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An Algorithmic Trading System Based On Machine Learning in Tehran Stock Exchange

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ABSTRACT

Successful trades in financial markets have to be conducted close to the key recurrent points. Researchers have recently developed diverse systems to help the identification of these points. Technical analysis is one of the most valid and all-purpose kinds of these systems. With its numerous rules, the technical analysis endeavours to create well-timed and correct signals so that these points are identified. However, one of the drawbacks of this system is its overdependence on human analysis and knowledge in selecting and applying these rules. Employing the three tools of genetic algorithm, fuzzy logic, and neural network, this study attempts to develop an intelligent trading system based on the recognized rules of the technical analysis. Indeed, the genetic algorithm will assist with the optimization of technical rules owing to computing complexities. The fuzzy inference will also help the recognition of the total current condition in the market. It is because a set of rules will be selected based on the market kind (trending or non-trending). Finally, the signal developed by every rule will be translated into a single result (buy, sell, or hold). The obtained results reveal that there is a statistically meaningful difference between a stock's buy and hold and the trading system proposed by this research. In other words, our proposed system displays an extremely higher profitability potential.

1 Introduction

Success in stock trades extensively depends on proper decisions concerning on-time and true enters and exits. This issue requires the investigation of information as well as a specialization for exploring investment opportunities. Recently, the researchers all over the world have carried out numerous scientific practices to generally train financial market analysis for the purpose of investing and practicing in these markets. However, owing to many reasons, the majority of traders are incapable of using scientific analysis in trades [1-6]. Consequently, there is an urgent need for an automatic approach to effectively and efficiently use the financial data so that it can support investment decisions.

One of the systems many efforts have been made for its intelligence is the stock trade system [7-15]. The stock trade system, employed as an auxiliary tool in investment decisions, is reckoned as a novel researching domain in the world. It enjoys a thorough potential in increasing profitability besides its researching potential. A trading system aims to conduct successful trades, the trades that should be

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conducted in the direction changing points of price trends [16-23]. This study aims to develop an intelligent trading system that exploits the conventional technical analysis tools and metaheuristic algorithms to generate correct trading signals in the return points of trends. Therefore, backed by this system, the investors in the financial markets will adopt on time and true decisions in their trades and maximize the profitability of their investments. This study comprises three separate phases. The variables will be optimized by the genetic algorithm in the first phase. There is a minimally m analytical rule, each of which includes n parameters for presenting signals. Thus, the computing complexity of this problem compels us to employ one of the meta-heuristic algorithms, such as the genetic algorithm. In the second phase, the market's current trend will be identified by the fuzzy inference system since a set of technical rules will be selected according to the market kind (neutral or with trends). In the third phase, the variables are aggregated, and with the help of a neural network, the final output signal will be presented as a buy, sell, or hold signal.

2 Literature review

Success in stock trades extensively depends on proper decisions concerning well-timed and true enters and exits. This issue requires the investigation of information as well as a specialization for exploring investment opportunities. Consequently, there is an urgent need for an automatic approach to effectively and efficiently using the financial data so that it can support investment decisions. During the past recent decades, many researchers have employed soft-computing technics, including the genetic algorithm and artificial neural networks [1]. These methods were successfully applied to solving diverse problems. The soft-computing technics were employed in making many smart systems. In the meantime, one of their applicative domains is financial problems, such that many researchers are now investigating the applications of the soft-computing technics to the financial domain [2]. The conventional technical analysis, which is the base of many trading systems, usually emerges in the forms of different trading rules and concentrates on the peak and bottom points of prices in trends, and it is extensively prevalent in the world's markets. Unfortunately, the stock trading systems that are based on using merely the technical rules will be no more suitable owing to their dependence on traders' experiences in selecting decision-making rules that are based on the assets' buy or sell. Hence, they cannot be used by all traders in the market. The main problem is that the technical rules are based on some parameters. If they are truly and smartly determined, they will deliver appropriate buy and sell signals for the investors' profitability. Another problem is that different technical rules may simultaneously create contradictory trading signals and problematize making decisions in such conditions. Refenes et al. [3] modelling the behavior of stock prices via neural networks and compared performance with regression models. In this study, the researchers employed neural networks as an alternative for the classic statistical technics to predict the stocks of great companies. The results of this study showed that neural networks performed better than statistical technics and provided better models.

Tan et al. [4] designed a system that predicted the considerable short-term changes in the stock price. At first, a pre-processing was conducted on the data, and; then, the neural network was modeld, which estimated highly thorough profitability situations. In their study entitled "a smart system for backing stock trading decisions by applying and aggregating the genetic algorithms based on fuzzy and artificial neural networks", Kuo et al. [5] developed a prediction system regarding stocks' hold, sell, and buy in the stock exchange markets. The characteristic of the developed system was that it allowed the quantification of qualitative variables interfering with the prediction of stock prices. These researchers have published a paper with the same title in 1998 regardless of using genetic algorithms. In the mentioned paper, the researchers used a questionnaire with the Fuzzy Delphi Method (FDM) to make use of experts' opinions in predicting stock prices. Yim [6] conducted a study to compare the econometrics method by ARMA and GARCH Model. The results showed the superiority of neural networks to the classic ARMA and GARCH model. In a study, Touri et al. [7] compared artificial neural networks (ANN) and autoregressive integrated moving average model (ARIMA) in the modelling and short-term prediction of the exchange rate in Iran. Their results revealed that the employed neural network enjoyed a better prediction power compared to the ARIMA model. In another study, Foroughi [8] predicted the profit of every stock according to the combination of artificial neural networks and the optimization algorithm of particle aggregative movement. Their results showed that the univariate and multivariate models predicted every stock's profit with 78.5% and 91.7% precisions, respectively.

Souto-Mairo [8] used fuzzy logic to predict the moving direction of the Brazil Stock Price Index, and their predictive results were finally evaluated to be suitable. During several recent decades, the researchers have employed artificial intelligence methods, including the genetic algorithm and artificial neural networks [1]. These methods were successfully applied to solving different problems. Artificial intelligence has successfully been employed in building smart systems. In the meantime, one of the applicative domains of artificial intelligence is financial problems. Today, numerous researchers investigate the applications of artificial intelligence to the financial domain [2]. Alejandro Rodríguez et al. [11] exploited neural networks to improve technical analysis indices. Recent studies employ the genetic algorithm to improve the prediction parameters that are used in technical analysis and enhance the ENS networks via improved parameters for the purpose of predicting turnover points. The results of studies show that the employed approach performs better than the buy and hold policy [12]. Rahnema et al. [13] adopted a genetic algorithm approach to optimize a portfolio comprising the mutual funds' stock of the Tehran Stock Exchange. The results indicated that the genetic algorithm could be more desirable for selecting the portfolios developed by the genetic algorithm. Tehrani and Abbasion [14] used only a neural network tool to investigate the schedule of entering the stock trades with a technical approach. Their results revealed that the system's performance was only suitable for Bear Market markets. In Bull markets, there was not a significant difference between the proposed trading system and the hold and buy method.

Brogaard et al. [17] investigate HFT around extreme price movements, classified as the top 0.1% of the individual stock price changes over 10-s trading intervals. The authors find that the net effect of HFT liquidity demand and supply is negatively associated with the direction of the price changes. Kevin Michell [18] use An embedded approach of STPG and FIS to generate trading rules. They use fuzzy inference system (FIS) and strongly typed genetic programming (STGP) to generate trading rules for the US stock market, a framework that called FISTGP. The results show that the proposed model outperforms the Buy and Hold (B&H) strategy by 28.62% in the test period, considering excesses of return, with almost the same risk (1.28% higher). Manahov [20] studied the effect of high frequency data with a STGP approach, to see if it is beneficial or not to the market, finding that it is actually harmful to institutional traders, on a millisecond basis. Ha and Moon [21] proposed GP to identify patterns in the cryptocurrency market. They focus the study on applying the signals in the market to increase investment return. Based on several experiments, they show that GP can create useful rules for trading, performing well in the test set. Davoodi et al. [22] has been investigate to prediction of stock prices of companies accepted in the Tehran Stock Exchange using artificial intelligence algorithm (non-sensory-parametric support vector regression algorithm in linear and nonlinear mode). The results of the research show that the PINSVR algorithm in nonlinear mode has been able to predict the stock price over the years, rather than linear mode. Again Davoodi et al. [24] in other research have been try to prediction stock price using the Chaid rule-based algorithm and particle swarm optimization. Stock prices in each industry are one of the major issues in the stock market. Given the increasing number of shareholders in the stock market and their attention to the price of different stocks in transactions, the prediction of the stock price trend has become significant. In this research, stock price prediction for 1170 years - company during 2011-2016 (a six-year period) of listed companies in stock exchange has been studied using the machine learning method (Chaid rule-based algorithm and Particle Swarm Optimization Algorithm). The results of the research show that there is a significant relationship between earnings per share, e / p ratio, company size, inventory turnover ratio, and stock returns with stock prices. Also, particle swarm optimization (pso) algorithm has a good ability to predict stock prices. Farshadfar and Porcopzuk [25] Improved Stock Return Forecasting by Deep Learning Algorithm. In this study they try to aim this object by two new methods. First, instead of using traditional variable, gold prices have been used as predictor and compare the results with Goyal's variables. Second, unlike previous researches new machine learning algorithm called Deep learning (DP) has been used to improve return forecasting and then compare the results with historical average methods as bench mark model and use Diebold and Mariano's and West's statistic (DMW) for statistical evaluation. Results indicate that the applied DP model has higher accuracy compared to historical average model. It also indicates that out of sample prediction improvement does not always depend on high input variables numbers. On the other hand when using gold price as input variables, it is possible to improve this forecasting capability. Result also indicate that gold price has better accuracy than Goyal's variable to predicting out of sample return.

3 Research Methodology

3.1 Research Model

This study comprises three separate phases. The variables will be optimized by the genetic algorithm in the first phase. There is a minimum *m* analytical rule, each of which includes *n* parameters for presenting signals. Thus, the computing complexity of this problem compels us to employ one of the meta-heuristic algorithms such as the genetic algorithm. In the second phase, the market's current trend will be identified by the fuzzy inference system since a set of technical rules will be selected according to the kind (neutral or with trends). In the third phase, the variables are aggregated, and with the help of a neural network, the final output signal will be presented as a buy, sell, or hold signal.

3.2 Parameters Optimization

The first phase deals tuning of the Parameters employed in Technical indicators. A change in the used parameters issues varying responses. It's common that experts determine the parameters empirically and by trial and error based on their personal experiences. For example, a 10-day moving average may offer relatively correct and on time signals for a certain stock, whereas a longer interval is needed for another stock. Accordingly, we must define an algorithm to properly adjust the parameters of the mentioned variables for every stock. The genetic pattern is one of the most suitable algorithms in terms of discovering correct and quick responses. Suppose the sequence of the expected trading points in which asset buy and sell signals exist is like T $(T_1, T_2, T_3, \ldots, T_n)$. For every expected trading point (Ti), we will look for operational signals (S_j) proposed by the different rules of the technical analysis. Evidently, every signal is placed between the two expected trading points $(Ti\text{-}1 < Sj < Ti+1)$.

According to the type of the trading point; i.e. a buy trading point and sell trading point, we will have the following conditions for the fitness function:

1) If Ti is an anticipated trading point for asset buying, there will be three conditions for the fitness function as below:

a) If Sj (trading signal) is a buy proposal, the magnitude of the fitness function at the Ti point will be computed as follows:

$$Fitness(T_i) = Close\,(S_j) - Close(T_i) \tag{1}$$

In recent trades:

Close (T_i) indicates the closing price at T_i.

Close (S_j) indicates the closing price at S_j.

The more the closing price at S_j is closer to the closing price at T_i, the smaller the magnitude of the fitness function.

b) If S_j is a proposed sell signal, and the price at S_j is close to the price at T_i, the magnitude of the fitness function will be computed by the below Equation:

$$Fitness(T_i) = 2\times(\max(close(T_{i-1} : T_{i+1})) - Close\,(T_i)) \tag{2}$$

The closeness term in the current equation is as below:

$$\frac{|close(Sj) - close(Ti)\,|}{close(Ti)} < 0.05 \tag{3}$$

In the above fitness function, *max (close (T_{i-1}: T_{i+1}))*, meaning maximum closing price, is between T_{i-1} and T_{i+1}. Since asset selling in minimum price points of a trend is a wrong trading policy, such a decision will accompany penalty.

c) If no operation between T_{i-1}-1 and T_{i+1}+1 is proposed, a penalty will be earmarked in the model for losing a trading opportunity. In this case, the fitness function will be as below:

$$Fitness\,(T_i) = max\,(close\,(T_{i-1}+1 : T_{i+1}-1)) - close\,(T_i) \tag{4}$$

2) Similarly, if T_i is an expected sell point, the fitness function will be a penalty as below:

a) If Sj is a proposed sell signal, the fitness function at Ti will be as below:

$$Fitness\,(T_i) = close\,(T_i) - Close(S_j) \tag{5}$$

b) If the price at Sj is close to the price at Ti, and Sj is erroneously considered as a buy point, the fitness function will be as below:

$$Fitness(T_i) = 2\times Close(T_i) - min(Close(T_{i-1}+1 : T_{i+1}-1)) \tag{6}$$

Such that min (close (T_{i-1}+1: T_{i+1}-1)), which means minimum closing price, is between T_{i-1}+1 and T_{i+1}-1.

c) If the trading opportunity is lost in the between T_{i-1}+1 and T_{i+1}-1 interval, the fitness function will be as below:

$$Fitness(T_i) = Close(T_i) - min(Close(T_{i-1}+1 : T_{i+1}-1)) \tag{7}$$

Finally, the fitness function of the trading points sequence S= {S1, S2, …, Sn} is defined as below:

$$Fitness\,(S) = \sum_{i=1}^{n} fitness(Ti) \tag{8}$$

It is anticipated that the genetic algorithm can deliver an optimal combination of parameters such that the magnitude of the fitness function is minimized. It has been explained in next sections how to optimize two of Technical indicator based on genetic Algorithm.

3.2.1 Relative Strength index (RSI)

RSI is an extremely useful and popular momentum oscillator developed by Welles Wilder. It compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset. It is calculated as follows:

$$\text{RSI} = 100 - \frac{100}{1+RS} \tag{9}$$

$$\text{RS} = \frac{Average\ of\ X\ days\ up\ closes}{Average\ of\ x\ days\ down\ closes} \tag{10}$$

RSI ranges from 0 to 100. Generally, if the RSI rises above overbought level (usually 80), it indicates a selling signal; if it falls below oversold level (usually 20), it indicates a buying signal.
However, in real market, the RSI is too sensitive and often breaks through overbought or oversold level ahead of time and then return after trend reversal happens. Hence, we introduce an oblique line to assist trading. when the RSI falls below overbought level, it's time to sell.

Fig. 1: RSI Analysis Approach

If the RSI rises above b, it is time to buy. GA helps to determine several parameters: the time span x of RSI, the values of overbought(a) and oversold(b).

3.2.2 Stochastic System

Stochastic oscillator developed by George C. Lane is a momentum indicator that can warn of strength or weakness in the market. In the up-trend, it tries to measure when the closing price would get close to the lowest price in the given period; in the down-trend, it means when the closing price would get close to the highest price in the given period. The original stochastic oscillator is plotted as two lines called %K and %D which is calculated according to the following equations:

$$\%k = 100 \times (H_3/L_3) \tag{11}$$

where H3 represents the sum of three (C - LL) and L3 represents that of three (HH - LL), in which C means current close; LL means the lowest low price in a specified period; and HH means the highest high price in a specified period.

$$\%D = 100 \times (H'_3/L'_3) \tag{12}$$

where H'_3 represents the sum of three H_3 and L'_3 represents that of three L3.

Generally, %K line is more sensitive than %D. Therefore, the crossover of %K and %D lines may indicate meaningful reversal. Take the left-hand crossover for example (see Fig. 2), in our system, when %K rises above %D and satisfies %K < a and %K- %D < b, it is time to buy. Conversely, when %K falls below %D and satisfies %K > c and %D - %K < d, it is time to sell. All the parameters a, b, c, d should be learned through GA.

Fig. 2: Stochastic Analysis Approach

3.3 Identifying the Market Regime

Every variable used in this study issues a proper signal according to a trending or non-trending market. For example, the stochastic oscillator will not enjoy the necessary efficiency in an up trending or down trending market. However, this oscillator can be more properly applied to a non-trending market. Accordingly, it is necessary to determine the kind and current situation of the market before using these kinds of variables. However, determining a market's situation is reckoned as the main challenge of the capital market activists. It is because there is no firm criterion for it, such that an expert may perceive a market situation as non-trending, and another one may perceive it has a trend. This problem is an intuitive issue, and we can define no definiteness for it. One of the strong mathematical tools extensively apply as an uncertainty explanation and description is the fuzzy logic theory. It is a novel tool for solving the problems that the probability theory does not offer a solution.

3.3.1 Fuzzification

In this phase, we consider membership functions for every input variable to transform crisp inputs to fuzzy ones and place them in the fuzzy inference system. The membership functions are of different kinds, such as triangular, trapezoidal, arch, etc. In this study, we use a trapezoidal kind. Here, the three variables, including the distance from moving average (d), the slope of moving average (s), and the Index of average directional movement (that is a kind of Technical indicator) are proposed as input linguistic variables. All these variables are thermalized in a numerical interval between -1and 1 according to the below Equation. For normalizing or fuzzification of numbers in fuzzy theory we should use from below equation:

$$v^{*}=\frac{|2v-(\max(v)+\min(v))|}{\max(v)-\min(v)} \tag{13}$$

Where max (v) is the maximum value in the training data, and min (v) is the minimum value in the total training data. The below Figure illustrates the membership function applied in this study, and var_a, var_b, var_c, and var_d indicate the linguistic value of the linguistic variables.

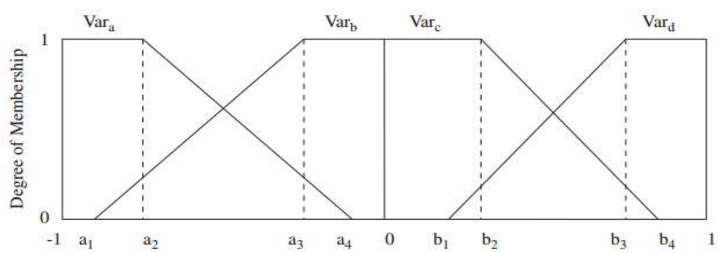

Fig. 3: Trapezoidal Membership Function for the Input Linguistic Variables

a_1 , a_2 , a_3, a_4 and b_1, b_2 ,b_3, b_4 are the parameters that specify the shape of the membership function. Table 1 outlines the selected interval for the above-mentioned parameters.

Table. 1: Selected Intervals for the Parameters of the Membership Function

Parameter	Lower bound	Upper bound
a1	-1	-0.5
a2	-1	-0.5
a3	-0.5	0
a4	-0.5	0
b1	0	0.5
b2	0	0.5
b3	0.5	1
b4	0.5	1

In the following, we present the membership functions employed in the study to determine the rate of membership degree:

$$\mu_{var_a}(x)=\begin{cases}1 & if\ x\ \leq\ a_2\\ 0 & if\ x \geq\ a_4\\ 1+(x-a_2)\left(\frac{-1}{a_4-a_2}\right) & if\ a_2<x<a_4\end{cases} \tag{14}$$

$$\mu_{var_b}(x)=\begin{cases}1 & if\ x\ \leq\ a_1\\ 0 & if\ x \geq\ a_3\\ \left(\frac{x-a_1}{a_3-a_1}\right) & if\ a_1<x<a_3\end{cases} \tag{15}$$

$$\mu_{var_c}(x)=\begin{cases}1 & if\ x\ \leq\ b_2\\ 0 & if\ x \geq\ b_4\\ 1+(x-b_2)\left(\frac{-1}{b_4-b_2}\right) & if\ b_2<x<b_4\end{cases} \tag{16}$$

$$\mu_{var_d}(x)=\begin{cases}1 & if\ x\ \leq\ b_1\\ 0 & if\ x \geq\ b_3\\ \left(\frac{x-b_1}{b_3-b_1}\right) & if\ a_1<x<b_3\end{cases} \tag{17}$$

Table. 2: A Summary of the Conditions of Linguistic Variables

Linguistic Value	Interval	Symbol	Linguistic Value
(vara) large	[-1, 0]	-d	D (Mat – Pt)
(varb) small			
(varc) small			
(vard) large	[0, 1]	+d	
(vara) high slope	[-1, 0]	-s	SMA(Mat– Mat-10)
(varb) low slope			
(varc) high slope			
(vard) low slope	[0, 1]	+s	
(vara) strong	[-1, 0]	-adx	Adx
(varb) weak			
(varc) weak			
(vard) strong	[0, 1]	+adx	
(vara) directional	[-1, 0]	neutral	Situation
(varb) neutral			
(varc) neutral			
(vard) directional	[0, 1]	directional	

Table 2 illustrates the characteristics of all linguistic variables that are employed in this system.

3.3.2 Rule Base

The rule base is defined as a fuzzy "if–then" set, which comprises the heart of the fuzzy inference system. There are two main methods for determining fuzzy rules: one is to use expert knowledge, and the other is to use self-organized knowledge such as novel algorithms and neural networks. This study uses the first method to determine fuzzy rules.

The knowledge base for fuzzy inference in this system is defined as below:

Rule 1: If +d is large and s- is small; then, the trend will be neutral.
Rule 2: If d- is small and –s is large; then, the trend will be directional.
Rule 3: If d- is small, –s is small, and adx is strong; then, the trend will be directional.
Rule 4: If –d is small, s- is small, and adx is weak; then, the trend will be neutral.
Rule 5: If d+ is small, –s is large, and adx is strong; then, the trend will be directional.
Rule 6: If d+ is small, –s is small, and adx is strong, then, the trend will be directional.
Rule 7: If d+ is small, –s is small, and adx is weak, then, the trend will be neutral.
Rule 8: If d- is large, –s is small, and adx id weak, then, the trend will be neutral.
Rule 9: If d+ is small and s+ is large, then, the trend will be directional.
Rule 10: If d+ is small, s+ is small, and adx is strong, then, the trend will be directional.
Rule 11: If d+ is small, s+ is small, and adx is weak, then, the trend will be neutral.
Rule 12: If –d is small and +s is large, then, the trend will be directional.
Rule 13: If –d is small, +s is small, and adx is strong, then, the trend will be directional.
Rule 14: If –d is small, +s is small, and adx is weak, then, the trend will be neutral.

3.3.3 Defuzzification

Defuzzification is a process that converts a fuzzy set into a crisp number. Thus, the input to the defuzzification process is a fuzzy set (the sum of output fuzzy sets), and its output is a number. Many methods are used for this purpose; however, in this study, we use the center of gravity (COG) method to create the crisp output.

$$\mathrm{COG} = \frac{\int_a^b \mu_A(x).x\, dx}{\int_a^b \mu_A(x) dx} \tag{18}$$

The created crisp output is compared by the confidence interval that we have defined. Accordingly, if COG is larger than 0.6, the market will be trending; otherwise, we will face a non-trending market.

3.4 Creating the Final Signal

In the previous two phases, we dealt with optimizing and determining the market situation. In the second phase, after determining the market situation, we will take the output signals from the variables with respect to the separation developed among them. The variable kinds can be separated as below:
The variables used in a trending market are: Double moving average, directional average indicator, parabolic SAR, moving average convergence/divergence (MACD), and OBV indicator. Additionally, the variables used in a non-trending market are: Momentum index, relative strength indicator (RSI), stochastic index, MACD indicator, and money flow index (MFI). Each of the above-mentioned indices will issue a signal that is not necessarily equal to another one. Hence, 5 issued signals should be integrated, and the tool used for this purpose is a neural network.

3.4.1 Neural Network Architecture Used in the Study

Every technical analysis rule, concerning the ending price, anticipates a future price and whether there will be a trend return close to the current ending price. Thus, we will have two conditions in this case. If it's time to buy an asset, the technical rule will generate the (-1) buy signal, and if it's time to

sell an asset, it will generate the (+1) sell signal. Furthermore, if it issues no suggestion respecting an asset buy or sell, it will generate the (0) signal. Different rules may produce different signals. Here, the neural network will help the model. The neural network, which is an Elman network here, takes different signals from the technical rules and determines if a correct signal is a buy or sell signal. The Elman network is a kind of back propagate neural network that has two main layers.
In this network type, a kind of feedback process is established between the output of the middle layers and input. This feedback enables the network to identify the strongest and most effective connection between inputs and outputs.

This network can record and hold stable target vectors. These stable vectors are considered as the network's memory [15]. Elman is a repeatable network with two main layers. In this network type, there is a relationship between the first layer's output and input. This recurrent connection enables the network to identify time-varying patterns, on the one hand, and create such patterns, on the other hand [16]. The Elman network has tansig neurons in its hidden layer (repeatable) and purelin neurons in its output layer. Such a composition enables the network to approximate any function type (with a few discontinuities). Moreover, we should consider a sufficient number of neurons in the hidden layer.

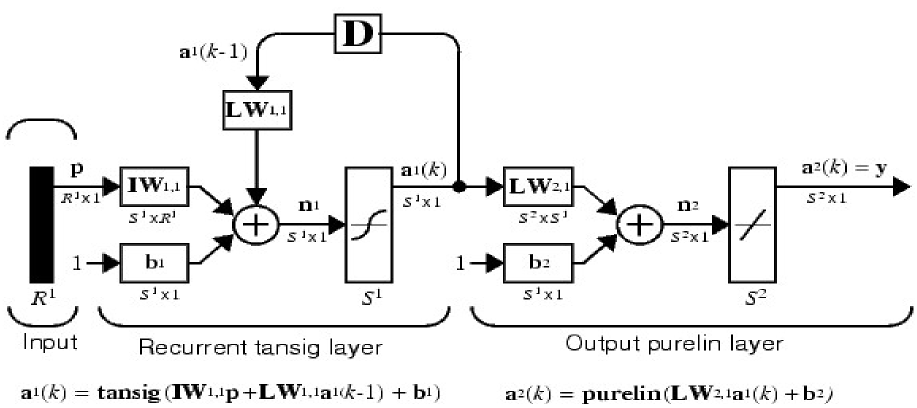

Fig. 5: A View from Elman Network

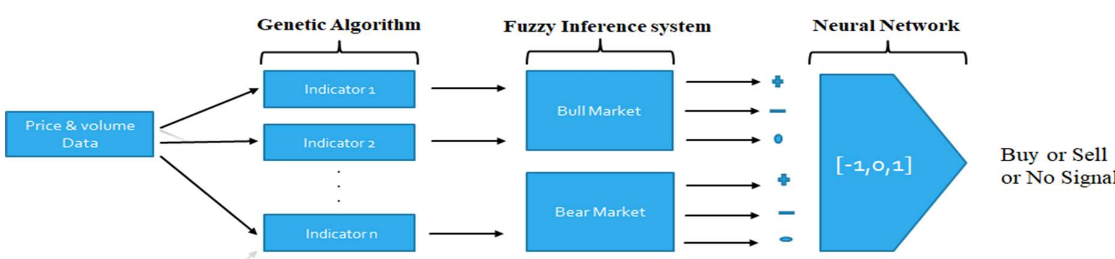

Fig. 6: Process of Research execution

The main difference between the two-layered Elman network and the other two-layered networks is that the connection in the first layer of the network is repeatable. The delay that occurs in this connection type triggers the storage of the past values as well as their uses in later steps. The feedback mechanism in this network is such that even two Elman networks with similar weights, biases, and inputs can have varying outputs. In Fig. 6, we show the whole process of research execution and also in Fig. 7 pseudocode of whole research is shown.

```
STEP 1:
#GA Algorithm for Tuning Parameters of Technical indicators():
   {
     for i=1 to n
>>Generate the initial population for indicator_i Parameters (a,b,c):
>>Evaluate fitness Function with initial Population
>>While (stopping GA Criteria not satisfied) Repeat
        { selection Chromosome
         Crossover Chromosome
         Mutation Chromosome
               Evaluate fitness }
     }
STEP 2:
# Fuzzy inference system(FIS) for discerning Market Regime( Trending or None-Trending)():
   {
>>STEP1: input Variables (D, SMA, ADX)
>>STEP2: Fuzzification (Transform linguistic Variable to Fuzzy Variable with membership Function)
>>STEP3: Define Rule Base ( if-then set)
>>STEP4: Difuzzification (converts a fuzzy set into a crisp number with with COG method)
>>STEP5: Market Regime ( output compared by  the confidence interval)
          if COG >= 0.6  then Market will be trending
          else
               Market will be None-trending
     }
STEP 3:
#Neural Network for weightening to indicators Signal ():
  {
>>while not stopCriterion do
            calculates e^p(W) for each pattern;
            e1 : = ∑_{p=1}^{P} e^p(W)^T e^p(W);
            Calculates J^p(w) for each pattern;
             repeat
                    Calculates ΔW ;
                    e2: = ∑_{p=1}^{P} e^p(W + ΔW)^T e^p(W + ΔW);
                     if  (e1 <= e2) then
                           μ := μ × β ;
                     endif ;
             until  ( e2 < e1 );
             μ := μ / β ;
             W := W + ΔW ;
>> endwhile ;
```

Fig. 7: Pseudocode of Research

4 Results and Analysis

The statistical population of this study is 50 distinguished companies enrolled in the Tehran Stock Exchange. Out of these 50 companies, 10 companies were selected as the sample. The research interval is the years 2011-2019, and the time series is extracted in daily frequency from the site www.tsetmc.com. This information includes open price, high price, low price, and ending price of a stock symbol per day. It is worth to mention that we exploit the data related to the adjusted price of every stock symbol in this study.

The entire phases of this problem, including the genetic algorithm, fuzzy logic, and neural network, were coded and implemented in the MATLAB software. The price data were called from an excel file via the MATLAB software and entered the codes' logic. At the end of the program execution, the orders were presented in vectors and included "buy", "sell", and "hold" orders in a time series. Table 3 displays the total return derived from buying and selling 10 stock symbols from early 2017 to late 2019 in both approaches. In the first approach, the trading policy is based on asset buying at the beginning of each year and holding it until the year's end. The second approach shows the use of the trading system proposed in this study.

Table. 3: Return Resulted from Two Approaches from Early 2017 to late 2019

Row	Company Name	Buy & Hold System	Algorithmic System
1	Iran khodro	316%	523%
2	Kalsimin	967%	1490%
3	Eghtesad Novin bank	42%	92%
4	Nafte Behran	547%	920%
5	Sakhtema Iran	410%	780%
6	Khark Petrochemical	1018%	1520%
7	Daroo Jabber	409%	720%
8	Golgohar	840%	1160%
9	Siman Tehran	873%	1210%
10	Meli mMes	722%	991%
Total Return with Equal Weight		614%	941%

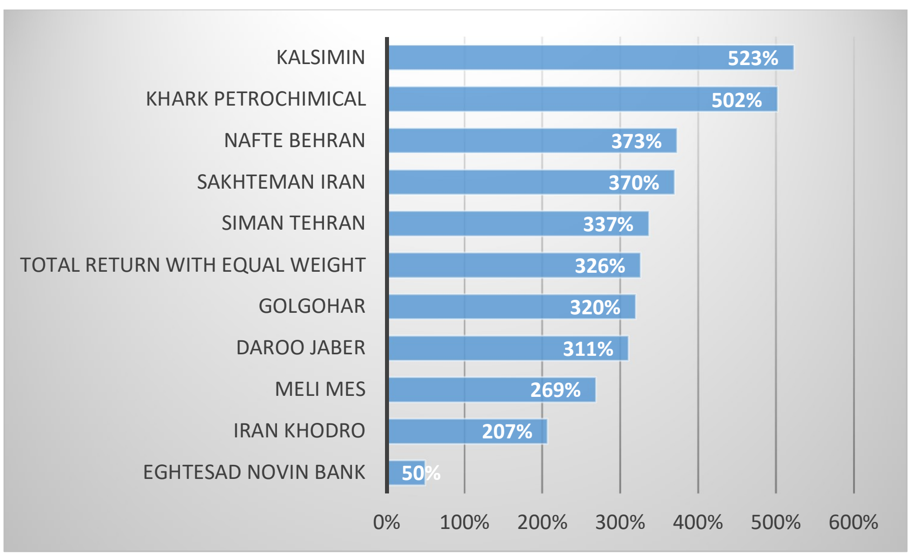

Fig. 8: Difference in the Total Return of Both Approaches in Every Stock Symbol

In the proposed system, those trades that are profitable will remain so long as a signal is not issued for an exit or sell situation in the indicators, and the trade will be closed as soon as a signal is offered. In all stock symbols, we witness a better condition of the trading approach that is based on the improved technical rules; consequently, this difference is observable on the whole, as well. Fig. 3 illustrates a comparison between the average annual return of every stock in the trading system and the buy and hold policy. In the Fig. 8, the difference in the total return of both approaches in every 10 stock symbol is presented. As Figure displays, we observe that the proposed trading system performs better than the asset buy and hold policy in every 10 assets. Table 4 compares the real signals on the test data and the ones proposed by the model. By correct signals, we mean the set of buy and sell signals that correspond to real signals in a trend's return points, and incorrect signals are the ones that don't correspond to a trading situation in a trend's recurrent point. Furthermore, a zero signal corresponding to the recurrent points is a trend where the system generates no trading signal.

Table. 4: Frequency of Trading Signals Proposed by System

Row	Company Name	The number of correct trading signals proposed by the network	The number of incorrect trading signals proposed by the network	The number of zero signals
1	Iran Khodro	16	4	4
2	Kalsimin	19	3	7
3	Eghtesad Novin	17	2	4
4	Naft Behran	12	1	2
5	Sakhteman Iran	14	3	4
6	Khark Petro	13	2	2
7	Daroo Jaber	12	1	3
8	Golgohar	17	2	5
9	Siman Tehran	15	2	4
10	Meli Mes	21	4	5

As observed, the major part of the signal frequency generated by the network is correct signals, such that over 63% of the issued signals are correct, and 16% of them are incorrect. In 21% of the cases, the system is unable to offer a signal at a proper time (Fig. 9).

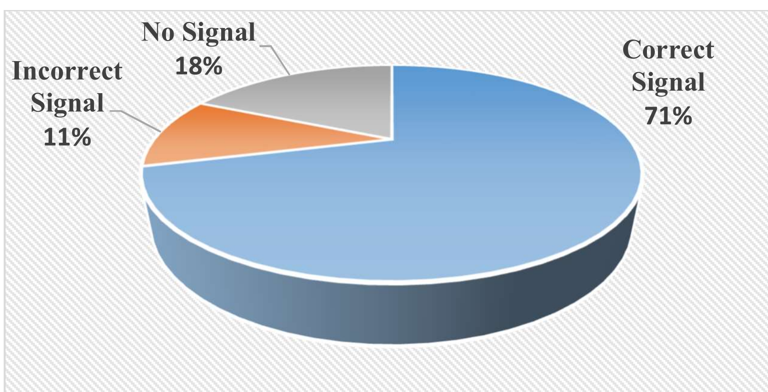

Fig. 9: Graph of Correct and Incorrect Signals in the Network

5 Discussion and Conclusion

The obtained results show that this approach enjoys a proper potential in making profits and taking trading decisions. Indeed, the intelligent trading system can be employed as an auxiliary tool and even the main one in making decisions. The results of this study reveal that the system possesses constancy and stability in addition to assisting with the gain of considerable profits. Tehrani and Abbasion [14] used only a neural network tool to investigate the schedule of entering the stock trades with a technical approach. Their results revealed that the system's performance was only suitable for downtrending markets. In uptrending markets, there was not a significant difference between the proposed trading system and the hold and buy method. However, by determining the market kind before entering the trade schedule phase, we enhanced the system's accountability in both uptrending and downtrending markets in our study. Adjusting the parameters of indicators via the genetic algorithm and leading them to a neural network, Lin et al. [12] concluded that the proposed system consisted of two separate phases in both uptrending and downtrending markets and delivered better results than the buy and hold policy. The results of their study showed that although the buy and hold policy test period had a 20.5% return, the proposed system encountered a 41.6% return.

The numbers of correct and incorrect signals were 64% and 36%, respectively, in their system. However, our proposed system with an extra phase had merely 11% incorrect signal. The average performance of the trading system designed in this study demonstrates that the technical analysis enjoys the necessary efficiency for the market traders in Iran's market. We can use artificial intelligence to increase trading efficiency by optimizing the decision-making parameters of the technical rules. Likewise, by exploiting the fuzzy logic, we can discriminate the situation and conditions of a market as properly as the intuitive method.

The most significant results of this study can be explained as below:

- Technical analysis enjoys the necessary efficiency in the trading market of Iran.
- The active approach in Iran's market has more potential than the inactive approach.
- We can use artificial intelligence to increase trading efficiency by optimizing the decision-making parameters of the technical rules.
- The performance of the technical analysis in this study can be a reason for the poor efficiency of the market.
- We can discriminate the situation and conditions of the market as properly as the intuitive method by exploiting the fuzzy logic.

The most significant suggestive topics for future studies can be described as below:

1. Comparing the performance of the trading system based on the technical analysis with other trading policies such as the reverse and momentum policies,
2. This study considered an equal weight for the portfolio assets. Distributing another weight and applying the rebalancing of the rate of investment in assets, future studies can develop a trading system and evaluate its performance.
3. Due to the presence of highly diversified technical rules, exploiting more rules to generate trading signals can be of attractive research areas.
4. Future studies may draw on the stop loss and take profit topics for getting out of a trading situation at a suitable time such that they maximize the system's profitability. Noticeably, this study specified the stop loss and take profit using trial and error, and we may be able to suggest a proper practical approach in determining these limits.
5. Exploiting other meta-heuristic algorithms in the first and third phases, such as changing the network type and replacing the genetic algorithm with other ones and comparing it with the present study.

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