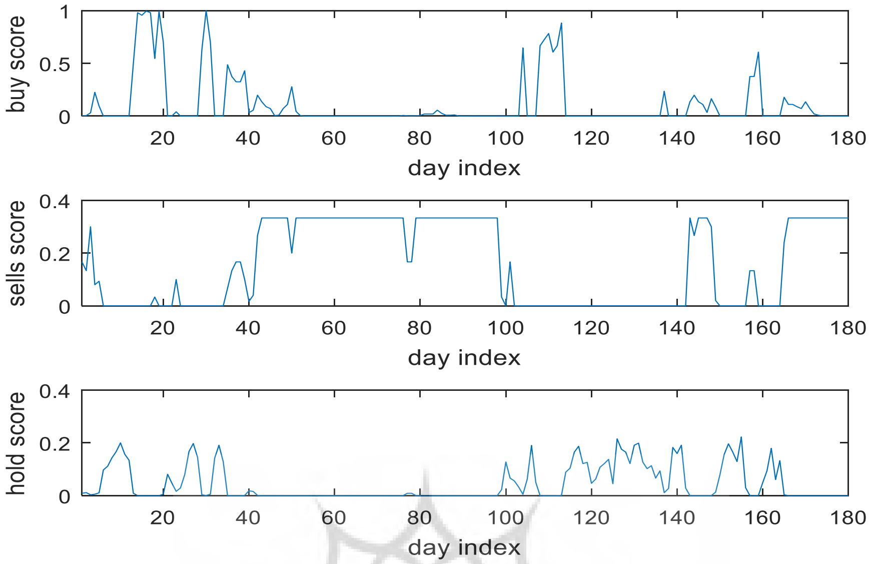


Figure 3. Signals strength for buying, holding and selling

The optimized system on 2000 test data discovered 59 trading positions which return situations along with their durations (daily-based) and their daily returns have been presented in Figures (4) to (6).

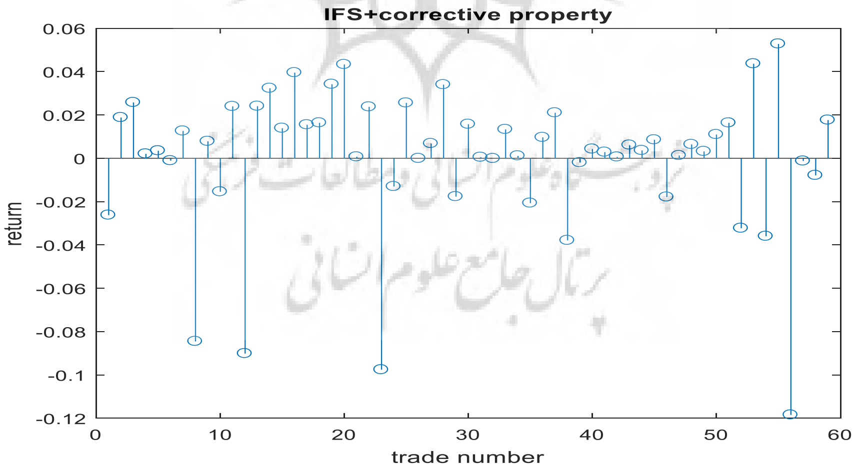


Figure 4. The resulted returns by 59 situations

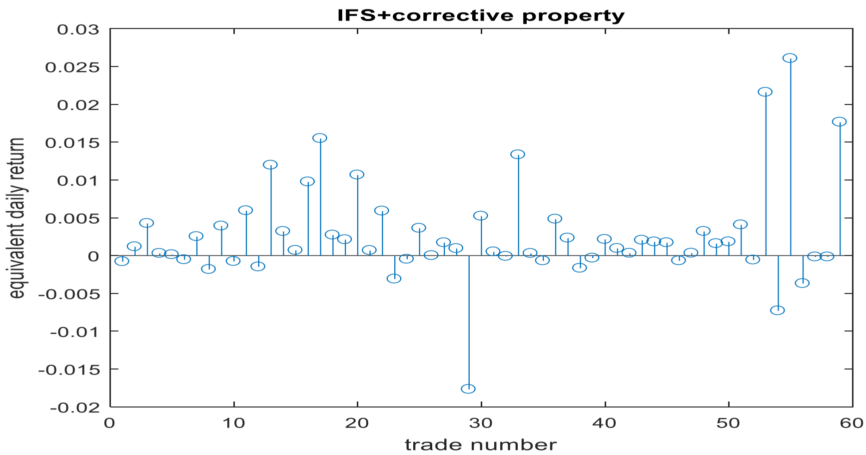


Figure 5. Equivalent daily return for each situation

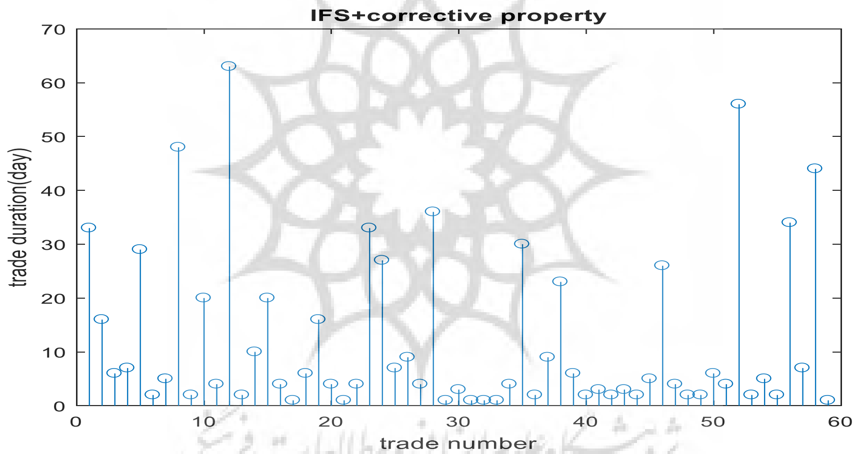


Figure 6. Duration for each situation

The statistical features of trading situations have been presented in table (5):

Table 5. Statistical description for the resulted situations

Statistical feature	Value
Daily return average	0.002659
Median	0.001166
Maximum	0.026052
Minimum	-0.017693
Daily return standard deviation	0.006517
Daily sharp ratio	0.4153
Trade time average	12.067

Based on the findings in Table (5), the daily return average of the corrective system in the present paper equals /002659. To acquire such a finding a risk of /006517 must be undertaken. Besides, the adjusted return compared to the sharp ratio equals /415.

RSI-driven trading systems

As stated earlier on of the purposes of combined systems is to better utilize information to obtain higher profitability over individual signals. In what follows the profitability of RSI-driven trading systems would be investigated. RSI Figure in test data has been presented in Figure 7 which fluctuates between 0 to100.

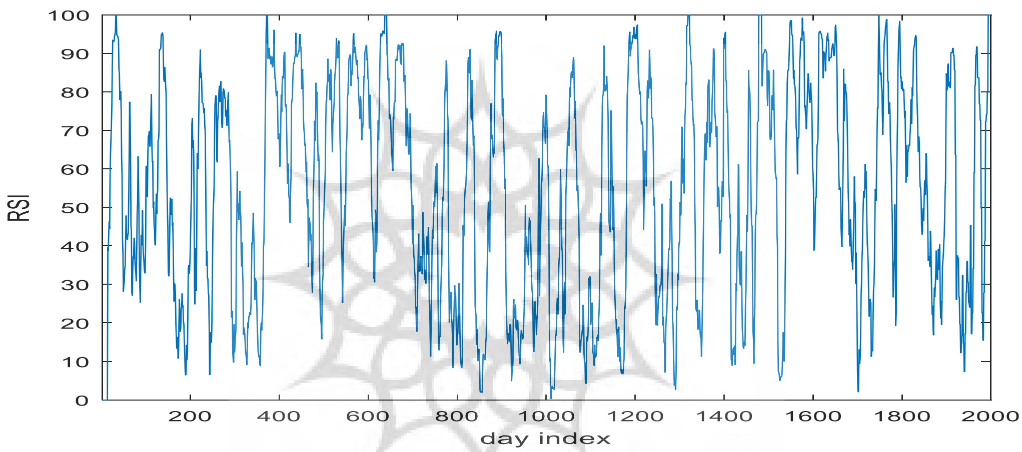


Figure 7. RSI oscillator on test data

18 returns of discovered trading situations (with two thresholds of 30 & 70) along with their equivalent daily returns and each trade duration has been presented in Figures (8) to (10).

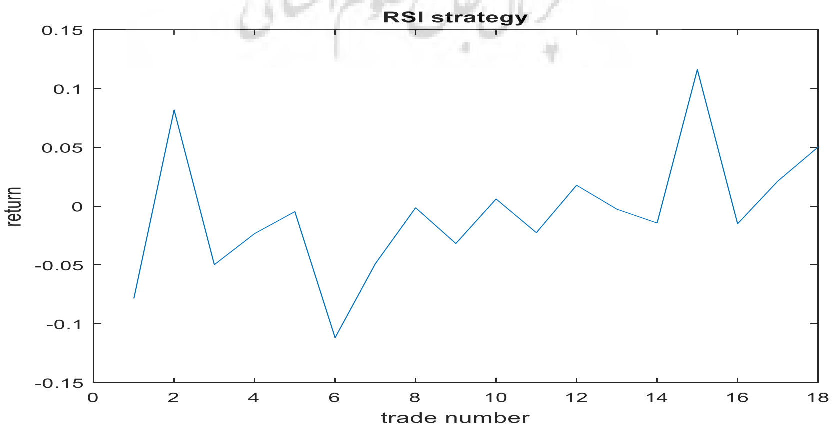


Figure 8. The resulted returns by 18 situations

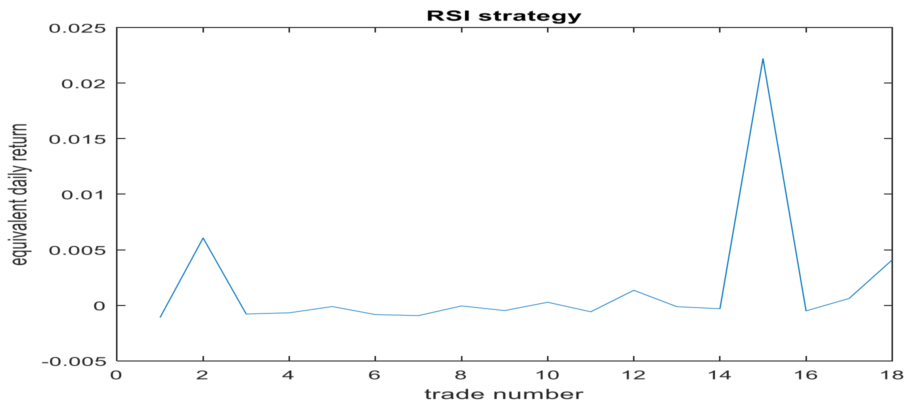


Figure 9. Equivalent daily return for each situation

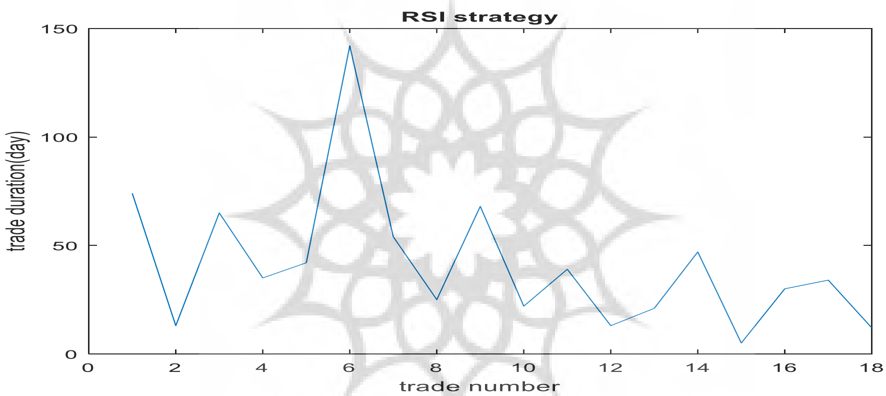


Figure 10. Trade duration

The statistical features of trading situations have been presented in table (6).

Table 6. Statistical description for the resulted situation

Statistical feature	**Value**
Daily return average	0.0016
Median	-0.0002
Maximum	0.0222
Minimum	0.0011
Daily return standard duration	0.0055
Daily sharp ratio	0.2851
Trade time average	41.1667

Concerning one outlier data in daily returns, the median stands as a better index than the mean. Meanwhile, it would be a loss to use RSI. Therefore, the trading system is weaker than the combined and corrective system of research on test data, both in terms of average daily returns and in terms of daily sharp ratio. To examine the statistically significant difference between the average daily return of the system and the system based on RSI, t-test was used for two statistical populations. The value of t-statistic at a significance level of 0.05 equals to 2.24 which indicates significant differences in returns.

SO-driven trading systems

In what follows the profitability of SO-driven trading systems is investigated. SO Figure on test data is indicated in Figure (11) which fluctuates between 0 -100.

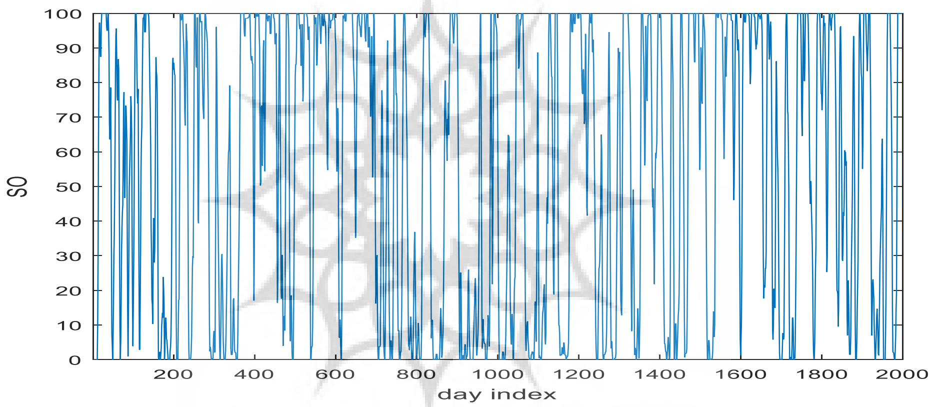


Figure 11. SO oscillator on test data

40 returns of discovered trading situations (with two thresholds of 20 & 80) along with their equivalent daily return and each trade duration has been shown in Figures (12)-(14).

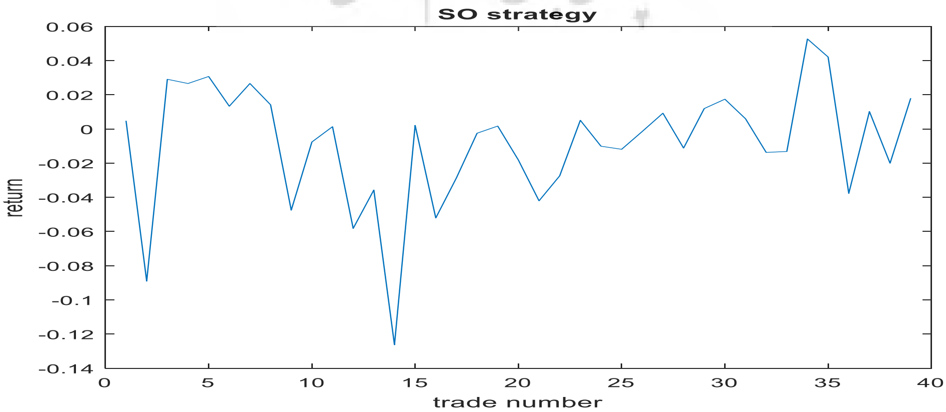


Figure 12. The resulted returns by 18 situations

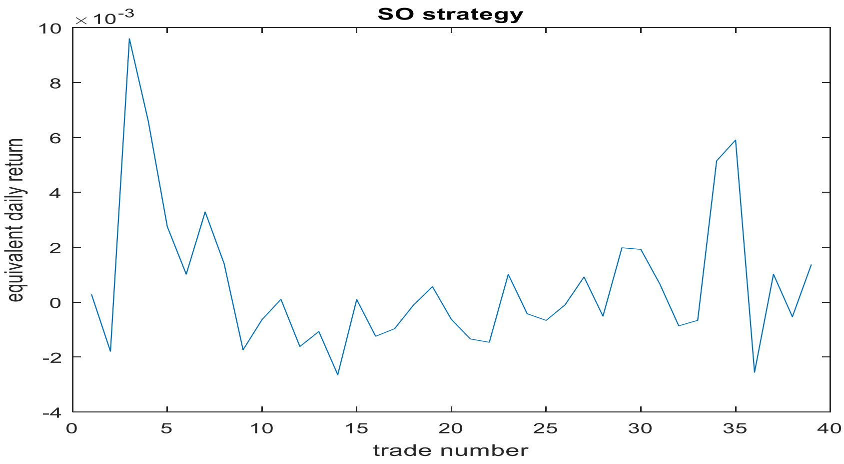


Figure 13. Equivalent daily return for each situation

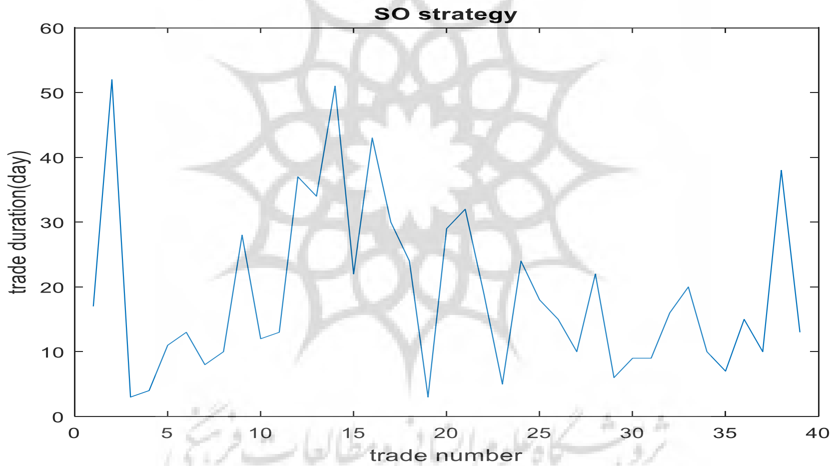


Figure 14. Trade duration

The statistical features of trading situations are presented in table (7).

Table 7. Statistical description for the resulted situations.

Statistical feature	**Value**
Daily return average	0.000617
median	0.000005
maximum	0.0096
minimum	-0.0026
Daily return standard deviation	0.0026
Daily sharp ratio	0.23730769
Trade time average	19.0256

Therefore, the system is weaker than the combined and corrective system of research on test data, both in terms of average daily return and in terms of daily Sharp ratio. To investigate the statistically significant difference between the average daily return of the system in this research and the system based on SO, t-test was used for two statistical populations. The value of t-statistic at a significant level of 0.05 equals to 2.33 which indicates significant differences in returns.

Market performance

Market performance is perceived as a random choice including buying and selling on a random day and its statistical features are presented in table (8).

Table 8. statistical description of market performance

Performance index	Value
Daily return average	0.0012
Daily return standard deviation	0.0081
Daily sharp ratio	0.14814815

Therefore, market performance, both in terms of average daily returns and in terms of daily sharp ratio, is weaker than the combined and corrective research system on test data. To investigate the statistically significant difference between the average daily return of the system in this research and market performance, t-test was used for two statistical populations. The value of t-statistic at a significant level of 0.05 equals to 2.61 which indicates significant differences in returns.

Conclusions and implications

The present paper aimed at introducing an algorithmic trading system based on the fuzzy inference system with the corrective property. This system turns its two technical inputs in the forms of rules, inspection periods and inspection data into buying and selling signals. The evaluation of the model performance in the Tehran stock exchange market revealed that the system in terms of daily average return, risk-taking and the daily sharp ratio is significantly superior over strategies based on individual signals and market performance. Thus, the present paper confirms the performance of combined systems and proposed such fuzzy systems with corrective property to be used in stock markets. The results of this research are compatible with the findings of other researches such as Wang et al (2016), Magda et al (2013), Theodorus and Dimitrus (2013) and Hirabayashi et al (2009). These researches are thoroughly delineated in the literature review. In these studies, it is confirmed that concurrent uses of a set of oscillator's information are more profitable than their individual use. Investors would be able to optimize corrective fuzzy systems using different inputs. Unless such systems achieve desired accuracy, they would be utilized in real buying and selling situations.

References

Alejandro, E., Juliano, M. & Sebastian, M. (2013). A Technical Analysis Indicator Based on Fuzzy Logic. *Journal of Electronic Notes on Theoretical Computer Science*, 8(3): 27-29.

Abbasi, I., Akefi, H. & Adibmehr, S. (2015). Parameter setting of technical analysis indicators using multi-objective particle swarm optimization and adaptive fuzzy inference system. *Journal of Investment Knowledge, 4*(15): 111-134. (in Persian)

Brown, C. (2018). The Composite Index: A Divergence Analysis Study. *IFTA Journal, 15(1)*: 25-34.

Fallahpour, S. & Hakimian, H. (2017). Evaluating the Performance of a Pairs Trading System in Tehran Stock Exchange: the Cointegration Approach and Sortino Ratio Analysis. *Journal of Financial Engineering and Securities Management, 8*(30): 1-17. (in Persian)

Ijegwa, A. D., Rebecca, V. O., Olusegun, F., & Isaac, O. O. (2014). A predictive stock market technical analysis using fuzzy logic. *Journal of Computer and information science, 7*(3): 1-17.

Hirabayashi, A., Aranha, Cl. & Iba, H. (2009). Optimization of the trading rule in foreign exchange using a genetic algorithm. *Proceedings of the 11th Annual Genetic and Evolutionary Computation Conference*, GECCO-2009. 1529-1536. 10.1145/1569901.1570106.

Lim, S., Yanyali, S. & Savidge, J.(2016).Do Ichimoku Cloud Figures Work and Do They Work Better in Japan?. *IFTA Journal*, 13(1):1-7.

Magda B.Fayek., Hatem M.El-Boghdad.& Sherin M.Omran.(2013).Multi-Objective Optimization of technical stock market indicators using GAS. *International Journal of Computer Applications*, 68(20):41-48.

Molaee, B., Nikokar, S., Nikokar, F. & Khosravani, F (2015). Evaluation of Price Momentum Strategy in Tehran Stock Exchange. *Paper presented at the International Conference on Management, Economics and Industrial Engineering*, Tehran.

Murphy, J. J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. Penguin.

Nabavi Chashami, S. A., Ayatollah, H. (2011). Investigation of MA Index Efficiency in Technical Analysis in Stock Price Forecasting. *Journal of Financial Knowledge of Securities Analysis 4*(10): 83-106. (in Persian)

Naranjo, R. & Santos, M. (2017). Fuzzy Candlesticks Forecasting Using Pattern Recognition for Stock Markets. J*ournal of Intelligent Systems and Computing*, 527(2): 323-333.

Nasrollah, K. S. K., Samadi R. S. & Prez Barzani, M.(2013). Evaluating the usefulness of Japanese candle patterns in Tehran Stock Exchange. *Journal of Financial Accounting Research, 3(17)*: 59-72. (in Persian)

Simutis, R. (2000). *Fuzzy logic based stock trading system* .Paper presented at the Proceedings of the IEEE/IAFE/INFORMS 2000 Conference on Computational Intelligence for Financial Engineering (CIFEr)(Cat. No. 00TH8520).

Sherbini, A.(2018).Time cycle oscillators.*IFTA Journal*, 15(1): 66-84.

Theodorus, Z. & Dimitrus, K. (2013). Short Term Prediction of Foreign Exchange Rates with a Neural-Network Based Ensemble of Financial Technical Indicators. *International Journal on Artificial Intelligence Tools*, 22(3): 220-241.

Tadi, M., Abkar, M. & Motahari Nia, V. (2018). Evaluation of paired trading strategy with a distance approach in Tehran Stock Exchange. *Journal of Investment Knowledge, 7*(26): 99-112. (in Persian)

Volna, E., Kotyrba, M. & Jarusek, R. (2013). Multi-classifier based on Elliott wave's recognition. *Journal of Computers & Mathematics with Applications*, 66(1): 213–225.

Wang, F., Yu, P. & Cheung, D. (2016). Combining technical trading rules using particle swarm optimization. J*ournal of Expert Systems with Applications*, 41(6): 3016-3026.

Zhou, X. S. & Don, M. (2004). Can fuzzy logic make technical analysis 20/20? *Financial analyst journal, 60(4):* 54-73.

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