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Applied-Research Paper

Evaluation of the Performance of a Dynamic Trading Strategy by Combining the Flag Pattern Detection Technique and an Exponential Moving Average

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ABSTRACT

Designing trading systems with good returns is critical for capital market investors. Trading systems are often based on a combination of several tools to use their combined information. For the first time in Iran, the present study aims to propose a pattern detection algorithm for a flag pattern based on Japanese candlestick charts and their arrangement. By recognizing the pattern and if the 4- and 10-day moving average is confirmed, a shopping position is developed, and the selling time is determined based on an optimized and dynamic process commensurate with price changes and the data scale. Our objective is to address the question of whether the returns resulting from this strategy have a more significant positive return compared to the purchase and maintenance strategy. The research sample includes the daily information of 16 active companies of basic metals in the Tehran Stock Exchange during 2007-2019, extracted from the database of Novin Rahavard software. Data analysis is performed in MATLAB software, and the obtained experimental evidence is described using a t-test. According to the results, the research strategy has a higher performance in terms of returns and risks compared to the market.

1 Introduction

Financial markets are the most important markets in every country. Financial markets make various assets available to investors, who pay attention to returns and asset risk to choose the type of investment [41]. The highest return based on the minimum risk is considered a proper criterion for investment [32]. Contrary to investors' expectations, these parameters are directly correlated, and the investment that seeks high returns must accept more risk [6, 14]. Financial markets are dynamic, complex, and nonlinear systems due to the effects of political, economic, and even psychological factors; therefore, their prediction is extremely challenging [3,8]. Nonetheless, some researchers believe that the stock market can be predicted by techniques such as technical analysis and time series analysis [23]. An accepted approach to predicting market behavior is to identify, test, and analyze the graphic patterns of the historical prices of financial assets based on indicators such as moving

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averages and artificial intelligence algorithms to assess predictive accuracy [39]. In [1, 2, 5, 11, 12, 18- 21, 34, 35, 40], the researchers propose and test various approaches to the identification of graph patterns. To date, no studies have investigated the profitability of a dynamic trading strategy using the combination of the flag pattern and an exponential moving average in the Tehran Stock Exchange (TSE). In the present study, the risk-adjusted profitable trade law is evaluated using technical analysis based on a new definition of the flag pattern proposed by Leigh et al. We also address the question of whether the returns resulting from this strategy lead to positive returns in the buy-and-hold strategy. This law defines the buying and selling time and the profit pursued in each operation, along with the maximum tolerable loss.

For this purpose, we attempt to define a strategy based on the recognition of the flag pattern, which is capable of automatic selection. We also filter the trades and improve the success of the strategy using the exponential moving average index. To exit the market, the values of the two parameters of profit and stop loss are determined using the cumulative particle algorithm. In addition, the student t-test is used to compare the results of the proposed strategy with the buy-and-hold strategy. The paper is organized into six sections; the second section contains the theoretical and brief discussions of the studies conducted in this regard. In the third section, the research methodology is explained. The fourth and fifth sections are dedicated to case studies, and their results are presented and analyzed. Finally, the sixth section contains suggestions and the limitations of our study.

2 Theoretical Foundations and Research Background

2.1 Stock Market Analysis

For decades, investors and researchers have been interested in determining the exact time of entry and exit into the capital market and stock trading. Recently, extensive research is focused on the exact time of the beginning and end of a price trend, and various tools and analyses have been invented and developed for this purpose. In general, these analyses and tools can be classified as fundamental analysis and technical analysis. In fundamental analysis, a review of the financial statements and fundamental variables of a company is performed in order to determine the value of the company's securities and meticulously examine the factors affecting these securities (e.g., risk, profit, growth, and competitive opportunities) [33]. In technical analysis, charts with historical data can be used to identify trends, patterns, and attempts to predict the behavior of stocks in the future based on technical indicators [4, 37]. Investors use these methods to predict the future direction of prices so that they could invest in the right positions. Technical analysis is considered an alternative to the use of small investors [29].

Technical indicators are functions that work based on mathematical formulas and are used to analyze charts and understand market conditions. The moving average is the main trending indicator used in the present study, which converts the irregular price signaling curve into a smooth curve, which is easily analyzed. The purpose of this variable is to determine whether the process has started or is ending its cycle. In this method, more weight is given to the most updated information [25], and the moving average is calculated using the following equations:

$$ema_n^n = \frac{x(1) + x(2) + \cdots + x(n)}{n} \tag{1}$$

$$ema_i^n = \frac{2}{1+n} x(i) + \left(1 - \frac{2}{1+n}\right) ema_{i-1}^n \quad i > n \tag{2}$$

2.2 Japanese Candlestick Chart

A time series is a set of data arranged in time. The first step in time series analysis is to draw a data graph and a time series diagram by placing the time on the horizontal axis and the desired variable on the vertical axis. The diagram shows the general direction of the variable's movement in relation to time, which varies depending on the desired variable. For instance, to create charts that should use the stock price information of companies (e.g., open/closed, high/low prices), the optimal approach to drawing involves the use of candlestick charts, such as Japanese candlestick patterns, which contain the associations between the open, closed, high, and low prices in the market.

Candlestick patterns were first used in rice markets in the 17th century and are designed to detect short-term price movements; therefore, they can be useful for short-term horizons (e.g., 10 days) [27]. Shortly after the introduction of these methods to the Western community, candlestick patterns were presented in most technical analysis software packages [28]. Candlestick patterns have two main components, including the body and the shadow. The distance between the open price and the closing of the candlestick is known as the body, and the part of the candlestick that is outside the opening and closing price range is known as the shadow. If the stock opening price is lower than the closing price, the candlestick is displayed in white, green, blue, or hollow (ascending/bullish candle), and if the stock opening price is higher than the closing price, the candlestick will be displayed in black, red, brown, or solid (bearish candle/bear). Fig. 1 depicts a schematic of this template.

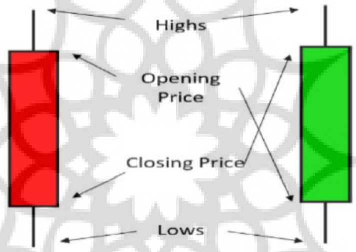


Fig. 1: Schematic of Candlestick [23]

2.3 Price Patterns

The patterns used in the technical analysis of prices are divided into two main categories of reversal and continuous. The patterns that are formed at the end of an uptrend or downtrend, which represents the return of the market, are known as an uptrend pattern, and the patterns that are formed in the middle of an uptrend or downtrend are known as a continuing pattern. Continuing patterns create low-risk trading opportunities for investors; if investors enter and exit in a timely manner, they can achieve good returns with low risk. This pattern encompasses multiple cases, and the flag pattern is used in the current research.

2.4 Flag Pattern

The flag pattern is a valid, continuous pattern, which often appears after the formation of a strong trend in the market and encompasses a period of short-term stability in a steep uptrend or downtrend. The slope of the stability period is opposite to the main trend or completely flat. As is shown in Fig. 2, this stability is enclosed between two lines of resistance and support, which are either parallel to each other or in the same direction, which resembles a flag. To calculate the pattern estimate, the height of the flagpole is initially calculated, which is the height of the movement before the pattern; the failure level is also added to this pattern.

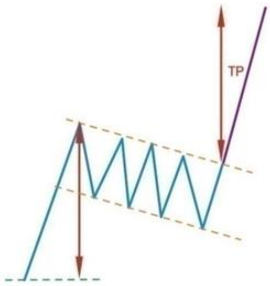
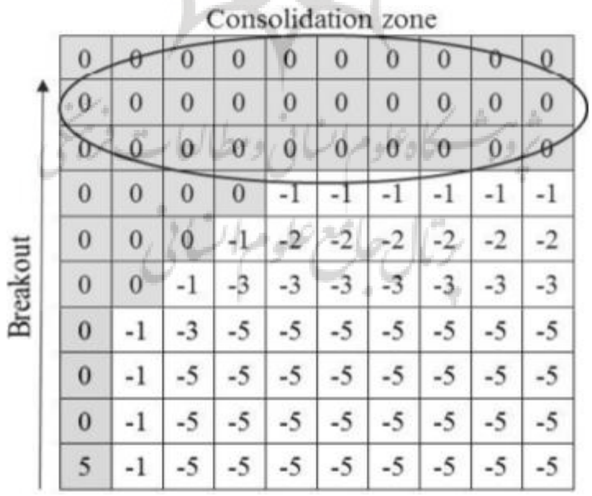


Fig. 2: A Flag Pattern

2.5 Detection of Flag Pattern

Lee et al. identified the flag pattern in three separate studies using a 10 10 10 weight grid, which allows for matching the pattern of the cow flag [18-20]. Fig. 3 depicts a weight grid that allows the identification of a bull flag pattern. To identify this pattern, the value should be placed only in non-negative cells (i.e., cells with a zero value), except for the cell on the bottom left, which carries the value of five. The first column in Fig. 3 shows a breakout, which indicates an increase in price, and the price should fluctuate on average in the upper area (zero points/gray area). The structure of the bear flag can also be obtained by multiplying a single anti-diagonal matrix in a bull flag pattern matrix.
The purpose of drawing this weight grid is to obtain the fit value, which is calculated from the sum of the points of the cells containing the candlestick. Therefore, the highest obtainable proportion value is five. When the proportion value is closer to five, the price window is more likely to be recognized as a standard flag pattern. If the candlestick is inside the cells with a negative weight (white background), the fit value will be lower and the price window is less likely a flag pattern.



0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	-1	-1	-1	-1	-1	-1
0	0	0	-1	-2	-2	-2	-2	-2	-2
0	0	-1	-3	-3	-3	-3	-3	-3	-3
0	-1	-3	-5	-5	-5	-5	-5	-5	-5
0	-1	-5	-5	-5	-5	-5	-5	-5	-5
0	-1	-5	-5	-5	-5	-5	-5	-5	-5
5	-1	-5	-5	-5	-5	-5	-5	-5	-5

Fig. 3: Flag Pattern Detection Format [2]

2.6 Particle Swarm Optimization (PSO)

Due to the limitations of mathematical methods in recent years, extensive research has been focused on the use of evolutionary optimization algorithms for optimization. Cumulative particle motion is a common orthodontic technique in this regard, which was introduced by Kenndy and Eberhart in 1995 [17]. The particle swarm algorithm is a group of stochastic optimization algorithms inspired by the social behaviors of birds in finding food. There is only one piece of food in the space in question, and none of the birds knows where to find the food. At each stage, the birds know their distance from the food site, and the optimal approach to finding the food is to follow the bird that is closest to the food. An effective strategy in this regard would be to follow the bird that has the shortest distance to the food. Particle swarm optimization (PSO) simulates this behavior in optimization problems [24]. In other words, a group of birds optimizes a specific target function, which indicates the value or suitability of the particle's location for each particle.

The PSO algorithm consists of a mass of particles that move in the search area at a certain speed, and each particle has a memory to remember the best position it reaches in the search space. Therefore, the velocity of the particle (direction and velocity value) is in two directions; one is the best experience that the particle has ever had (best amount of fit), and the other is the best experience that the adjacent particles have ever had. Fig. 4 shows the process of changing the position of the particles in the PSO algorithm [9]. Suppose there is a D-dimensional search area, and the *i*th particle of the group can be represented by a velocity vector and a position vector. Changing the position of each particle is possible by changing the previous position structure and velocity. In each *t* period, each *i* particle remembers the best experience or location (pbest), and all the particles from the best collective experience (gbest) show that they are aware. In this algorithm, the particles try to optimize their velocity and position vectors based on the following equations to attain the optimal answer:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1 \left(pbest_{ij}(t) - x_{ij}(t)\right) + c_2 r_2 \left(gbest_j(t) - x_{ij}(t)\right) \tag{3}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{4}$$

Weight parameter *w* ensures convergence and controls the effects of the previous velocity records on the current velocities. The appropriate value of this parameter often creates a balance between the general search capability and the local search, which reduces the repetition rate to find the optimal answer by selecting the appropriate value of this parameter. Furthermore, parameters c_1 and c_2 are known as the individual learning coefficient and collective learning coefficient, respectively. Appropriate work causes these parameters to rapidly converge from the beginning to the minimum point.

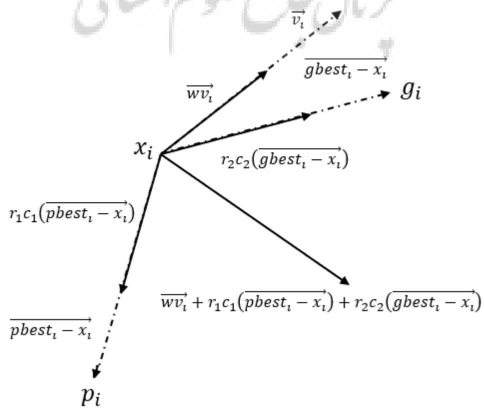


Fig. 4: Formulation of Particle Cumulative Algorithm

The higher learning factor of the individual increases the importance of their personal experience and their collective intelligence to a lesser extent, while a higher collective learning factor increases the importance of the optimal collective situation; in such a case, personal experiences are less significant, and their common selection is as follows:

$$0 \leq c_1 \leq 2 \qquad and \qquad 0 \leq c_2 \leq 2$$

Parameters r_1 and r_2 are used to maintain diversity within the group and are two random numbers with uniform distribution within the range of 0-1. These values allow the particles to move in random steps within the range between gbest and pbest [31].

2.7 Research Background

Tsinaslanidis and Guijarro [36] propose a new trading system based on the detection of new patterns, as well as the patterns that are proven profitable by other researchers (including the flag pattern), to evaluate the performance of the proposed system. They also examine the correlation between the profitability of the trading system and a set of parameters such as profit levels and stop loss, reporting that the proposed system is superior to the market index on average in terms of the mean-variance. Moreover, a positive significant correlation is observed between the means and profit, while no significant correlation is denoted with stop loss. In another study, Arevalo et al [2] propose a technical rule for short-term and midterm automated trading based on the flag pattern with a moving average indicator that can be updated with a moving window to profit and stop losses, thereby limiting the maximum amount of capital loss. Their strategy has favorable returns on purchase and maintenance strategy. Wang et al. [40] have also developed a dynamic trading method in the crude oil futures market using means and a genetic algorithm. To obtain the optimal values of existing parameters (e.g., failure levels, profit, loss limits, and portfolio optimization) in the problem, the researchers used meta-innovative algorithms, which yield effective outcomes owing to more relevance to the buy-and-hold strategy. In another study, Deng et al. [10] review and compare the performance of two cumulative particle motion optimization algorithms with the genetic algorithm in terms of selecting an efficient portfolio based on the Markowitz portfolio selection model.

According to their findings, all the cases of the cumulative particle motion optimization algorithm are more efficient than the genetic algorithm. On the other hand, Hsu et al. [16] introduce an efficient strategy for conducting mutual fund transactions using the cumulative particle motion optimization algorithm, reporting that the strategy has a high capability and achieves the highest possible returns with a minimum risk. Golmakani and Fazel [13] also propose a method to solve the Markowitz mean-variance portfolio selection model and compare the performance of two algorithms with the genetic algorithm in terms of optimizing the cumulative motion of particles. The obtained results indicate that by selecting an optimal portfolio, the cumulative particle motion optimization algorithm has a better performance compared to the genetic algorithm. Moreover, Li et al. [22] have used the meta-heuristic cumulative particle motion optimization algorithm to solve the stock portfolio optimization problem, comparing the obtained results with the genetic algorithm. The findings of the mentioned study show that the cumulative particle motion algorithm is more efficient than the genetic algorithm in solving the stock portfolio optimization problem.

Zhou and Dong [42] have used the fuzzy inference system to find the graphical patterns of technical analysis based on a fuzzy neural system as an example to predict the head and shoulder pattern through fuzzy thinking on a decision tree, and the obtained results are positive. Peymani Foroushani et al. [30] have used the daily stock prices of the companies listed on the TSE, examining the rate of returns and the percentage of investment success based on candlestick charts. According to the findings, the candlestick for sale is in a one-day holding period, and the purchased candles have the highest efficiency with a 10-day storage period. Vakili et al. [38] have designed an automated control system using an exponential moving average as the most common indicator of technical analysis for decision-making on stock buying and selling. Moreover, they integrate Markowitz's model with GARCH and FIGARCH models to model risk and calculate the optimal weights of the assets in the portfolio. In the mentioned study, the system designed based on the FIGARCH turbulence prediction model has the highest efficiency compared to the other models owing to its long-term memory. On the other hand, Saghafi Kalvanagh et al. [33] have evaluated the usefulness of a group of short-term technical analysis models known as Japanese candlestick patterns. According to the findings, the Japanese candlestick patterns can accurately predict the future direction of price and profitability, while these profits are eliminated considering the transaction fee.

Nabavi and Hassanzadeh [26] have also investigated the efficiency of moving averages, moving average weights, and exponential moving averages in technical analysis to predict stock prices. The obtained results indicate that the exponential moving average has a higher validity in stock price prediction and is more reliable in terms of validation indicators (i.e., mean absolute deviation and tracking signal). In another research, Demouri et al. [7] examined and compared the ability of the particle cumulative motion optimization algorithm with traditional models in predicting the total stock price index in the TSE, reporting that the cumulative particle motion optimization algorithm has a higher predictive accuracy compared to conventional methods such as ARIMA.

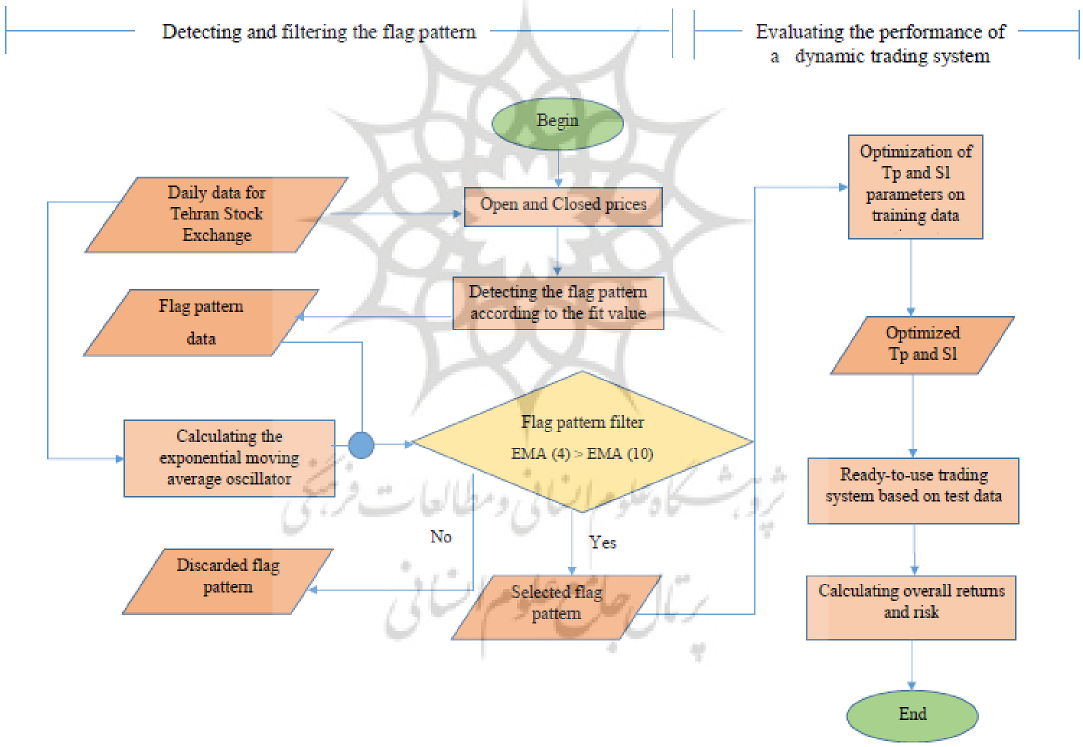


Fig. 5: Flowchart of Proposed Trading System

3 Research Methodology

This descriptive research is conducted based on the objective of field research and the data collection method. New data collection software and the TSE client software are used to collect data, and MATLAB software is utilized to sort the data and perform statistical calculations. The statistical population consists of active basic metal companies (steel industry) in the TSE from the beginning of 2007 to May 2019. The number of the studied companies is reduced to 16 after imposing the following restrictions:

- All the companies have to trade on the TSE within a specific period.
- The number of open days during the period of the review has to be more than 90% of trading days.

Fig. 5 shows the implementation of the study framework, which is based on the study by Arevalo. We address the question of whether the returns due to the strategy are based on the flag pattern and whether the moving average of the returns is based on the returns of the buy-and-hold strategy (market). Furthermore, we evaluate whether there can any positive means.

3.1 Procedure

As mentioned in the previous section, the flag pattern is initially identified using a Japanese candlestick-based scoring system, and the 10-day stock price within the frame is set at 10 by 10 images. The following conversion is applied for the image of point x_1 on y_1 and point x_2 on point y_2:

$$y - y_1 = \frac{y_2 - y_1}{x_2 - x_1}(x - x_1) \tag{5}$$

In the next stage, the frame score is calculated from the total score of the boxes filled by the candles, which correspond to the prices in the frame. The minimum value obtained with this approach is -203, and the maximum value is five. Following that, we consider a short-term four-day moving average and a 10-day long-term moving average to provide a pattern for entering the market. On the last day (day 10) and after obtaining the appropriate score, the developed pattern has a higher short-term moving average than the long-term moving average (i.e., probability of market ascent).

After receiving the buy signal, a mechanism is provided to close the trading position and exit the market. In the present study, we use two levels for this purpose, which are profit and stop loss. To calculate these parameters, the cumulative particle optimization approach is applied to the training data, and the price data is divided into two categories of training and test data. By maximizing the objective function (i.e., average daily returns of trading positions) using the particle swarm algorithm, parameters *tp* and *sl* are optimized (Table 1). Afterward, the distance between the maximum and minimum prices in the 10-day framework is calculated (R). If the purchase price is indicated in *pbuy*, the trading position will be closed on the first day after the purchase, as follows:

$$-pbuy \geq tp.R \quad or \quad p - pbuy \leq -sl.R \tag{6}$$

Table 1: Specifications of Particle Cumulative Algorithm

```
MaxIt=200; % Maximum Number of Iterations
nPop=100; % Swarm Size
% w=1; % Inertia Weight
% wdamp=0.99; % Inertia Weight Damping Ratio
% c1=2; % Personal Learning
% c2=2; % Global Learning
Phi1=2.05;
phi2=2.05;
phi=phi1+phi2;
chi=2/(phi-2+sqrt(phi^2-4*phi));
w=chi; % Inertia Weight
wdamp=1; % Inertia Weight Damping Ratio
c1=chi*phi1; % Personal Learning Coefficient
c2=chi*phi2; % Global Learning Coefficient
```

Under such circumstances, the investor leaves the market with a good return or an intention of preventing further losses. With two optimal parameters in hand, the trading system is complete and ready to use on the test data. The trading positions that are created based on the trading system and the test data are recorded for statistical inference. If the number of *n* positions is available after identifying the trading positions, the result will be as follows:

number	*trade time*	*return*
1	t_1	r_1
2	t_2	r_2
$\vdots$	$\vdots$	$\vdots$
n	t_n	r_n

For each position equal to the daily return in this case, the obtained return (rd) is calculated by:

$$rd_i = (1 + r_i)^{\frac{1}{t_i}} - 1 \quad i = 1,2,\cdots,n \tag{7}$$

where t_i is the time interval between the sales, and r_i is the obtained efficiency. The efficiency, risk, and sharp ratio of the trading positions are calculated by:

$$Return\ = \frac{\sum_{i=1}^{n} rd_i}{n} \tag{8}$$

$$Risk = \frac{1}{n}\left(\sum_{i=1}^{n}(rd_i - return)^2\right) \tag{9}$$

$$Sharp\,ratio = \frac{return}{risk} \tag{10}$$

The calculated statistical parameters are compared with the market strategy, which involves the random selection of a day in the test data and trading on the same day.

4 Data Analysis

For data analysis, we use the daily opening and closing prices of the shares of 16 basic metal companies during 2007-2019. First, the price data are divided into two equal categories of training and test data, and the data are used to calculate the daily return, fitness value, and statistical indicators. Table 2 shows the number of the identified positions for the value of the ratio, duration of the trade, and the average return. If the flag pattern detection is subject to a score of +5 and the short-term moving average is higher than the long-term moving average, only 26 positions are identified, which is 0.07% of the sample data. To obtain statistical significance, scores between -5 and +5 are considered.

According to the information in Table 2, the flag pattern with the highest return is the pattern with a score of +1 and a total of 30 positions, as well as the average daily return and average trading return of 0.01274 and 0.03131, respectively. As mentioned earlier, the research strategy requires the calculation of the 4- and 10-day moving average of the price, which is a graph of part of the data on the national share of Iran's copper industry, along with two short-term and long-term moving averages (Fig.6).

Table 2: Summary of Results by Proportional Values (Trading Points)

Fit value	Number	Probability of detected position	Term of transaction	Average daily returns	Average transaction returns
+5	26	0.07027	344	0.00395	0.00368
+4	21	0.05676	309	-0.00373	-0.01901
+3	22	0.05946	315	-0.00122	-0.01915
+2	23	0.06216	236	-0.00961	-0.00872
+1	30	0.08108	304	0.01274	0.03131
0	26	0.07027	278	-0.00247	-0.02189
-1	40	0.10811	432	-0.00343	0.01914
-2	33	0.08919	397	0.00237	0.01194
-3	36	0.09730	398	-0.00955	0.01808
-4	44	0.11892	434	-0.00121	-0.01026
-5	69	0.18649	930	0.00861	0.01365

Table 3: Statistical Description of Market Position

Company symbol	Daily number	Average	Standard deviation	skewness	Elongation	Bara Jark statistics
Fasiman	2538	0	0.35	-1.932	90.493	811090.2
Fabahonar	2590	0.001	0.28	-0.012	16.225	18873.88
Fapanta	1701	0.003	0.039	10.05	256.193	4572199
Fajr	2043	0.002	0.027	3.522	135.029	1488088
Fakhas	2227	0.001	0.021	1.246	99.828	870552.855
Fakhooz	2336	0.001	0.029	-5.526	197.925	3710138
Faravar	2360	0.001	0.044	1.914	172.827	2837485.036
Faroos	1891	0.001	0.027	-4.826	117.19	1034733.937
Fasrab	2430	0.001	0.035	0.587	91.094	785894.549
Falooleh	2297	0.001	0.026	-1.609	18.702	24586.754
Famli	2667	0.0004	0.026	-8.729	210.168	4803205.473
Fanval	1841	0.001	0.04	-4.745	155.308	1786356.407
Fanvard	1711	0.002	0.036	14.473	460.182	14960819.13
Foolad	2644	0.001	0.025	-5.459	82.008	700830.906
Kamanganz	2328	0.001	0.032	-3.098	113.566	1189541
Vetoka	2580	0	0.028	-4.61	83.069	698331.598

Tables 3 and 4 show the statistical description of the daily stock returns of the surveyed companies in the market positions and research system. For instance, the national share of Iran's copper industry in the market has an average daily return of 0.0004, and achieving this return bears a risk of 0.026. In the research trading system, the average trading positions produce a daily return of 0.0002, which bears a risk of 0.03.

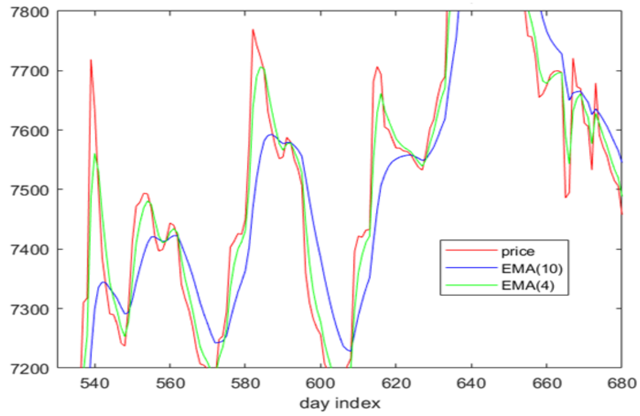


Fig. 6: Family Stock Price with Mean Short-Term and Long-Term Moving Averages

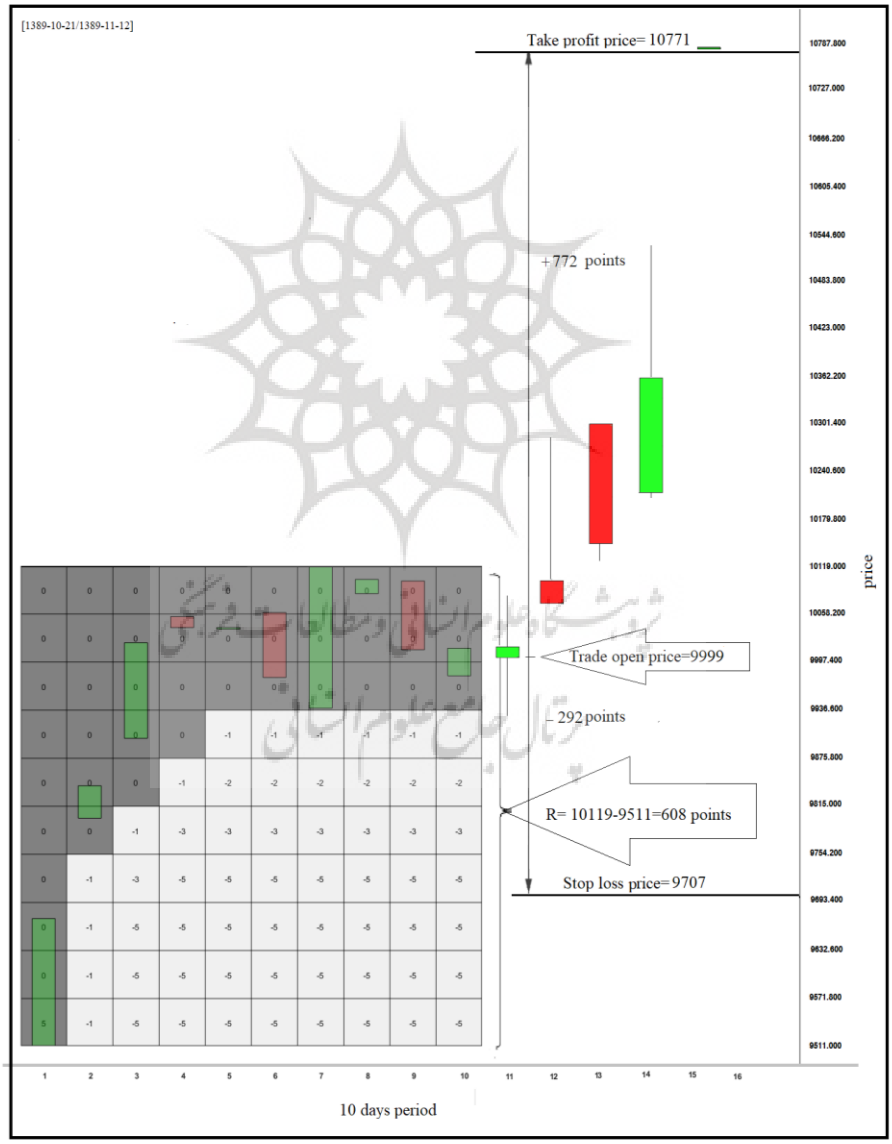


Fig. 7: Profit Level and Stop Loss for a Family Company Trading Position

In addition, the stock statistics in both positions indicate that at the confidence level of 0.95, the daily stock return distribution does not follow a normal distribution. In the last two columns of Table 4, the profit and loss limits are presented. In addition, Fig. 7 shows the level of profit and stop loss in the trading position of the National Iranian Copper Industries Company, where *R* is the maximum and minimum distance. The price experienced in the 10-day frame is calculated using Equation 6, and the levels of profit and stop loss are estimated at 9,707 and 10,771, respectively.

Table 4: Statistical Description of the Discovered Positions and the Optimal Parameters of the Trading System

Company symbol	Daily number	Average	Standard deviation	skewness	Elongation	Bara Jark statistics	Profit limit	Loss limit
Fasiman	37	0.007	0.073	-2.649	60.73	5181.267	0.86	0.51
Fabahonar	23	-0.002	0.018	0.086	1.179	14873.88	0.64	0.83
Fapanta	21	0.006	0.043	10.613	194.045	32330.143	0.79	0.54
Fajr	20	0.0176	0.051	4.192	128.246	13130.710	0.92	0.28
Fakhas	13	0.006	0.023	1.239	101.48	5256.578	1.41	0.71
Fakhooz	36	0.002	0.017	-1.526	226.356	74845.826	0.81	0.59
Faravar	18	0.004	0.03	1.098	152.313	16724.396	0.98	0.67
Faroos	17	0.01	0.013	1.027	92.721	5704.971	1.03	0.56
Fasrab	20	0.02	0.091	0.857	49.445	1800.062	0.74	0.42
Falooleh	22	0.01	0.03	-2.498	13.533	124.579	1.15	0.36
Famli	36	0.0002	0.03	-5984	225.611	74548.336	1.27	0.48
Fanval	20	0.007	0.016	-4.485	155.554	19460.987	1.25	0.62
Fanoord	13	0.008	0.033	13.247	411.074	90580.924	0.68	0.43
Foolad	31	0.003	0.023	-4.383	62.947	4741.0439	0.72	0.51
Kamanganz	22	0.005	0.024	-5.603	70.733	4320.556	1.02	0.61
Vetoka	21	0.005	0.025	-4.095	99.069	8134.288	0.83	0.57

5 Results

Table 5 shows a summary of market performance and research system. Market strategy refers to the random selection of a day in the test data and trading on the same day. The data in the table show that the research trading system has a different performance (in terms of return and risk) from market performance. Therefore, the research strategy in return and risk has a higher performance than the market, and the return of the research system further increases the market return, while the risk decreases almost relative to the market and has a sharper ratio. In addition, the adjusted return is significantly higher compared to the sharp market ratio.

To examine the similarity of the average daily efficiency of the research system and the system based on market performance, the independent t-test is used for two communities of different sizes. According to the information in Table 6, the homogeneity test is initially at the significance level of 0.25687. Since this significance level is higher than 0.05, the variance of the two positions is the same. Moreover, the calculated t-test statistic is estimated at 2.59630, which is not at the confidence interval of 0.95. Therefore, the difference between the means is considered significant.

Table 5: Comparison of Market Performance and Research System on Test Data

	Performance of research system on test data			Market performance on test data		
Company Symbol	**Daily Return Average**	**Daily Risk**	**Daily Sharp**	**Daily Return Average**	**Daily Risk**	**Daily Sharp**
Fasiman	0.00682	0.07347	0.09277	0.00139	0.03489	0.03976
Fabahonar	0.00240	0.01763	0.13570	-0.036042	0.02833	-1.27222
Fapanta	0.006463	0.04334	0.14911	0.00389	0.03887	0.10008
Fajr	0.01762	0.05057	0.34843	0.00028	0.02713	0.01018
Fakhas	0.00612	0.02299	0.26622	0.00167	0.02137	0.07796
Fakhooz	0.00223	0.01717	0.12993	0.00094	0.02888	0.03271
Faravar	0.00448	0.02988	0.14993	0.00249	0.04354	0.05718
Faroos	0.01152	0.01276	0.90305	0.00683	0.02746	0. 24866
Fasrab	0.01761	0.09050	0.19462	0.00859	0.03515	0.24429
Falooleh	0.01053	0.03044	0.34575	0.00548	0.02639	0.20747
Famli	0.00029	0.02967	0.00976	0.00046	0.02551	0.01821
Fanval	0.00725	0.01659	0.43722	0.00081	0.04023	0.01971
Fanoord	0.00847	0.03319	0.25505	0.00074	0.03581	0.02061
Foolad	0.00281	0.01340	0.20911	0.00073	0.02483	0.02927
Kamanganz	0.00527	0.01388	0.37969	0.00035	0.03229	0.01076
Vetoka	0.00526	0.02467	0.21316	0.00093	0.02824	0.03275

Table 6: Equality Test for Daily Average Efficiency

Variable	Average	Equality test of variances F	Mean comparison test T
Average system efficiency	0.0072	0.25687	2.59630
Average market efficiency	-0.000032		

6 Discussion and Conclusion

Financial markets, which are one of the most attractive inventions of our time, have a significant impact on several areas, such as trade, education, technology, and economics [15]. Due to the complexity of financial markets and the importance of speed in decision-making, automated trading systems have received great attention. Price patterns are widely used by investors who seek maximum returns, while in general, pattern detection techniques are often convincing and do not provide stock forecasts [40]. Instead of using pattern detection techniques alone to predict stocks, it is better to combine these methods with other techniques that have proven superior. In the present study, we attempt to define a strategy capable of automatic selection based on the detection of the flag pattern and the previous studies regarding the exponential moving average and cumulative particle algorithm [7, 10, 13, 16, 22, 26]. To filter trades and improve the success of the strategy, the exponential moving average index is used. To exit the market, the values of the two parameters of profit and stop loss are determined using the cumulative particle algorithm. The results of the student t-test regarding the proposed strategy are compared with the buy-and-hold strategy, and the obtained results show that the proposed strategy is superior in return and almost in risk compared to the buy-and-hold strategy. Therefore, the strategy can predict the future price movement of the stock.

7 Suggestions and Limitations

Although the results of our study are generally promising and show that technical analysis is effective in the Iranian trading market, further research is required in this regard. Researchers are advised to dynamically determine all parameter values to fully automate the trading system or to optimize the parameters by several machine learning techniques. In subsequent market research (e.g., gold and dollars) researchers should consider other oscillators, such as the relative power oscillator or the random oscillator, as they can also be used to replace the moving average oscillator. Other technical analysis models can also be used for this purpose, such as the head and shoulder pattern. Considering that Arevalo et al. (2017) have examined their strategy based on price during the day (price within the day), our study also employs price during the day although these data are not easily available for the TSE. Daily open and closed prices are also used in the present study. The main limitation of our research is the lack of easy access to some of the required data. Considering the restrictions in selecting the companies, caution should be exercised in generalizing our findings to all the companies listed on the TSE.

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